STATA USER'S GUIDE
RELEASE 19

A Stata Press Publication
StataCorp LLC
College Station, Texas

Copyright © 1985–2025 StataCorp LLC
All rights reserved
Version 19

Published by Stata Press, 4905 Lakeway Drive, College Station, Texas 77845

ISBN-10: 1-59718-449-7
ISBN-13: 978-1-59718-449-6

This manual is protected by copyright. All rights are reserved. No part of this manual may be reproduced, stored in a retrieval system, or transcribed, in any form or by any means—electronic, mechanical, photocopy, recording, or otherwise—without the prior written permission of StataCorp LLC unless permitted subject to the terms and conditions of a license granted to you by StataCorp LLC to use the software and documentation. No license, express or implied, by estoppel or otherwise, to any intellectual property rights is granted by this document.

StataCorp provides this manual "as is" without warranty of any kind, either expressed or implied, including, but not limited to, the implied warranties of merchantability and fitness for a particular purpose. StataCorp may make improvements and/or changes in the product(s) and the program(s) described in this manual at any time and without notice.

The software described in this manual is furnished under a license agreement or nondisclosure agreement. The software may be copied only in accordance with the terms of the agreement. It is against the law to copy the software onto DVD, CD, disk, diskette, tape, or any other medium for any purpose other than backup or archival purposes.

The automobile dataset appearing on the accompanying media is Copyright © 1979 by Consumers Union of U.S., Inc., Yonkers, NY 10703-1057 and is reproduced by permission from CONSUMER REPORTS, April 1979.

Stata, STATA, Stata Press, Mata, MATA, and NetCourse are registered trademarks of StataCorp LLC.

Stata and Stata Press are registered trademarks with the World Intellectual Property Organization of the United Nations.

StataNow and NetCourseNow are trademarks of StataCorp LLC.

Other brand and product names are registered trademarks or trademarks of their respective companies.

For copyright information about the software, type `help copyright` within Stata.

The suggested citation for this software is

> StataCorp. 2025. *Stata 19*. Statistical software. StataCorp LLC.

The suggested citation for this manual is

> StataCorp. 2025. *Stata 19 User's Guide* . College Station, TX: Stata Press.

Contents

Stata basics

Elements of Stata

Advice

Stata basics

1 Read this—it will help

Contents

1.1 Getting started with Stata

To get started with Stata, you should

1. Read the *Getting Started* (GSM, GSU, or GSW) manual for your operating system.
2. Then turn to the other manuals; see **[U] 1.2 The Stata Documentation**.

1.2 The Stata Documentation

The *User's Guide* is divided into three sections: *Stata basics*, *Elements of Stata*, and *Advice*. The table of contents lists the chapters within each of these sections. Click on the chapter titles to see the detailed contents of each chapter.

The *Guide* is full of a lot of useful information about Stata; we recommend that you read it. If you only have time, however, to read one or two chapters, then read **[U] 11 Language syntax** and **[U] 12 Data**.

The other manuals are the *Reference* manuals. The Stata *Reference* manuals are each arranged like an encyclopedia—alphabetically. Look at the *Base Reference Manual*. Look under the name of a command. If you do not find the command, look in the subject index in [I] *Stata Index*. A few commands are so closely related that they are documented together, such as `ranksum` and `median`, which are both documented in [R] **ranksum**.

Not all the entries in the *Base Reference Manual* are Stata commands; some contain technical information, such as [R] **Maximize**, which details Stata's iterative maximization process, or [R] **Error messages**, which provides information on error messages and return codes.

Like an encyclopedia, the *Reference* manuals are not designed to be read from cover to cover. When you want to know what a command does, complete with all the details, qualifications, and pitfalls, or when a command produces an unexpected result, read its description. Each entry is written at the level of the command. The descriptions assume that you have little knowledge of Stata's features when they are explaining simple commands, such as those for using and saving data. For more complicated commands, they assume that you have a firm grasp of Stata's other features.

If a Stata command is not in the *Base Reference Manual*, you can find it in one of the other *Reference* manuals. The titles of the manuals indicate the types of commands that they contain. The *Programming Reference Manual*, however, contains commands not only for programming Stata but also for manipulating matrices (not to be confused with the matrix programming language described in the *Mata Reference Manual*).

The complete list of Stata Documentation is as follows:

[GSM]	*Getting Started with Stata for Mac*
[GSU]	*Getting Started with Stata for Unix*
[GSW]	*Getting Started with Stata for Windows*
[U]	*Stata User's Guide*
[R]	*Stata Base Reference Manual*
[ADAPT]	*Stata Adaptive Designs: Group Sequential Trials Reference Manual*
[BAYES]	*Stata Bayesian Analysis Reference Manual*
[BMA]	*Stata Bayesian Model Averaging Reference Manual*
[CAUSAL]	*Stata Causal Inference and Treatment-Effects Estimation Reference Manual*
[CM]	*Stata Choice Models Reference Manual*
[D]	*Stata Data Management Reference Manual*
[DSGE]	*Stata Dynamic Stochastic General Equilibrium Models Reference Manual*
[ERM]	*Stata Extended Regression Models Reference Manual*
[FMM]	*Stata Finite Mixture Models Reference Manual*
[FN]	*Stata Functions Reference Manual*
[G]	*Stata Graphics Reference Manual*
[H2OML]	*Machine Learning in Stata Using H2O: Ensemble Decision Trees Reference Manual*
[IRT]	*Stata Item Response Theory Reference Manual*
[LASSO]	*Stata Lasso Reference Manual*
[XT]	*Stata Longitudinal-Data/Panel-Data Reference Manual*
[META]	*Stata Meta-Analysis Reference Manual*
[ME]	*Stata Multilevel Mixed-Effects Reference Manual*
[MI]	*Stata Multiple-Imputation Reference Manual*
[MV]	*Stata Multivariate Statistics Reference Manual*
[PSS]	*Stata Power, Precision, and Sample-Size Reference Manual*
[P]	*Stata Programming Reference Manual*
[RPT]	*Stata Reporting Reference Manual*
[SP]	*Stata Spatial Autoregressive Models Reference Manual*
[SEM]	*Stata Structural Equation Modeling Reference Manual*
[SVY]	*Stata Survey Data Reference Manual*
[ST]	*Stata Survival Analysis Reference Manual*
[TABLES]	*Stata Customizable Tables and Collected Results Reference Manual*
[TS]	*Stata Time-Series Reference Manual*
[I]	*Stata Index*
[M]	*Mata Reference Manual*

In addition, installation instructions may be found in the *Installation Guide*.

1.2.1 PDF manuals

Every copy of Stata comes with Stata's complete PDF documentation.

The PDF documentation may be accessed from within Stata by selecting **Help** > **PDF documentation**. Even more convenient, every help file in Stata links to the equivalent manual entry. If you are reading **help regress**, simply click on `(View complete PDF manual entry)` below the title of the help file to go directly to the [R] **regress** manual entry.

We provide some tips for viewing Stata's PDF documentation at https://www.stata.com/support/faqs/resources/pdf-documentation-tips/.

1.2.1.1 Video example

PDF documentation in Stata

1.2.2 Example datasets

Various examples in this manual use what is referred to as the automobile dataset, `auto.dta`. We have created a dataset on the prices, mileages, weights, and other characteristics of 74 automobiles and have saved it in a file called `auto.dta`. (These data originally came from the April 1979 issue of *Consumer Reports* and from the United States Government EPA statistics on fuel consumption; they were compiled and published by Chambers et al. [1983].)

In our examples, you will often see us type

```
. use https://www.stata-press.com/data/r19/auto
```

We include the `auto.dta` file with Stata. If you want to use it from your own computer rather than via the internet, you can type

```
. sysuse auto
```

See [D] **sysuse**.

You can also access `auto.dta` by selecting **File > Example datasets...**, clicking on *Example datasets installed with Stata*, and clicking on `use` beside the `auto.dta` filename.

There are many other example datasets that ship with Stata or are available over the web. Here is a partial list of the example datasets included with Stata:

`auto.dta`	1978 automobile data
`bplong.dta`	Fictional blood-pressure data, long form
`bpwide.dta`	Fictional blood-pressure data, wide form
`cancer.dta`	Patient survival in drug trial
`census.dta`	1980 Census data by state
`citytemp.dta`	US city temperature data
`educ99gdp.dta`	Education and gross domestic product
`gnp96.dta`	US gross national product, 1967–2002
`lifeexp.dta`	1998 life expectancy
`network1.dta`	Fictional network diagram data
`nlsw88.dta`	1988 US National Longitudinal Survey of Young Women (NLSW), extract
`pop2000.dta`	2000 US Census population, extract
`sandstone.dta`	Subsea elevation of Lamont sandstone in an area of Ohio
`sp500.dta`	S&P 500 historic data
`surface.dta`	NOAA sea surface temperature
`tsline1.dta`	Simulated time-series data
`uslifeexp.dta`	US life expectancy, 1900–1999
`voter.dta`	1992 US presidential voter data

All of these datasets may be used or described from the **Example datasets...** menu listing.

Even more example datasets, including most of the datasets used in the reference manuals, are available at the Stata Press website (https://www.stata-press.com/data/). You can download the datasets with your browser, or you can `use` them directly from the Stata command line:

```
. use https://www.stata-press.com/data/r19/nlswork
```

An alternative to the `use` command for these example datasets is `webuse`. For example, typing

```
. webuse nlswork
```

is equivalent to the above `use` command. For more information, see [D] **webuse**.

1.2.2.1 Video example

Example datasets included with Stata

1.2.3 Cross-referencing

The *Getting Started* manual, the *User's Guide*, and the *Reference* manuals cross-reference each other.

[R] **regress**
[D] **reshape**
[XT] **xtreg**

The first is a reference to the `regress` entry in the *Base Reference Manual*, the second is a reference to the `reshape` entry in the *Data Management Reference Manual*, and the third is a reference to the `xtreg` entry in the *Longitudinal-Data/Panel-Data Reference Manual*.

[GSW] B Advanced Stata usage
[GSM] B Advanced Stata usage
[GSU] B Advanced Stata usage

are instructions to see the appropriate section of the *Getting Started with Stata for Windows*, *Getting Started with Stata for Mac*, or *Getting Started with Stata for Unix* manual.

1.2.4 The index

The *Stata Index* contains a combined index for all the manuals.

To find information and commands quickly, you can use Stata's `search` command; see [R] **search**. At the Stata command prompt, type `search geometric mean`. `search` searches Stata's keyword database and the internet to find more commands and extensions for Stata written by Stata users.

1.2.5 The subject table of contents

A subject table of contents for the *User's Guide* and all the *Reference* manuals is located in the *Stata Index*. This subject table of contents may also be accessed by clicking on **Contents** in the PDF bookmarks.

1.2.6 Typography

We mix the ordinary typeface that you are reading now with a typewriter-style typeface `that looks like this`. When something is printed in the typewriter-style typeface, it means that something is a command or an option—it is something that Stata understands and something that you might actually type into your computer. Differences in typeface are important. If a sentence reads, "You could list the result …", it is just an English sentence—you *could* list the result, but the sentence provides no clue as to how you might actually do that. On the other hand, if the sentence reads, "You could `list` the result …", it is telling you much more—you could list the result, and you could do that by using the `list` command.

We will occasionally lapse into periods of inordinate cuteness and write, "We `described` the data and then `listed` the data." You get the idea. `describe` and `list` are Stata commands. We purposely began the previous sentence with a lowercase letter. Because `describe` is a Stata command, it must be typed in lowercase letters. The ordinary rules of capitalization are temporarily suspended in favor of preciseness.

We also mix in words printed in italic type, such as "To perform the rank-sum test, type `ranksum` *varname*`, by(`*groupvar*`)`". Italicized words are not supposed to be typed; instead, you are to substitute another word for them.

We would also like users to note our rule for punctuation of quotes. We follow a rule that is often used in mathematics books and British literature. The punctuation mark at the end of the quote is included in the quote only if it is a part of the quote. For instance, the pleased Stata user said she thought that Stata was a "very powerful program". Another user simply said, "I love Stata."

In this manual, however, there is little dialogue, and we follow this rule to precisely clarify what you are to type, as in, type "`cd c:`". The period is outside the quotation mark because you should not type the period. If we had wanted you to type the period, we would have included two periods at the end of the sentence: one inside the quotation and one outside, as in, type "the orthogonal polynomial operator, `p.`".

We have tried not to violate the other rules of English. If you find such violations, they were unintentional and resulted from our own ignorance or carelessness. We would appreciate hearing about them.

We have heard from Nicholas J. Cox of the Department of Geography at Durham University, UK, and express our appreciation. His efforts have gone far beyond dropping us a note, and there is no way with words that we can fully express our gratitude.

1.2.7 Vignette

If you look, for example, at the entry [R] **brier**, you will see a brief biographical vignette of Glenn Wilson Brier (1913–1998), who did pioneering work on the measures described in that entry. A few such vignettes were added without fanfare in the Stata 8 manuals, just for interest, and many more were added in Stata 9, and even more have been added in each subsequent release. A vignette could often appropriately go in several entries. For example, George E. P. Box deserves to be mentioned in entries other than [TS] **arima**, such as [R] **boxcox**. However, to save space, each vignette is given once only, and an index of all vignettes is given in the *Stata Index*.

Most of the vignettes were written by Nicholas J. Cox, Durham University, and were compiled using a wide range of reference books, articles in the literature, internet sources, and information from individuals. Especially useful were the dictionaries of Upton and Cook (2014) and Everitt and Skrondal (2010) and the compilations of statistical biographies edited by Heyde and Seneta (2001) and Johnson and Kotz (1997). Of these, only the first provides information on people living at the time of publication.

1.3 What's new

There are a lot of new features in Stata 19.

For a thorough overview of the most important new features, visit

https://www.stata.com/new-in-stata/

For a brief overview of all the new features that were added with the release of Stata 19, in Stata type

```
. help whatsnew18to19
```

Stata is continually being updated. For a list of new features that have been added since the release of Stata 19, in Stata type

```
. help whatsnew19
```

1.4 References

Chambers, J. M., W. S. Cleveland, B. Kleiner, and P. A. Tukey. 1983. *Graphical Methods for Data Analysis*. Belmont, CA: Wadsworth.

Everitt, B. S., and A. Skrondal. 2010. *The Cambridge Dictionary of Statistics*. 4th ed. Cambridge: Cambridge University Press.

Gould, W. W. 2014. Putting the Stata Manuals on your iPad. *The Stata Blog: Not Elsewhere Classified*. https://blog.stata.com/2014/10/28/putting-the-stata-manuals-on-your-ipad/.

Heyde, C. C., and E. Seneta, eds. 2001. *Statisticians of the Centuries*. New York: Springer.

Johnson, N. L., and S. Kotz, eds. 1997. *Leading Personalities in Statistical Sciences: From the Seventeenth Century to the Present*. New York: Wiley.

Pinzon, E., ed. 2015. *Thirty Years with Stata: A Retrospective*. College Station, TX: Stata Press.

Upton, G. J. G., and I. T. Cook. 2014. *A Dictionary of Statistics*. 3rd ed. Oxford: Oxford University Press.

2 A brief description of Stata

Stata is a statistical package for managing, analyzing, and graphing data.

Stata is available for a variety of platforms. Stata may be used either as a point-and-click application or as a command-driven package.

Stata's GUI provides an easy interface for those new to Stata and for experienced Stata users who wish to execute a command that they seldom use.

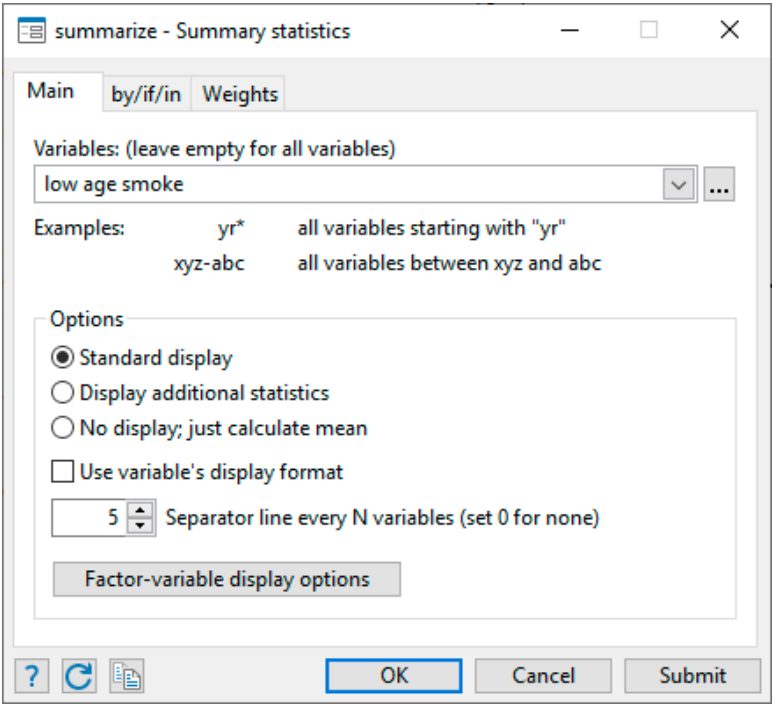
The command language provides a fast way to communicate with Stata and to communicate more complex ideas.

Here is an extract of a Stata session using the GUI:

(Throughout the Stata manuals, we will refer to various datasets. These datasets are all available from https://www.stata-press.com/data/r19/. For easy access to them within Stata, type `webuse` *dataset_name*, or select **File > Example datasets...** and click on *Stata 19 manual datasets*.)

```
. webuse lbw
(Hosmer & Lemeshow data)
```

We select **Data > Describe data > Summary statistics** and choose to summarize variables `low`, `age`, and `smoke`, whose names we obtained from the Variables window. We click on **OK**.

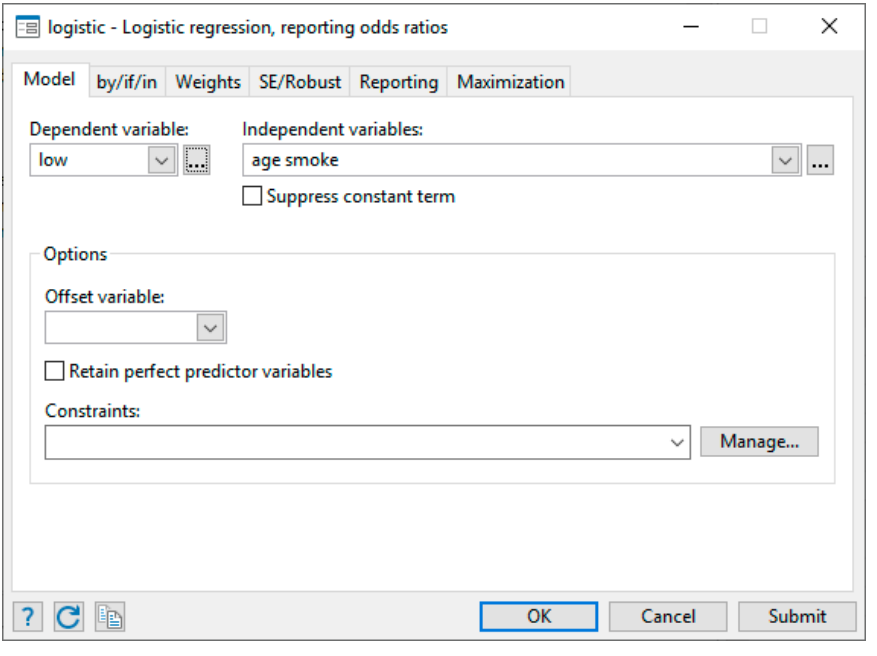


```
. summarize low age smoke
```

Variable	Obs	Mean	Std. dev.	Min	Max
low	189	.3121693	.4646093	0	1
age	189	23.2381	5.298678	14	45
smoke	189	.3915344	.4893898	0	1

Stata shows us the command that we could have typed in command mode—`summarize low age smoke`—before displaying the results of our request.

Next we fit a logistic regression model of `low` on `age` and `smoke`. We select **Statistics > Binary outcomes > Logistic regression**, fill in the fields, and click on **OK**.




```
. logistic low age smoke
Logistic regression                                     Number of obs =    189
                                                        LR chi2(2)    =   7.40
                                                        Prob > chi2   = 0.0248
Log likelihood = -113.63815                             Pseudo R2     = 0.0315
```

low	Odds ratio	Std. err.	z	P>|z|	[95% conf.	interval]
age	.9514394	.0304194	-1.56	0.119	.8936482	1.012968
smoke	1.997405	.642777	2.15	0.032	1.063027	3.753081
_cons	1.062798	.8048781	0.08	0.936	.2408901	4.689025

Note: **_cons** estimates baseline odds.

Here is an extract of a Stata session using the command language:

```
. use https://www.stata-press.com/data/r19/auto
(1978 automobile data)
. summarize mpg weight
```

Variable	Obs	Mean	Std. dev.	Min	Max
mpg	74	21.2973	5.785503	12	41
weight	74	3019.459	777.1936	1760	4840

The user typed `summarize mpg weight` and Stata responded with a table of summary statistics. Other commands would produce different results:

```
. generate gp100m = 100/mpg
. label var gp100m "Gallons per 100 miles"
. format gp100m %5.2f
. correlate gp100m weight
(obs=74)
```

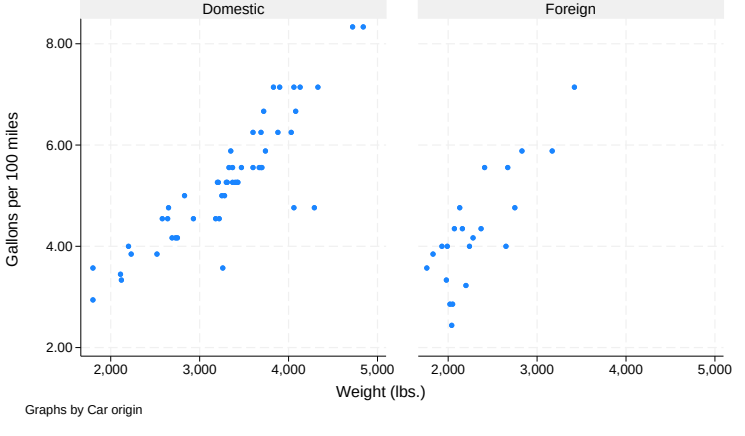
	gp100m	weight
gp100m	1.0000	
weight	0.8544	1.0000

```
. regress gp100m weight gear_ratio
```

Source	SS	df	MS		
Model	87.4543721	2	43.7271861	Number of obs	= 74
Residual	32.1218886	71	.452420967	F(2, 71)	= 96.65
				Prob > F	= 0.0000
				R-squared	= 0.7314
				Adj R-squared	= 0.7238
Total	119.576261	73	1.63803097	Root MSE	= .67262

gp100m	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
weight	.0014769	.0001556	9.49	0.000	.0011665	.0017872
gear_ratio	.1566091	.2651131	0.59	0.557	-.3720115	.6852297
_cons	.0878243	1.198434	0.07	0.942	-2.301786	2.477435

```
. scatter gp100m weight, by(foreign)
```



The user-interface model is type a little, get a little, etc., so that the user is always in control.

Stata's model for a dataset is that of a table—the rows are the observations and the columns are the variables:

```
. list mpg weight gp100m in 1/10
```

	mpg	weight	gp100m
1.	22	2,930	4.55
2.	17	3,350	5.88
3.	22	2,640	4.55
4.	20	3,250	5.00
5.	15	4,080	6.67
6.	18	3,670	5.56
7.	26	2,230	3.85
8.	20	3,280	5.00
9.	16	3,880	6.25
10.	19	3,400	5.26

Observations are numbered; variables are named.

Stata is fast. That speed is due partly to careful programming, and partly because Stata keeps the data in memory. Stata's file model is that of a word processor: a dataset may exist on disk, but the dataset in memory is a copy. Datasets are loaded into memory, where they are worked on, analyzed, changed, and then perhaps stored back on disk.

Working on a copy of the data in memory makes Stata safe for interactive use. The only way to harm the permanent copy of your data on disk is if you explicitly save over it.

Having the data in memory means that the dataset size is limited by the amount of computer memory. Stata stores the data in memory in an efficient format—you will be surprised how much data can fit. Nevertheless, if you work with extremely large datasets, you may run into memory constraints. You will want to learn how to store your data as efficiently as possible; see [D] **compress**.

3 Resources for learning and using Stata

Contents

3.1 Overview

The *Getting Started* manual, *User's Guide*, and *Reference* manuals are the primary tools for learning about Stata; however, there are many other sources of information. A few are listed below.

- Stata itself. Stata has a `search` command that makes it easy search a topic to find and to execute a Stata command. See **[U] 4 Stata's help and search facilities**.
- The Stata website. Visit https://www.stata.com. Much of the site is dedicated to user support; see **[U] 3.2.1 The Stata website (www.stata.com)**.
- The Stata YouTube Channel. Visit https://www.youtube.com/user/statacorp. The site is regularly updated with video demonstrations of Stata.

- *The Stata Blog*, Twitter, and Facebook. Visit https://blog.stata.com, https://twitter.com/stata, and https://www.facebook.com/statacorp. See **[U] 3.2.3 The Stata Blog: Not Elsewhere Classified** and **[U] 3.2.5 Stata on social media**.
- The Stata Press website. Visit https://www.stata-press.com. This site contains the datasets used throughout the Stata manuals; see **[U] 3.3 Stata Press**.
- The Stata Forum. An active group of Stata users communicate over an internet forum; see **[U] 3.2.4 The Stata Forum**.
- The *Stata Journal*. The *Stata Journal* contains reviewed papers, regular columns, book reviews, and other material of interest to researchers applying statistics in a variety of disciplines. See **[U] 3.4 The Stata Journal**.
- The Stata software distribution site and other user-provided software distribution sites. Stata itself can download and install updates and additions. We provide official updates to Stata—type `update query` or select **Help > Check for updates**. We also provide community-contributed additions to Stata and links to other user-provided sites—type `net` or select **Help > SJ and community-contributed features**; see **[U] 3.5 Updating and adding features from the web**.
- NetCourses. We offer training via the internet. Details are in **[U] 3.6.2 NetCourses**.
- Classroom training courses. We offer in-depth training courses at third-party sites around the United States. Details are in **[U] 3.6.3 Classroom training courses**.
- Web-based training courses. We offer the same content from our classroom training over the web. Details are in **[U] 3.6.4 Web-based training courses**.
- Organizational training courses. We offer both in-person and virtual customized training for your institution. Details are in **[U] 3.6.5 Organizational training courses**.
- Webinars. We offer free, short online webinars to learn about Stata from our experts. Details are in **[U] 3.6.6 Webinars**.
- Books and support materials. Supplementary Stata materials are available; see **[U] 3.7 Books and other support materials**.
- Technical support. We provide technical support by email and telephone; see **[U] 3.8 Technical support**.

3.2 Stata on the internet (www.stata.com and other resources)

3.2.1 The Stata website (www.stata.com)

Point your browser to https://www.stata.com and click on **Support**. More than half our website is dedicated to providing support to users.

- The website provides answers to FAQs (frequently asked questions) on Windows, Mac, Unix, statistics, programming, Mata, internet capabilities, graphics, and data management. These FAQs run the gamut from "I cannot save/open files" to "What does 'completely determined' mean in my logistic regression output?" Most users will find something of interest.
- The website provides detailed information about NetCourses, along with the current schedule; see **[U] 3.6.2 NetCourses**.

- The website provides information about Stata courses and meetings, both in the United States and elsewhere. See **[U] 3.6.1 Conferences and users group meetings**, **[U] 3.6.3 Classroom training courses**, **[U] 3.6.4 Web-based training courses**, and **[U] 3.6.5 Organizational training courses**.
- The website provides an online bookstore for Stata-related books and other supplementary materials; see **[U] 3.7 Books and other support materials**.
- The website provides links to information about statistics: other statistical software providers, book publishers, statistical journals, statistical organizations, and statistical listservers.
- The website provides links to resources for learning Stata at https://www.stata.com/links/resources-for-learning-stata. Be sure to look at these materials, as many outstanding resources about Stata are listed here.

In short, the website provides up-to-date information on all support materials and, where possible, provides the materials themselves. Visit https://www.stata.com if you can.

3.2.2 The Stata YouTube Channel

Visit Stata's YouTube Channel at https://www.youtube.com/user/statacorp to view video demonstrations on a wide variety of topics ranging from basic data management and graphics to more advanced statistical analyses, such as ANOVA, regression, and SEM. New demonstrations are regularly added.

3.2.3 The Stata Blog: Not Elsewhere Classified

Stata's official blog can be found at https://blog.stata.com and contains news and advice related to the use of Stata. The articles appearing in the blog are individually signed and are written by the same people who develop, support, and sell Stata.

3.2.4 The Stata Forum

Statalist is a forum dedicated to Stata, where thousands of Stata users discuss Stata and statistics. It is run and moderated by Stata users and maintained by StataCorp. Statalist has a long history of high-quality discussion dating back to 1994.

Many knowledgeable users are active on the forum, as are the StataCorp technical staff. Anyone may join, and new-to-Stata members are welcome. Instructions for joining can be found at https://www.statalist.org. Register and participate, or simply lurk and read the discussions.

Before posting a question to Statalist, you will want to read the Statalist FAQ, which can be found at https://www.statalist.org/forums/help/.

3.2.5 Stata on social media

StataCorp has an official presence on Twitter, Facebook, Instagram, and LinkedIn. You can follow us on Twitter at https://twitter.com/stata. You find us on Facebook and Instagram at https://www.facebook.com/statacorp and https://www.instagram.com/statacorp. Connect with us on LinkedIn at https://www.linkedin.com/company/statacorp. These are good ways to stay up-to-the-minute with the latest Stata information.

3.2.6 Other internet resources on Stata

Many other people have published information on the internet about Stata such as tutorials, examples, and datasets. Visit https://www.stata.com/links/ to explore other Stata and statistics resources on the internet.

3.3 Stata Press

Stata Press is the publishing arm of StataCorp LLC and publishes books, manuals, and journals about Stata statistical software and about general statistics topics for professional researchers of all disciplines.

Point your browser to https://www.stata-press.com. This site is devoted to the publications and activities of Stata Press.

- Datasets that are used in the Stata *Reference* manuals and other books published by Stata Press may be downloaded. Visit https://www.stata-press.com/data/. These datasets can be used in Stata by simply typing `use https://www.stata-press.com/data/r19/`*dataset_name*; for example, type `use https://www.stata-press.com/data/r19/auto`. You could also type `webuse auto`; see [D] **webuse**.
- An online catalog of all our books and multimedia products is at https://www.stata-press.com/books/. We have tried to include enough information, such as table of contents and preface material, so that you may tell whether the book is appropriate for you.
- Information about forthcoming publications is posted at https://www.stata-press.com/forthcoming/.

3.4 The Stata Journal

The *Stata Journal* (SJ) is a printed and electronic journal, published quarterly, containing articles about statistics, data analysis, teaching methods, and effective use of Stata's language. The SJ publishes reviewed papers together with shorter notes and comments, regular columns, tips, book reviews, and other material of interest to researchers applying statistics in a variety of disciplines. The SJ is a publication for all Stata users, both novice and experienced, with different levels of expertise in statistics, research design, data management, graphics, reporting of results, and in Stata, in particular.

The SJ is published by and available from SAGE Publishing. Tables of contents for past issues and abstracts of the articles are available at https://www.stata-journal.com/archives/. PDF copies of articles published at least three years ago are available for free from SAGE Publishing's SJ webpage.

We recommend that all users subscribe to the SJ. Visit https://www.stata-journal.com to learn more about the SJ. Subscription information is available at https://www.stata-journal.com/subscription.

To obtain any programs associated with articles in the SJ, type

```
. net from https://www.stata-journal.com/software
```

or

- Select **Help > SJ and community-contributed features**
- Click on **Stata Journal**

3.5 Updating and adding features from the web

Stata itself can open files on the internet. Stata understands http, https, and ftp protocols.

First, try this:

```
. use https://www.stata.com/manual/oddeven, clear
```

That will load an uninteresting dataset into your computer from our website. If you have a home page, you can use this feature to share datasets with coworkers. Save a dataset on your home page, and researchers worldwide can use it. See [R] **net**.

3.5.1 Official updates

Although we follow no formal schedule for the release of updates, we typically provide updates to Stata approximately once a month. Installing the updates is easy. Type

```
. update query
```

or select **Help > Check for updates**. Do not be concerned; nothing will be installed unless and until you say so. Once you have installed the update, you can type

```
. help whatsnew
```

or select **Help > What's new?** to find out what has changed. We distribute official updates to fix bugs and to add new features.

3.5.2 Unofficial updates

There are also "unofficial" updates—additions to Stata written by Stata users, which includes members of the StataCorp technical staff. Stata is programmable, and even if you never write a Stata program, you may find these additions useful, some of them spectacularly so. Start by typing

```
. net from https://www.stata.com
```

or select **Help > SJ and community-contributed features**.

Be sure to visit the Statistical Software Components (SSC) Archive, which hosts a large collection of free additions to Stata. The `ssc` command makes it easy for you to find, install, and uninstall packages from the SSC Archive. Type

```
. ssc whatsnew
```

to find out what's new at the site. If you find something that interests you, type

```
. ssc describe pkgname
```

for more information. If you have already installed a package, you can check for and optionally install updates by typing

```
. ado update pkgname
```

To check for and optionally install updates to all the packages you have previously installed, type

```
. ado update all
```

See **[U] 29 Using the internet to keep up to date**.

3.6 Conferences and training

3.6.1 Conferences and users group meetings

Every year, users around the world meet in a variety of locations to discuss Stata software and to network with other users. At these meetings, users and StataCorp developers alike share new features, novel Stata uses, and best practices. StataCorp organizes and hosts the Stata Conference in both the United States and Canada, as well as supports meetings worldwide.

Visit https://www.stata.com/meeting/ for a list of upcoming conferences and meetings.

3.6.2 NetCourses

We offer courses on Stata at both introductory and advanced levels. Courses on software are typically expensive and time consuming. They are expensive because, in addition to the direct costs of the course, participants must travel to the course site. Courses over the internet save everyone time and money.

We offer courses over the internet and call them Stata NetCourses.

- **What is a NetCourse?**
  A NetCourse is a course offered through the Stata website that varies in length from 7 to 8 weeks. Everyone with an email address and a web browser can participate.
- **How does it work?**
  Every Friday a lesson is posted on a password-protected website. After reading the lesson over the weekend or perhaps on Monday, participants then post questions and comments on a message board. Course leaders typically respond to the questions and comments on the same day they are posted. Other participants are encouraged to amplify or otherwise respond to the questions or comments as well. The next lesson is then posted on Friday, and the process repeats.
- **How much of my time does it take?**
  It depends on the course, but the introductory courses are designed to take roughly 3 hours per week.
- **There are three of us here—can just one of us enroll and then redistribute the NetCourse materials ourselves?**
  We ask that you not. NetCourses are priced to cover the substantial time input of the course leaders. Moreover, enrollment is typically limited to prevent the discussion from becoming unmanageable. The value of a NetCourse, just like a real course, is the interaction of the participants, both with each other and with the course leaders.
- **I've never taken a course by internet before. I can see that it might work, but then again, it might not. How do I know I will benefit?**
  All Stata NetCourses come with a 30-day satisfaction guarantee. The 30 days begins after the conclusion of the final lesson.

You can learn more about the current NetCourse offerings by visiting https://www.stata.com/netcourse.

NetCourseNow

A NetCourseNow offers the same material as NetCourses but it allows you to choose the time and pace of the course, and you have a personal NetCourse instructor.

- **What is a NetCourseNow?**
  A NetCourseNow offers the same material as a NetCourse, but allows you to move at your own pace and to specify a starting date. With a NetCourseNow, you also have the added benefit of a personal NetCourse instructor whom you can email directly with questions about lessons and exercises. You must have an email address and a web browser to participate.
- **How does it work?**
  All course lessons and exercises are posted at once, and you are free to study at your own pace. You will be provided with the email address of your personal NetCourse instructor to contact when you have questions.
- **How much of my time does it take?**
  A NetCourseNow allows you to set your own pace. How long the course takes and how much time you spend per week is up to you.

3.6.3 Classroom training courses

Classroom training courses are intensive, in-depth courses that will teach you to use Stata or, more specifically, to use one of Stata's advanced statistical procedures. Courses are taught by StataCorp at third-party sites around the United States.

- **How is a classroom training course taught?**
  These are interactive, hands-on sessions. Participants work along with the instructor so that they can see firsthand how to use Stata. Questions are encouraged.
- **Do I need my own computer?**
  Because the sessions are in computer labs running the latest version of Stata, there is no need to bring your own computer. Of course, you may bring your own computer if you have a registered copy of Stata you can use.
- **Do I get any notes?**
  You get a complete set of printed notes for each class, which includes not only the materials from the lessons but also all the output from the example commands.

See https://www.stata.com/training/classroom-and-web/ for all course offerings.

3.6.4 Web-based training courses

Web-based training courses, like classroom training courses, are intensive, in-depth courses that will teach you to use Stata or, more specifically, to use one of Stata's advanced statistical procedures. Courses are taught by StataCorp, and you join the course online from your home or office.

- **How is a web-based training course taught?**
  These are interactive, hands-on sessions. Participants work along with the instructor so that they can see firsthand how to use Stata. Questions are encouraged.
- **Do I need my own computer and Stata license?**
  You will need a computer with a high-speed internet connection to join the course and to run Stata. If you do not have a license for the current version of Stata, you will be provided with a temporary license.
- **Do I get any notes?**
  You get a complete set of notes for each class, which includes not only the materials from the lessons but also all the output from the example commands.

See https://www.stata.com/training/classroom-and-web/ for all course offerings.

3.6.5 Organizational training courses

Organizational training courses are courses that are tailored to the needs of each institution. StataCorp personnel can come to your site to teach what you need, whether it be to teach new users or to show how to use a specialized tool in Stata. This training is also available virtually.

- **How is an organizational training course taught?**
  These are interactive, hands-on sessions, just like our classroom training courses. You will need a computer for each participant.
- **What topics are available?**
  We offer training in anything and everything related to Stata. You work with us to put together a curriculum that matches your needs.
- **How does licensing work?**
  We will supply you with the licenses you need for the training session, whether the training is in a lab or for individuals working on laptops. We will send the licensing and installation instructions so that you can have everything up and running before the session starts.

See https://www.stata.com/training/organizational/ for all the details.

3.6.6 Webinars

Webinars are free, live demonstrations of Stata features for both new and experienced Stata users. The *Ready. Set. Go Stata.* webinar shows new users how to quickly get started manipulating, graphing, and analyzing data. Already familiar with Stata? Discover a few of our developers' favorite features of Stata in our *Tips and tricks* webinar. The one-hour specialized feature webinars provide both new and experienced users with an in-depth look at one of Stata's statistical, graphical, data management, or reporting features.

- **How do I access the webinar?**
  Webinars are given live using either Adobe Connect software or Zoom.
- **Do I need my own computer and Stata license?**
  You will need a computer with high-speed internet connection to join the webinar and to run Adobe Connect or Zoom. You do not need access to Stata to attend.
- **What is the cost to attend?**
  Webinars are free, but you must register to attend. Registrations are limited so we recommend registering early.

See https://www.stata.com/training/webinar/ for all the details.

3.7 Books and other support materials

3.7.1 For readers

There are books published about Stata, both by us and by others. Visit the Stata Bookstore at https://www.stata.com/bookstore/. We include the table of contents and comments written by a member of our technical staff, explaining why we think this book might interest you.

3.7.2 For authors

If you have written a book related to Stata and would like us to consider adding it to our bookstore, email bookstore@stata.com.

If you are writing a book, join our free Author Support Program. Stata professionals are available to review your Stata code to ensure that it is efficient and reflects modern usage, production specialists are available to help format Stata output, and editors and statisticians are available to ensure the accuracy of Stata-related content. Visit https://www.stata.com/authorsupport/.

If you are thinking about writing a Stata-related book, consider publishing it with Stata Press. Email editor@stata-press.com.

3.7.3 For editors

If you are editing a book that demonstrates Stata usage and output, join our free Editor Support program. Stata professionals are available to review the Stata content of book proposals, review Stata code and ensure output is efficient and reflects modern usage, provide advice about formatting of Stata output (including graphs), and review the accuracy of Stata-related content. Visit https://www.stata.com/publications/editor-support-program/.

3.7.4 For instructors

Teaching your course with Stata provides your students with tools and skills that translate to their professional life. Our teaching resources page provides access to resources for instructors, including links to our video tutorials, *Ready. Set. Go Stata.* webinar, Stata cheat sheets, and more. Visit https://www.stata.com/teaching-with-stata/.

3.8 Technical support

We are committed to providing superior technical support for Stata software. To assist you as efficiently as possible, please follow the procedures listed below.

3.8.1 Register your software

You must register your software to be eligible for technical support, updates, special offers, and other benefits. By registering, you will receive the *Stata News*, and you may access our support staff for free with any question that you encounter. You may register your software electronically.

After installing Stata and successfully entering your License and Activation Key, your default web browser will open to the online registration form at the Stata website. You may also manually point your web browser to https://www.stata.com/register/ if you wish to register your copy of Stata at a later time.

3.8.2 Before contacting technical support

Before you spend the time gathering the information our technical support department needs, make sure that the answer does not already exist in the help files. You can use the `help` and `search` commands to find all the entries in Stata that address a given subject. Be sure to try selecting **Help > Contents**. Check the manual for a particular command. There are often examples that address questions and concerns. Another good source of information is our website. You should keep a bookmark to our frequently asked questions page (https://www.stata.com/support/faqs/).

If you do need to contact technical support, visit https://www.stata.com/support/tech-support/ for more information.

3.8.3 Technical support by email

This is the preferred method of asking a technical support question. It has the following advantages:

- You will receive a prompt response from us saying that we have received your question and that it has been forwarded to *Technical Services* to answer.
- We can route your question to a specialist for your particular question.
- Questions submitted via email may be answered after normal business hours, or even on weekends or holidays. Although we cannot promise that this will happen, it may, and your email inquiry is bound to receive a faster response than leaving a message on Stata's voicemail.
- If you are receiving an error message or an unexpected result, it is easy to include a log file that demonstrates the problem.

Please visit https://www.stata.com/support/tech-support/ for information about contacting technical support.

3.8.4 Technical support by phone

Our installation support telephone number is 979-696-4600. Please have your serial number handy. It is also best if you are at your computer when you call. Telephone support is reserved for installation questions. If your question does not involve installation, the question should be submitted via email.

Visit https://www.stata.com/support/tech-support/ for information about contacting technical support.

3.8.5 Comments and suggestions for our technical staff

By all means, send in your comments and suggestions. Your input is what determines the changes that occur in Stata between releases, so if we do not hear from you, we may not include your most desired new feature! Email is preferred, as this provides us with a permanent copy of your request. When requesting new features, please include any references that you would like us to review should we develop those new features. Email your suggestions to service@stata.com.

4 Stata's help and search facilities

Contents

4.1 Introduction

To access Stata's help, you will either

1. select **Help** from the menus, or
2. use the `help` and `search` commands.

Regardless of the method you use, results will be shown in the Viewer or Results windows. Blue text indicates a hypertext link, so you can click to go to related entries.

4.2 Getting started

The first time you use help, try one of the following:

1. select **Help > Advice** from the menu bar, or
2. type `help advice`.

Either step will open the `help_advice` help file within a Viewer window. The advice file provides you with steps to search Stata to find information on topics and commands that interest you.

4.3 help: Stata's help system

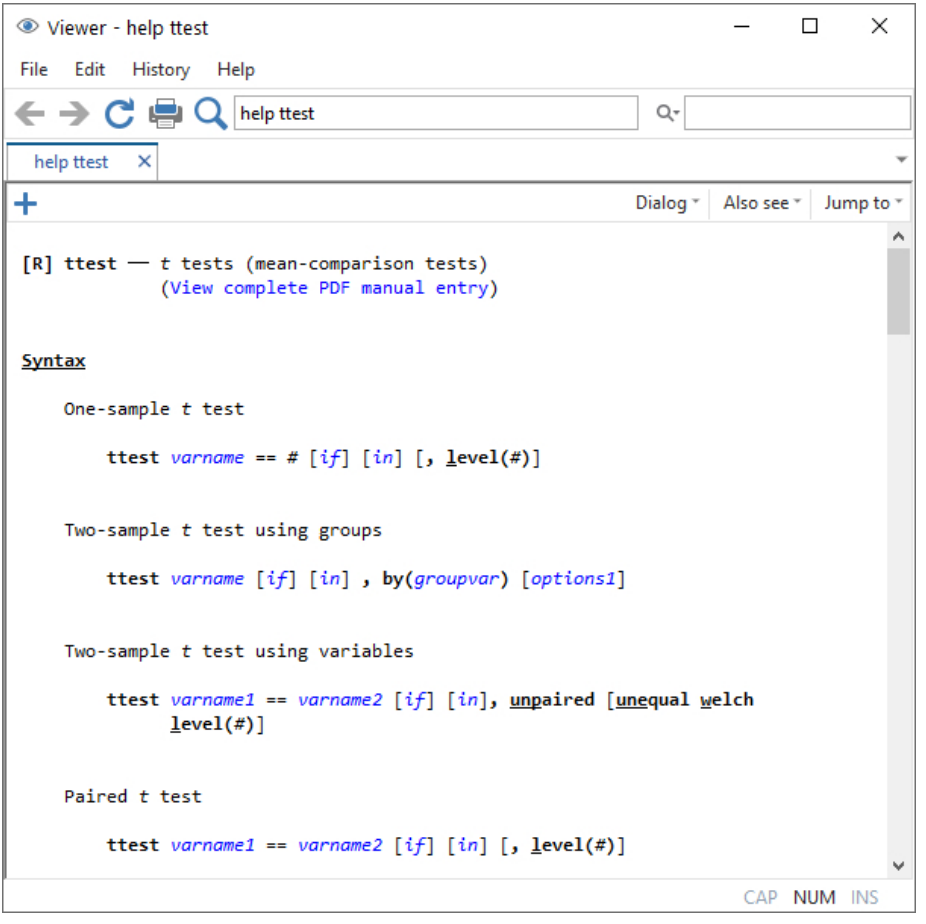
When you

1. Select **Help > Stata command...**
   Type a command name in the Command edit field
   Click on OK, or
2. Type `help` followed by a command name

you access Stata's help files. These files provide shortened versions of what is in the printed manuals. Let's access the help file for Stata's `ttest` command. Do one of the following:

1. Select **Help > Stata command...**
   Type `ttest` in the Command edit field
   Click on OK, or
2. Type `help ttest`

Regardless of which you do, the result will be



The trick is in already knowing that Stata's command for testing equality of means is `ttest` and not, say, `meanstest`. The solution to that problem is searching.

4.4 Accessing PDF manuals from help entries

Every help file in Stata links to the equivalent manual entry. If you are reading `help ttest`, simply click on `(View complete PDF manual entry)` below the title to go directly to the [R] **ttest** manual entry.

We provide some tips for viewing Stata's PDF documentation at https://www.stata.com/support/faqs/resources/pdf-documentation-tips/.

4.5 Searching

If you do not know the name of the Stata command you are looking for, you can search for it by keyword,

1. Select **Help > Search...**
   Type keywords in the edit field
   Click on OK
2. Type `search` followed by the keywords

`search` matches the keywords you specify to a database and returns matches found in Stata commands, FAQs at www.stata.com, official blogs, and articles that have appeared in the *Stata Journal*. It can also find community-contributed additions to Stata available over the web.

`search` does a better job when what you want is based on terms commonly used or when what you are looking for might not already be installed on your computer.

4.6 More on search

However you access `search`—command or menu—it does the same thing. You tell `search` what you want information about, and it searches for relevant entries. By default, `search` looks for the topic across all sources, including the system help, the FAQs at the Stata website, the *Stata Journal*, and all Stata-related internet sources including community-contributed additions.

`search` can be used broadly or narrowly. For instance, if you want to perform the Kolmogorov–Smirnov test for equality of distributions, you could type

```
. search Kolmogorov-Smirnov test of equality of distributions
[R]     ksmirnov . . . . . Kolmogorov-Smirnov equality of distributions test
        (help ksmirnov)
```

In fact, we did not have to be nearly so complete—typing `search Kolmogorov-Smirnov` would have been adequate. Had we specified our request more broadly—looking up `equality of distributions`—we would have obtained a longer list that included `ksmirnov`.

Here are guidelines for using `search`.

- Capitalization does not matter. Look up `Kolmogorov-Smirnov` or `kolmogorov-smirnov`.
- Punctuation does not matter. Look up `kolmogorov smirnov`.
- Order of words does not matter. Look up `smirnov kolmogorov`.
- You may abbreviate, but how much depends. Break at syllables. Look up `kol smir`. `search` tends to tolerate a lot of abbreviation; it is better to abbreviate than to misspell.
- The words a, an, and, are, for, into, of, on, to, the, and with are ignored. Use them—look up `equality of distributions`—or omit them—look up `equality distributions`—it makes no difference.
- `search` tolerates plurals, especially when they can be formed by adding an *s*. Even so, it is better to look up the singular. Look up `normal distribution`, not `normal distributions`.
- Specify the search criterion in English, not in computer jargon.
- Use American spellings. Look up `color`, not `colour`.
- Use nouns. Do not use -ing words or other verbs. Look up `median tests`, not `testing medians`.

- Use few words. Every word specified further restricts the search. Look up `distribution`, and you get one list; look up `normal distribution`, and the list is a sublist of that.
- Sometimes words have more than one context. The following words can be used to restrict the context:
    a. `data`, meaning in the context of data management. Order could refer to the order of data or to order statistics. Look up `order data` to restrict order to its data management sense.
    b. `statistics` (abbreviation `stat`), meaning in the context of statistics. Look up `order statistics` to restrict order to the statistical sense.
    c. `graph` or `graphs`, meaning in the context of statistical graphics. Look up `median graphs` to restrict the list to commands for graphing medians.
    d. `utility` (abbreviation `util`), meaning in the context of utility commands. The `search` command itself is not data management, not statistics, and not graphics; it is a utility.
    e. `programs` or `programming` (abbreviation `prog`), to mean in the context of programming. Look up `programming scalar` to obtain a sublist of scalars in programming.

`search` has other features, as well; see **[U] 4.8 search: All the details**.

4.7 More on help

Both `help` and `search` are understanding of some mistakes. For instance, you may abbreviate some command names. If you type either `help regres` or `help regress`, you will bring up the help file for `regress`.

When `help` cannot find the command you are looking for among Stata's official help files or any community-contributed additions you have installed, Stata automatically performs a search. For instance, typing `help ranktest` causes Stata to reply with "help for ranktest not found", and then Stata performs `search ranktest`. The search tells you that `ranktest` is available in the *Enhanced routines for IV/GMM estimation and testing* article in Stata Journal, Volume 7, Number 4.

Stata can run into some problems with abbreviations. For instance, Stata has a command with the inelegant name `ksmirnov`. You forget and think the command is called `ksmir`:

```
. help ksmir
No entries found for search on "ksmir"
```

A help file for `ksmir` was not found, so Stata automatically performed a search on the word. The message indicates that a search of `ksmir` also produced no results. You should type `search` followed by what you are really looking for: `search kolmogorov smirnov`.

4.8 search: All the details

The `search` command actually provides a few features that are not available from the **Help** menu. The full syntax of the `search` command is

`search` *word* [*word* ...] [`,` [`all` | `local` | `net`] `author` `entry` `exact` `faq` `historical` `or` `manual` `sj`]

where underlining indicates the minimum allowable abbreviation and [`brackets`] indicate optional.

`all`, the default, specifies that the search be performed across both the local keyword database and the net materials.

`local` specifies that the search be performed using only Stata's keyword database.

`net` specifies that the search be performed across the materials available via Stata's `net` command. Using `search word` [*word* ...]`, net` is equivalent to typing `net search word` [*word* ...] (without options); see [R] **net**.

`author` specifies that the search be performed on the basis of author's name rather than keywords.

`entry` specifies that the search be performed on the basis of entry IDs rather than keywords.

`exact` prevents matching on abbreviations.

`faq` limits the search to the FAQs posted on the Stata and other select websites.

`historical` adds to the search entries that are of historical interest only. By default, such entries are not listed.

`or` specifies that an entry be listed if any of the words typed after `search` are associated with the entry. The default is to list the entry only if all the words specified are associated with the entry.

`manual` limits the search to entries in the *User's Guide* and all the *Reference* manuals.

`sj` limits the search to entries in the *Stata Journal*.

4.8.1 How search works

`search` has a database—files—containing the titles, etc., of every entry in the *User's Guide*, *Reference* manuals, undocumented help files, NetCourses, Stata Press books, FAQs posted on the Stata website, videos on StataCorp's YouTube channel, selected articles on StataCorp's official blog, selected community-contributed FAQs and examples, and the articles in the *Stata Journal*. In this file is a list of words associated with each entry, called keywords.

When you type `search` *xyz*, `search` reads this file and compares the list of keywords with *xyz*. If it finds *xyz* in the list or a keyword that allows an abbreviation of *xyz*, it displays the entry.

When you type `search` *xyz abc*, `search` does the same thing but displays an entry only if it contains both keywords. The order does not matter, so you can `search linear regression` or `search regression linear`.

How many entries `search` finds depends on how the search database was constructed. We have included a plethora of keywords under the theory that, for a given request, it is better to list too much rather than risk listing nothing at all. Still, you are in the position of guessing the keywords. Do you look up normality test, normality tests, or tests of normality? Normality test would be best, but all would work. In general, use the singular and strike the unnecessary words. We provide guidelines for specifying keywords in **[U] 4.6 More on search** above.

4.8.2 Author searches

`search` ordinarily compares the words following `search` with the keywords for the entry. If you specify the `author` option, however, it compares the words with the author's name. In the search database, we have filled in author names for *Stata Journal* articles, Stata Press books, StataCorp's official blog, and FAQs.

For instance, in the *Acknowledgments* of [R] **kdensity**, you will discover the name Isaías H. Salgado-Ugarte. You want to know if he has written any articles in the *Stata Journal*. To find out, type

```
. search Salgado-Ugarte, author
  (output omitted)
```

Names like Salgado-Ugarte are confusing to some people. `search` does not require you specify the entire name; what you type is compared with each "word" of the name, and if any part matches, the entry is listed. The hyphen is a special character, and you can omit it. Thus you can obtain the same list by looking up Salgado, Ugarte, or Salgado Ugarte without the hyphen.

4.8.3 Entry ID searches

If you specify the `entry` option, `search` compares what you have typed with the entry ID. The entry ID is not the title—it is the reference listed to the left of the title that tells you where to look. For instance, in

```
regress  . . . . . Linear regression
   (help regress)
```

"[R] regress" is the entry ID. In

```
GS       . . . . . Getting Started manual
```

"GS" is the entry ID. In

```
SJ-14-4  gr0059  . . . . . Plotting regression coefficients and other estimates
        (help  coefplot if installed)  . . . . . B. Jann
        Q4/14   SJ 14(4):708--737
        alternative to marginsplot that plots results from any
        estimation command and combines results from several models
        into one graph
```

"SJ-14-4 gr0059" is the entry ID.

`search` with the `entry` option searches these entry IDs.

Thus you could generate a table of contents for the *Reference* manuals by typing

```
. search [R], entry
  (output omitted)
```

4.8.4 FAQ searches

To search across the FAQs, specify the `faq` option:

```
. search logistic regression, faq
  (output omitted)
```

4.8.5 Return codes

In addition to indexing the entries in the *User's Guide* and all the *Stata Reference* manuals, `search` also can be used to look up return codes.

To see information about return code 131, type

```
. search rc 131
[R]     error messages  . . . . . . . . . . . . . . . . . . . .  Return code 131
        not possible with test;
        You requested a test of a hypothesis that is nonlinear in the
        variables.  test tests only linear hypotheses.  Use testnl.
```

To get a list of all Stata return codes, type

```
. search rc
  (output omitted)
```

4.9 net search: Searching net resources

When you select **Help > Search...**, there are two types of searches to choose. The first, which has been discussed in the previous sections, is to **Search documentation and FAQs**. The second is to **Search net resources**. This feature of Stata searches resources over the internet.

When you choose **Search net resources** in the search dialog box and enter *keywords* in the field, Stata searches all community-contributed programs on the internet, including community-contributed additions published in the *Stata Journal*. The results are displayed in the Viewer, and you can click to go to any of the matches found.

Equivalently, you can type `net search` *keywords* on the Stata command line to display the results in the Results window. For the full syntax for using the `net search` command, see [R] **net search**.

5 Editions of Stata

Contents

5.1 StataNow

First and foremost, StataNow is Stata. It is a continuous-release version of Stata that offers new features as soon as they are ready. StataNow is the result of our ongoing effort to deliver the best Stata—the most current Stata—to our users.

Before StataNow, most new features became available only at the time of a major release such as Stata 17, Stata 18, and so on. StataNow provides access to new features sooner. Beginning with Stata 18, StataNow was introduced, and StataNow contains features that will be part of a future major release. For instance, features introduced after the release of Stata 18 were included in the Stata 19 release. Similarly, features introduced after the release of Stata 19 will be included in the future major release, Stata 20. View the list of the latest StataNow features at https://www.stata.com/new-in-stata/#statanow.

The features in StataNow are fully tested, fully certified, well documented, and version controlled (if needed), as well as polished to our customary high quality. These features are prioritized in the development cycle to be released as soon as they are ready so that users can take advantage of them right away. As always, all versions of Stata are updated regularly with any corrections and necessary improvements.

The new features in StataNow are released continuously throughout the current release until the next major release. They are not released according to any preset schedule. All StataNow features are marked as such throughout the Stata documentation and the Stata website.

Because StataNow is Stata, when we mention "Stata" throughout our documentation and website, we also mean "StataNow". We will be specific about StataNow for features available only in StataNow. And because StataNow is Stata, it is available in all editions (StataNow/MP, StataNow/SE, and StataNow/BE) and on all supported platforms (Windows, Mac, and Linux). Throughout the documentation and website, we will usually refer to just Stata/MP, Stata/SE, and Stata/BE for simplicity. If you have a StataNow license, you can take this to mean StataNow/MP, StataNow/SE, and StataNow/BE.

For more information, see https://www.stata.com/statanow/.

5.2 Platforms

Stata is available for a variety of systems, including

Stata for Windows, 64-bit x86-64

Stata for Mac, 64-bit x86-64

Stata for Linux, 64-bit x86-64

Which version of Stata you run does not matter—Stata is Stata. You instruct Stata in the same way and Stata produces the same results, right down to the random-number generator. Even files can be shared. A dataset created on one computer can be used on any other computer, and the same goes for graphs, programs, or any file Stata uses or produces. Moving files across platforms is simply a matter of copying them; no translation is required.

Some computers, however, are faster than others. Some computers have more memory than others. Computers with more memory, and faster computers, are better.

When you purchase Stata, you may install it on any of the above platforms. Stata licenses are not locked to a single operating system.

5.3 Stata/MP, Stata/SE, or Stata/BE

Stata is available in three editions, although perhaps sizes would be a better word. The editions are, from largest to smallest, Stata/MP, Stata/SE, and Stata/BE. (Prior to Stata 17, the various editions of Stata were called flavors, and Stata/BE was called Stata/IC.) If you have a StataNow license, you can take Stata/MP, Stata/SE, and Stata/BE to mean StataNow/MP, StataNow/SE, and StataNow/BE, respectively.

Stata/MP is the multiprocessor version of Stata. It runs on multiple CPUs or on multiple cores, from 2 to 64. Stata/MP uses however many cores you tell it to use (even one), up to the number of cores for which you are licensed. Stata/MP is the fastest version of Stata. Even so, all the details of parallelization are handled internally and you use Stata/MP just like you use any other editions of Stata. You can read about how Stata/MP works and see how its speed increases with more cores at https://www.stata.com/statamp/.

Stata/SE is like Stata/MP, but for single CPUs. Stata/SE will run on multiple CPUs or multiple-core computers, but it will use only one CPU or core. SE stands for standard edition.

In addition to being the fastest version of Stata, Stata/MP is also the largest. Stata/MP allows up to 1,099,511,627,775 observations in theory, but you can undoubtedly run out of memory first. You may have up to 120,000 variables with Stata/MP. Statistical models may have up to 65,532 variables.

Stata/SE allows up to 2,147,583,647 observations, assuming you have enough memory. You may have up to 32,767 variables with Stata/SE. Statistical models may have up to 10,998 variables.

Stata/BE is the basic version of Stata. Up to 2,147,583,647 observations and 2,048 variables are allowed, depending on memory. Statistical models may have up to 800 variables.

5.3.1 Determining which version you own

Check your License and Activation Key. Included with every copy of Stata is a License and Activation Key that contains codes that you will input during installation. This determines which editions of Stata you have and for which platform.

Contact us or your distributor if you want to upgrade from one edition to another. Usually, all you need is an upgraded License and Activation Key with the appropriate codes.

If you purchased one edition of Stata and want to use a lesser version, you may. You might want to do this if you had a large computer at work and a smaller one at home. Please remember, however, that you have only one license (or however many licenses you purchased). You may, both legally and ethically, install Stata on both computers and then use one or the other, but you should not use them both simultaneously.

5.3.2 Determining which version is installed

If Stata is already installed, you can find out which Stata you are using by entering Stata as you normally do and typing `about`:

```
. about

StataNow/MP 19.5 for Windows (64-bit x86-64)
Revision date
Copyright 1985-2025 StataCorp LLC

Total usable memory: 8388608 KB

Stata license: 10-user 32-core network perpetual
Serial number: 19
  Licensed to: Stata Developer
               StataCorp LLC
```

5.4 Size limits of Stata/MP, SE, and BE

Stata/MP allows more variables and observations, longer macros, and a longer command line than Stata/SE. Stata/SE allows more variables, larger models, longer macros, and a longer command line than Stata/BE. The longer command line and macro length are required because of the greater number of variables allowed. The larger model means that Stata/MP and Stata/SE can fit statistical models with more independent variables. See [R] **Limits** for the maximum size limits for Stata/MP, Stata/SE, and Stata/BE.

5.5 Speed comparison of Stata/MP, SE, and BE

We have written a white paper called the Stata/MP Performance Report, which compares the performance of Stata/MP with Stata/SE. The paper is available at https://www.stata.com/statamp/. The white paper includes command-by-command performance measurements.

In summary, on a dual-core computer, Stata/MP will run commands in 71% of the time required by Stata/SE. There is variation; some commands run in half the time and others are not sped up at all. Statistical estimation commands run in 59% of the time. Numbers quoted are medians. Average performance gains are higher because commands that take longer to execute are generally sped up more.

Stata/MP running on four cores runs in 50% (all commands) and 35% (estimation commands) of the time required by Stata/SE. Both numbers are median measures.

Stata/MP supports up to 64 cores.

Stata/BE is slower than Stata/SE, but those differences emerge only when processing datasets that are pushing the limits of Stata/BE. Stata/SE has a larger memory footprint and uses that extra memory for larger look-aside tables to more efficiently process large datasets. The real benefits of the larger tables become apparent only after exceeding the limits of Stata/BE. Stata/SE was designed for processing large datasets.

The differences are all technical and internal. From the user's point of view, Stata/MP, Stata/SE, and Stata/BE work the same way.

5.6 Feature comparison of Stata/MP, SE, and BE

The features of MP, SE, and BE editions of Stata on all platforms are the same. The differences are in speed and in limits as discussed above. To learn more, type `help stata/mp`, `help stata/se`, or `help stata/be`.

The StataNow version of Stata contains additional features as listed at https://www.stata.com/new-in-stata/features/#statanow. These features are the same across the MP, SE, and BE editions of StataNow on all platforms.

6 Managing memory

Contents

6.1 Memory-size considerations

Stata works with a copy of data that it loads into memory. To be precise, Stata can work with multiple datasets in memory at the same time. See [D] **frames intro**.

Memory allocation is automatic. Stata automatically sizes itself up and down as your session progresses. Stata obtains memory from the operating system and draws no distinction between real and virtual memory. Virtual memory is memory that resides on disk that operating systems supply when physical memory runs short. Virtual memory is slow but adequate in cases when you have a dataset that is too large to load into real memory. If you wish to limit the maximum amount of memory Stata can use, you can set `max_memory`; see [D] **memory**. If you use the Linux operating system, we strongly suggest you set `max_memory`; see *Serious bug in Linux OS* in [D] **memory**.

6.2 Compressing data

Stata stores data in memory. The `compress` command reduces the amount of memory required to store the data without loss of precision or any other disadvantages; see [D] **compress**. Typing `compress` every so often is a good idea.

`compress` works by examining the values you have stored and changing the data types of variables when that can be done without loss of precision. For instance, you may have a variable stored as `float` but that records only integer values between −127 and 100. `compress` would change the storage type of that variable to `byte` and save 3 bytes per observation. If you had 100 variables like that, the savings would be 300 bytes per observation, and if you had 3,000,000 observations, the total savings would be nearly 900 megabytes.

6.3 Setting maxvar

If you get the error message "no room to add more variables", r(900), do not jump to the conclusion that you have exceeded Stata's capacity.

`maxvar` specifies the maximum number of variables you can use. The default setting depends on whether you are using Stata/MP, Stata/SE, or Stata/BE. To determine the current setting, type `query memory` at the Stata prompt.

If you use Stata/MP, you can reset this maximum number to 120,000. If you use Stata/SE, you can reset this maximum number to 32,767. Set `maxvar` to more than you need—at least 20 more than you need but not too much more than you need. Figure that each 10,000 variables consumes roughly 0.5 megabytes of memory.

You reset maxvar using the set maxvar command,

set maxvar # [, permanently]

where 2,048 $\leq$ # $\leq$ 120,000, depending on your edition of Stata. You can reset maxvar repeatedly during a session. If you specify the permanently option, you change maxvar not only for this session but also for future sessions. Each additional 10,000 variables specified with set maxvar requires Stata to set aside roughly 1.3 megabytes of memory for variable names, not including the data stored in those variables.

6.4 The memory command

The memory command will show you the major components of Stata's memory footprint.

```
. use https://www.stata-press.com/data/r19/regsmpl
(NLS women 14-26 in 1968)
. memory
Memory usage
                                        Used                Allocated
-------------------------------------------------------------------------------
Data                                 856,020               67,108,864
strLs                                      0                        0
-------------------------------------------------------------------------------
Data & strLs                         856,020               67,108,864
-------------------------------------------------------------------------------
Data & strLs                         856,020               67,108,864
Variable names, %fmts, ...             4,644                  182,379
Overhead                           1,081,344                1,081,744
Stata matrices                             0                        0
ado-files                             34,589                   34,589
Stored results                             0                        0
Mata matrices                              0                        0
Mata functions                             0                        0
set maxvar usage                   5,281,738                5,281,738
Other                                  4,066                    4,066
-------------------------------------------------------------------------------
Total                              7,252,861               73,693,380
```

See [D] **memory**.

6.5 Setting aside memory for temporary storage of preserved datasets

Stata has a feature to preserve and restore datasets, allowing you to manipulate the data during an analysis and bring them back without harm. Stata/MP uses memory to make copies of these datasets as fast as possible. Stata/SE and Stata/BE make the copies on disk.

To control the amount of memory Stata/MP will use for these temporary dataset copies before it falls back to slower disk storage, use the set max_preservemem setting. See [P] **preserve** for more details.

7 –more– conditions

Contents

7.1 Description

By default, Stata does not pause its output. If a command generates more than a screenful of output, you can scroll back to see what you missed.

Some users prefer for Stata to pause every time the screen is full of output. You can enable this with Stata's `set more` command. See [R] **more**.

If you `set more on`, Stata will pause any time a command generates more than a screenful of output. When you see —`more`— at the bottom of the screen,

Press …	and Stata …
letter *l* or *Enter*	displays the next line
letter *q*	acts as if you pressed *Break*
Spacebar or any other key	displays the next screen

Also, from the menu, you can press the *More* button, the green button with the down arrow.

—`more`— is Stata's way of telling you that it has something more to show you, but showing you that something more will cause the information on the screen to scroll off.

7.2 The set more command

If you type `set more on`, —`more`— conditions will arise at the appropriate places.

If you type `set more off` (Stata's default behavior), —`more`— conditions will never arise and Stata's output will scroll by at full speed.

Programmers: If `set more` is used within a do-file or program, Stata automatically restores the previous `set more` setting when the do-file or program concludes.

See [R] **more**.

7.3 The more programming command

Ado-file programmers need take no special action to have —`more`— conditions arise when the screen is full. Stata handles that automatically.

If, however, you wish to force a —`more`— condition early, you can include the `more` command in your program. Simply type `more`, because the command takes no arguments.

For more information, see [P] **more**.

8 Error messages and return codes

Contents

8.1 Making mistakes

When an error occurs, Stata produces an error message and a *return code*. For instance,

```
. list myvar
no variables defined
r(111);
```

We ask Stata to list the variable named `myvar`. Because we have no data in memory, Stata responds with the message "no variables defined" and a line that reads "`r(111)`".

The "no variables defined" is called the error message.

The 111 is called the return code. You can click on blue return codes to get a detailed explanation of the error.

8.1.1 Mistakes are forgiven

After "no variables defined" and `r(111)`, all is forgiven; it is as if the error never occurred.

Typically, the message will be enough to guide you to a solution, but if it is not, the numeric return codes are documented in [P] **error**.

8.1.2 Mistakes stop user-written programs and do-files

Whenever an error occurs in a user-written program or do-file, the program or do-file immediately stops execution and the error message and return code are displayed.

For instance, consider the following do-file:

begin `myfile.do`

```
use https://www.stata-press.com/data/r19/auto
decribe
list
```

end `myfile.do`

Note the second line—you meant to type `describe` but typed `decribe`. Here is what happens when you execute this do-file by typing `do myfile`:

```
. do myfile
. use https://www.stata-press.com/data/r19/auto
(1978 automobile data)
. decribe
command decribe is unrecognized
r(199);
end of do-file
r(199);
. _
```

The first error message and return code were caused by the illegal `decribe`. This then caused the do-file itself to be aborted; the valid `list` command was never executed.

8.1.3 Advanced programming to tolerate errors

Errors are not only of the typographical kind; some are substantive. A command that is valid in one dataset might not be valid in another. Moreover, in advanced programming, errors are sometimes anticipated: use one dataset if it is there, but use another if you must.

Programmers can access the return code to determine whether an error occurred, which they can then ignore, or, by examining the return code, code their programs to take the appropriate action. This is discussed in [P] **capture**.

You can also prevent do-files from stopping when errors occur by using the `do` command's `nostop` option.

```
. do myfile, nostop
```

8.2 The return message for obtaining command timings

In addition to error messages and return codes, there is something called a return message, which you normally do not see. Normally, if you typed `summarize tempjan`, you would see

```
. use https://www.stata-press.com/data/r19/citytemp
(City temperature data)
. summarize tempjan
    Variable |        Obs        Mean    Std. dev.       Min        Max
-------------+---------------------------------------------------------
     tempjan |        954    35.74895    14.18813         2.2       72.6
```

If you were to type

```
. set rmsg on
r; t=0.00 10:21:22
```

sometime during your session, Stata would display return messages:

```
. summarize tempjan
    Variable |        Obs        Mean    Std. dev.       Min        Max
-------------+---------------------------------------------------------
     tempjan |        954    35.74895    14.18813         2.2       72.6
r; t=0.01 10:21:26
```

The line that reads `r; t=0.01 10:21:26` is called the return message.

The `r;` indicates that Stata successfully completed the command.

The `t=0.01` shows the amount of time, in seconds, it took Stata to perform the command (timed from the point you pressed *Enter* to the time Stata typed the message). This command took a hundredth of a second. Stata also shows the time of day with a 24-hour clock. This command completed at 10:21 a.m.

Stata can run commands stored in files (called do-files) and can log output. Some users find the detailed return message helpful with do-files. They construct a long program and let it run overnight, logging the output. They come back the next morning, look at the output, and discover a mistake in some portion of the job. They can look at the return messages to determine how long it will take to rerun that portion of the program.

You may `set rmsg on` whenever you wish.

When you want Stata to stop displaying the detailed return message, type `set rmsg off`.

There is another way to obtain timings of subsets of code that is of interest to programmers. See [P] **timer**.

9 The Break key

Contents

9.1 Making Stata stop what it is doing

When you want to make Stata stop what it is doing and return to the Stata dot prompt, you click on *Break*:

Stata for Windows:	click on the **Break** button (it is the button with the big red X), or press *Ctrl*+*Pause/Break*
Stata for Mac:	click on the **Break** button or press *Command*+. (period)
Stata for Unix(GUI):	click on the **Break** button or press *Ctrl*+*k*
Stata for Unix(console):	press *Ctrl*+*c* or press *q*

Elsewhere in this manual, we describe this action as simply clicking on *Break*. Break tells Stata to cancel what it is doing and return control to you as soon as possible.

If you click on *Break* in response to the input prompt or while you are typing a line, Stata ignores it, because you are already in control.

If you click on *Break* while Stata is doing something—creating a new variable, sorting a dataset, making a graph, etc.—Stata stops what it is doing, undoes it, and issues an input prompt. The state of the system is the same as if you had never issued the command.

▷ Example 1

You are fitting a logit model, type the command, and, as Stata is working on the problem, realize that you omitted an important variable:

```
. logit foreign mpg weight
Iteration 0:  Log likelihood =  -45.03321
Iteration 1:  Log likelihood = -29.898968
--Break--
r(1);

. _
```

When you clicked on *Break*, Stata responded by displaying `--Break--` and `r(1);`. Clicking on *Break* always results in a return code of 1—that is why return codes are called return codes and not error codes. The 1 does not indicate an error, but it does indicate that the command did not complete its task.

◁

9.2 Side effects of clicking on Break

In general, there are no side effects of clicking on Break. We said above that Stata undoes what it is doing so that the state of the system is the same as if you had never issued the command. There are two exceptions to that statement.

If you are reading data from disk by using `import delimited`, `infile`, or `infix`, whatever data have already been read will be left behind in memory, the theory being that perhaps you stopped the process so you could verify that you were reading the right data correctly before sitting through the whole process. If not, you can always `clear`.

```
. infile v1-v9 using workdata
(eof not at end of obs)
(4 observations read)
--Break--
r(1);
```

The other exception is `sort`. You have a large dataset in memory, decide to sort it, and then change your mind.

```
. sort price
--Break--
r(1);
```

If the dataset was previously sorted by, say, the variable `prodid`, it is no longer. When you click on *Break* in the middle of a `sort`, Stata marks the data as unsorted.

9.3 Programming considerations

There are basically no programming considerations for handling Break because Stata handles it all automatically. If you write a program or do-file, execute it, and then click on *Break*, Stata stops execution just as it would with an internal command.

Advanced programmers may be concerned about cleaning up after themselves; perhaps they have generated a temporary variable they intended to drop later or a temporary file they intended to erase later. If a Stata user clicks on *Break*, how can you ensure that these temporary variables and files will be erased?

If you obtain names for such temporary items from Stata's `tempname`, `tempvar`, and `tempfile` commands, Stata will automatically erase the temporary items; see **[U] 18.7 Temporary objects**.

There are instances, however, when a program must commit to executing a group of commands without interruption, or the user's data would be left in an intermediate or undefined state. In these instances, Stata provides a

```
nobreak {
        ...
}
```

construct; see [P] **break**. Also see [M-5] **setbreakintr( )** to read about Break-key processing in Mata.

10 Keyboard use

Contents

10.1 Description

The keyboard should operate much the way you would expect, with a few additions:

- There are some unexpected keys you can press to obtain previous commands you have typed. Also, you can click once on a command in the History window to reload it, or click on it twice to reload and execute; this feature is discussed in the *Getting Started* manuals.
- There are a host of command-editing features for Stata for Unix(console) users because their user interface does not offer such features.
- Regardless of operating system or user interface, if there are *F*-keys on your keyboard, they have special meaning and you can change the definitions of the keys.

10.2 F-keys

Windows users: *F3* and *F10* are reserved internally by Windows; you cannot program these keys.

By default, Stata defines the *F*-keys to mean

F-key	Definition
F1	`help advice;`
F2	`describe;`
F7	`save`
F8	`use`

The semicolons at the end of some entries indicate an implied *Enter*.

Stata provides several methods for obtaining help. To learn about these methods, select **Help > Advice**. Or you can just press *F1*.

`describe` is the Stata command to report the contents of data loaded into memory. It is explained in [D] **describe**. Normally, you type `describe` and press *Enter*. You can also press *F2*.

`save` is the command to save the data in memory into a file, and `use` is the command to load data; see [D] **use** and [D] **save**. The syntax of each is the same: `save` or `use` followed by a filename. You can type the commands or you can press *F7* or *F8* followed by the filename.

You can change the definitions of the *F*-keys. For instance, the command to list data is `list`; you can read about it in [D] **list**. The syntax is `list` to list all the data, or `list` followed by the names of some variables to list just those variables (there are other possibilities).

If you wanted *F9* to mean `list`, you could type

```
. global F9 "list "
```

In the above, `F9` refers to the letter *F* followed by *9*, not the *F9* key. Note the capitalization and spacing of the command.

You type `global` in lowercase, type `F9`, and then type `"list "`. The space at the end of `list` is important. In the future, rather than typing `list mpg weight`, you want to be able to press the *F9* key and then type only `mpg weight`. You put a space in the definition of `F9` so that you would not have to type a space in front of the first variable name after pressing *F9*.

Now say you wanted *F5* to mean list all the data—`list` followed by *Enter*. You could define

```
. global F5 "list;"
```

Now you would have two ways of listing all the data: press *F9*, and then press *Enter*, or press *F5*. The semicolon at the end of the definition of *F5* will press *Enter* for you.

If you really want to change the definitions of *F9* and *F5*, you will probably want to change the definition every time you invoke Stata. One way would be to type the two `global` commands every time you invoke Stata. Another way would be to type the two commands into a text file named `profile.do`. Stata executes the commands in `profile.do` every time it is launched if `profile.do` is placed in the appropriate directory:

Windows:	see [GSW] B.3 Executing commands every time Stata is started
Mac:	see [GSM] B.1 Executing commands every time Stata is started
Unix:	see [GSU] B.1 Executing commands every time Stata is started

You can use the *F*-keys any way you desire: they contain a string of characters, and pressing the *F*-key is equivalent to typing those characters.

❑ Technical note

[*Stata for Unix(console) users.*] Sometimes Unix assigns a special meaning to the *F*-keys, and if it does, those meanings supersede our meanings. Stata provides a second way to get to the *F*-keys. Press *Ctrl+F*, release the keys, and then press a number from `0` through `9`. Stata interprets *Ctrl+F* plus 1 as equivalent to the *F1* key, *Ctrl+F* plus 2 as *F2*, and so on. *Ctrl+F* plus 0 means *F10*. These keys will work only if they are properly mapped in your `termcap` or `terminfo` entry.

❑

❑ Technical note

On some international keyboards, the left single quote is used as an accent character. In this case, we recommend mapping this character to one of your function keys. In fact, you might find it convenient to map both the left single quote (‘) and the right single quote (’) characters so that they are next to each other.

Within Stata, open the Do-file Editor. Type the following two lines in the Do-file Editor:

```
global F4 ‘
global F5 ’
```

Save the file as `profile.do` into your Stata directory. If you already have a `profile.do` file, append the two lines to your existing `profile.do` file.

Exit Stata and restart it. You should see the startup message

```
running C:\Program Files\Stata19\profile.do ...
```

or some variant of it depending on where your Stata is installed. Press *F4* and *F5* to verify that they work.

If you did not see the startup message, you did not save the `profile.do` in your home folder.

You can, of course, map to any other function keys, but *F1*, *F2*, *F7*, and *F8* are already used.

❑

10.3 Editing keys in Stata

Users have available to them the standard editing keys for their operating system. So, Stata should just edit what you type in the natural way—the Stata Command window is a standard edit window.

Also, you can fetch commands from the History window into the Command window. Click on a command in the History window, and it is loaded into the Command window, where you can edit it. Alternatively, if you double-click on a line in the History window, it is loaded and executed.

Another way to get lines from the History window into the Command window is with the *PgUp* and *PgDn* keys. Press *PgUp* and Stata loads the last command you typed into the Command window. Press it again and Stata loads the line before that, and so on. *PgDn* goes in the opposite direction.

Another editing key that interests users is *Esc*. This key clears the Command window.

In summary,

Press	Result
PgUp	Steps back through commands and moves command from History window to Command window
PgDn	Steps forward through commands and moves command from History window to Command window
Esc	Clears Command window

10.4 Editing keys in Stata for Unix(console)

Certain keys allow you to edit the line that you are typing. Because Stata supports a variety of computers and keyboards, the location and the names of the editing keys are not the same for all Stata users.

Every keyboard has the standard alphabet keys (*QWERTY* and so on), and every keyboard has a *Ctrl* key. Some keyboards have extra keys located to the right, above, or left, with names like *PgUp* and *PgDn*.

Throughout this manual we will refer to Stata's editing keys using names that appear on nobody's keyboard. For instance, PrevLine is one of the Stata editing keys—it retrieves a previous line. Hunt all you want, but you will not find it on your keyboard. So, where is PrevLine? We have tried to put it where you would naturally expect it. On keyboards with a key labeled *PgUp*, *PgUp* is the PrevLine key, but on everybody's keyboard, no matter which version of Unix, brand of keyboard, or anything else, *Ctrl+R* also means PrevLine.

When we say press PrevLine, now you know what we mean: press *PgUp* or *Ctrl+R*. The editing keys are the following:

Name for editing key	Editing key	Function
Kill	*Esc* on PCs and *Ctrl+U*	Deletes the line and lets you start over.
Dbs	*Backspace* on PCs and *Backspace* or *Delete* on other computers	Backs up and deletes one character.
Lft	←, *4* on the numeric keypad for PCs, and *Ctrl+H*	Moves the cursor left one character without deleting any characters.
Rgt	→, *6* on the numeric keypad for PCs, and *Ctrl+L*	Moves the cursor forward one character.
Up	↑, *8* on the numeric keypad for PCs, and *Ctrl+O*	Moves the cursor up one physical line on a line that takes more than one physical line. Also see PrevLine.
Dn	↓, *2* on the numeric keypad for PCs, and *Ctrl+N*	Moves the cursor down one physical line on a line that takes more than one physical line. Also see NextLine.
PrevLine	*PgUp* and *Ctrl+R*	Retrieves a previously typed line. You may press PrevLine multiple times to step back through previous commands.
NextLine	*PgDn* and *Ctrl+B*	The inverse of PrevLine.
Seek	*Ctrl+Home* on PCs and *Ctrl+W*	Goes to the line number specified. Before pressing Seek, type the line number. For instance, typing *3* and then pressing Seek is the same as pressing PrevLine three times.
Ins	*Ins* and *Ctrl+E*	Toggles insert mode. In insert mode, characters typed are inserted at the position of the cursor.
Del	*Del* and *Ctrl+D*	Deletes the character at the position of the cursor.
Home	*Home* and *Ctrl+K*	Moves the cursor to the start of the line.
End	*End* and *Ctrl+P*	Moves the cursor to the end of the line.
Hack	*Ctrl+End* on PCs, and *Ctrl+X*	Hacks off the line at the cursor.
Tab	→| on PCs, *Tab*, and *Ctrl+I*	Expand variable name.
Btab	|← on PCs, and *Ctrl+G*	The inverse of Tab.

▷ Example 1

It is difficult to demonstrate the use of editing keys in print. You should try each of them. Nevertheless, here is an example:

```
. summarize price waht
```

You typed `summarize price waht` and then pressed the *Lft* key (← key or *Ctrl+H*) three times to maneuver the cursor back to the `a` of `waht`. If you were to press *Enter* right now, Stata would see the command `summarize price waht`, so where the cursor is does not matter when you press *Enter*. If you wanted to execute the command `summarize price`, you could back up one more character and then press the Hack key. We will assume, however, that you meant to type `weight`.

If you were now to press the letter *e* on the keyboard, an `e` would appear on the screen to replace the `a`, and the cursor would move under the character `h`. We now have `weht`. You press *Ins*, putting Stata into insert mode, and press *i* and *g*. The line now says `summarize price weight`, which is correct, so

you press *Enter*. We did not have to press *Ins* before every character we wanted to insert. The *Ins* key is a toggle: If we press it again, Stata turns off insert mode, and what we type replaces what was there. When we press *Enter*, Stata forgets all about insert mode, so we do not have to remember from one command to the next whether we are in insert mode.

◁

❑ Technical note

Stata performs its editing magic from the information about your terminal recorded in `/etc/termcap`(5) or, under System V, `/usr/lib/terminfo`(4). If some feature does not appear to work, the entry for your terminal in the `termcap` file or `terminfo` directory is probably incorrect. Contact your system administrator.

❑

10.5 Editing previous lines in Stata

In addition to what is said below, remember that the History window also shows the contents of the review buffer.

One way to retrieve lines is with the PrevLine and NextLine keys. Remember, PrevLine and NextLine are the names we attach to these keys—there are no such keys on your keyboard. You have to look back at the previous section to find out which keys correspond to PrevLine and NextLine on your computer. To save you the effort this time, PrevLine probably corresponds to *PgUp* and NextLine probably corresponds to *PgDn*.

Suppose you wanted to reissue the third line back. You could press PrevLine three times and then press *Enter*. If you made a mistake and pressed PrevLine four times, you could press NextLine to go forward in the buffer. You do not have to count lines because, each time you press PrevLine or NextLine, the current line is displayed on your monitor. Simply press the key until you find the line you want.

Another method for reviewing previous lines, `#review`, is convenient for Unix(console) users.

▷ Example 2

Typing `#review` by itself causes Stata to list the last five commands you typed. For instance,

```
. #review
5 list make mpg weight if abs(res)>6
4 list make mpg weight if abs(res)>5
3 tabulate foreign if abs(res)>5
2 regress mpg weight weight2
1 test weight2=0
. _
```

We can see from the listing that the last command typed by the user was `test weight2=0`. Or, you may just look at the History window to see the history of commands you typed.

◁

▷ Example 3

Perhaps the command you are looking for is not among the last five commands you typed. You can tell Stata to go back any number of lines. For instance, typing `#review 15` tells Stata to show you the last 15 lines you typed:

```
. #review 15
%20 regress mpg weight weight2
%19 generate predmpg=_pred
%18 generate resmpg=mpg-_pred
%17 summarize resmpg, detail
%16 regress mpg weight weight2 foreign
15 replace resmpg=mpg-pred
14 summarize resmpg, detail
13 drop predmpg
12 describe
11 sort foreign
10 by foreign: summarize mpg weight
9 * lines that start with a * are comments.
8 * they go into the review buffer too.
7 summarize resmpg, detail
6 list make mpg weight
5 list make mpg weight if abs(res)>6
4 list make mpg weight if abs(res)>5
3 tabulate foreign if abs(res)>5
2 regress mpg weight weight2
1 test weight2=0
. _
```

If you wanted to resubmit the 10th previous line, you could type `10` and press Seek, or you could press PrevLine 10 times. No matter which of the above methods you prefer for retrieving lines, you may edit previous lines by using the editing keys.

◁

10.6 Tab expansion of variable names

Another way to quickly enter a variable name is to take advantage of Stata's tab-completion feature. Simply type the first few letters of the variable name in the Command window and press the *Tab* key. Stata will automatically type the rest of the variable name for you. If more than one variable name matches the letters you have typed, Stata will complete as much as it can and beep at you to let you know that you have typed a nonunique variable abbreviation.

The tab-completion feature also applies to typing filenames. If you start by typing a double quote, `"`, you can type the first few letters of a filename or directory and press the *Tab* key. Stata will automatically type the rest of the name for you. If more than one filename or directory matches the letters you have typed, Stata will complete as much as it can and beep at you to let you know that you have typed a nonunique abbreviation. After the entire filename or directory has been typed, type another double quote.

Elements of Stata

11 Language syntax

Contents

11.1 Overview

With few exceptions, the basic Stata language syntax is

[by *varlist*:] *command* [*varlist*] [=*exp*] [if *exp*] [in *range*] [*weight*] [, *options*]

where square brackets distinguish optional qualifiers and options from required ones. In this diagram, *varlist* denotes a list of variable names, *command* denotes a Stata command, *exp* denotes an algebraic expression, *range* denotes an observation range, *weight* denotes a weighting expression, and *options* denotes a list of options.

11.1.1 varlist

Most commands that take a subsequent *varlist* do not require that you explicitly type one. If no *varlist* appears, these commands assume *varlist* of `_all`, the Stata shorthand for indicating all the variables in the dataset. In commands that alter or destroy data, Stata requires that the *varlist* be specified explicitly. See **[U] 11.4 varname and varlists** for a complete description.

Some commands take *varname*, rather than *varlist*. *varname* refers to exactly one variable. The `tabulate` command requires *varname*; see [R] **tabulate oneway**.

▷ Example 1

The `summarize` command lists the mean, standard deviation, and range of the specified variables. In [R] **summarize**, we see that the syntax diagram for summarize is

`summarize` [*varlist*] [*if*] [*in*] [*weight*] [`,` *options*]

Farther down on the manual page is a table summarizing `options`, but let's focus on the syntax diagram itself first. Because everything except the word `summarize` is enclosed in square brackets, the simplest form of the command is "`summarize`". Typing `summarize` without arguments is equivalent to typing `summarize _all`; all the variables in the dataset are summarized. Underlining denotes the shortest allowed abbreviation, so we could have typed just `su`; see **[U] 11.2 Abbreviation rules**.

The table that defines *options* looks like this:

options	Description
Main	
`detail`	display additional statistics
`meanonly`	suppress the display; calculate only the mean; programmer's option
`format`	use variable's display format
`separator(#)`	draw separator line after every # variables; default is `separator(5)`

Thus we learn we could also type, for instance, `summarize, detail` or `summarize, detail format`.

As another example, the `drop` command eliminates variables or observations from a dataset. When dropping variables, its syntax is

`drop` *varlist*

`drop` has no option table because it has no options.

In fact, nothing is optional. Typing `drop` by itself would result in the error message "varlist or in range required". To drop all the variables in the dataset, we must type `drop _all`.

Even before looking at the syntax diagram, we could have predicted that *varlist* would be required—`drop` is destructive, so Stata requires us to spell out our intent. The syntax diagram informs us that *varlist* is required because *varlist* is not enclosed in square brackets. Because `drop` is not underlined, it cannot be abbreviated.

◁

11.1.2 by varlist:

The by *varlist*: prefix causes Stata to repeat a command for each subset of the data for which the values of the variables in *varlist* are equal. When prefixed with by *varlist*:, the result of the command will be the same as if you had formed separate datasets for each group of observations, saved them, and then gave the command on each dataset separately. The data must already be sorted by *varlist*, although by has a sort option; see **[U] 11.5 by varlist: construct** for more information.

▷ Example 2

Typing summarize marriage_rate divorce_rate produces a table of the mean, standard deviation, and range of marriage_rate and divorce_rate, using all the observations in the data:

```
. use https://www.stata-press.com/data/r19/census12
(1980 Census data by state)
. summarize marriage_rate divorce_rate
    Variable |        Obs        Mean    Std. dev.       Min        Max
-------------+---------------------------------------------------------
marriage_r~e |         50    .0133221    .0188122   .0074654   .1428282
divorce_rate |         50    .0056641    .0022473   .0029436   .0172918
```

Typing by region: summarize marriage_rate divorce_rate produces one table for each region of the country:

```
. sort region
. by region: summarize marriage_rate divorce_rate
-------------------------------------------------------------------------------
-> region = N Cntrl
    Variable |        Obs        Mean    Std. dev.       Min        Max
-------------+---------------------------------------------------------
marriage_r~e |         12    .0099121    .0011326   .0087363   .0127394
divorce_rate |         12    .0046974    .0011315   .0032817   .0072868
-------------------------------------------------------------------------------
-> region = NE
    Variable |        Obs        Mean    Std. dev.       Min        Max
-------------+---------------------------------------------------------
marriage_r~e |          9    .0087811     .001191   .0075757   .0107055
divorce_rate |          9     .004207    .0010264   .0029436   .0057071
-------------------------------------------------------------------------------
-> region = South
    Variable |        Obs        Mean    Std. dev.       Min        Max
-------------+---------------------------------------------------------
marriage_r~e |         16    .0114654    .0025721   .0074654   .0172704
divorce_rate |         16     .005633    .0013355   .0038917   .0080078
-------------------------------------------------------------------------------
-> region = West
    Variable |        Obs        Mean    Std. dev.       Min        Max
-------------+---------------------------------------------------------
marriage_r~e |         13    .0218987    .0363775   .0087365   .1428282
divorce_rate |         13    .0076037    .0031486   .0046004   .0172918
```

The dataset must be sorted on the by variables:

```
. use https://www.stata-press.com/data/r19/census12
(1980 Census data by state)
. by region: summarize marriage_rate divorce_rate
not sorted
r(5);
. sort region
. by region: summarize marriage_rate divorce_rate
(output appears)
```

We could also have asked that by sort the data:

```
. by region, sort: summarize marriage_rate divorce_rate
(output appears)
```

by *varlist*: can be used with most Stata commands; we can tell which ones by looking at their syntax diagrams. For instance, we could obtain the correlations by region, between marriage_rate and divorce_rate, by typing by region: correlate marriage_rate divorce_rate.

◁

❑ Technical note

varlist in by *varlist*: may contain up to 120,000 variables with Stata/MP, 32,767 variables with Stata/SE, or 2,048 variables with Stata/BE; these are the maximum allowed in the dataset. For instance, if we had data on automobiles and wished to obtain means according to market category (market) broken down by manufacturer (origin), we could type by market origin: summarize. That *varlist* contains two variables: market and origin. If the data were not already sorted on market and origin, we would first type sort market origin.

varlist in by *varlist*: may also contain string variables, numeric variables, or both. In the example above, region is a string variable, in particular, a str7. The example would have worked, however, if region were a numeric variable with values 1, 2, 3, and 4, or even 12.2, 16.78, 32.417, and 152.13.

❑

11.1.3 if exp

The if *exp* qualifier restricts the scope of a command to those observations for which the value of the expression is *true* (which is equivalent to the expression being nonzero; see **[U] 13 Functions and expressions**).

▷ Example 3

Typing summarize marriage_rate divorce_rate if region=="West" produces a table for the western region of the country:

```
. summarize marriage_rate divorce_rate if region == "West"
    Variable |        Obs        Mean    Std. dev.       Min        Max
-------------+---------------------------------------------------------
marriage_r~e |         13    .0218987    .0363775   .0087365   .1428282
divorce_rate |         13    .0076037    .0031486   .0046004   .0172918
```

The double equal sign in region=="West" is not an error. Stata uses a *double* equal sign to denote equality testing and one equal sign to denote assignment; see **[U] 13 Functions and expressions**.

A command may have at most one `if` qualifier. If you want the summary for the West restricted to observations with values of `marriage_rate` in excess of 0.015, do *not* type `summarize marriage_rate divorce_rate if region=="West" if marriage_rate>.015`. Instead type

```
. summarize marriage_rate divorce_rate if region == "West" & marriage_rate > .015
    Variable |        Obs        Mean    Std. dev.       Min        Max
-------------+---------------------------------------------------------
marriage_r~e |          1    .1428282           .    .1428282   .1428282
divorce_rate |          1    .0172918           .    .0172918   .0172918
```

You may not use the word *and* in place of the symbol "`&`" to join conditions. To select observations that meet one condition *or* another, use the "`|`" symbol. For instance, `summarize marriage_rate divorce_rate if region=="West" | marriage_rate>.015` summarizes all observations for which `region` is West *or* `marriage_rate` is greater than 0.015.

◁

▷ Example 4

`if` may be combined with `by`. Typing `by region: summarize marriage_rate divorce_rate if marriage_rate>.015` produces a set of tables, one for each region, reflecting summary statistics on `marriage_rate` and `divorce_rate` among observations for which `marriage_rate` exceeds 0.015:

```
. by region: summarize marriage_rate divorce_rate if marriage_rate > .015
-------------------------------------------------------------------------------
-> region = N Cntrl
    Variable |        Obs        Mean    Std. dev.       Min        Max
-------------+---------------------------------------------------------
marriage_r~e |          0
divorce_rate |          0
-------------------------------------------------------------------------------
-> region = NE
    Variable |        Obs        Mean    Std. dev.       Min        Max
-------------+---------------------------------------------------------
marriage_r~e |          0
divorce_rate |          0
-------------------------------------------------------------------------------
-> region = South
    Variable |        Obs        Mean    Std. dev.       Min        Max
-------------+---------------------------------------------------------
marriage_r~e |          2    .0163219    .0013414    .0153734   .0172704
divorce_rate |          2    .0061813    .0025831    .0043548   .0080078
-------------------------------------------------------------------------------
-> region = West
    Variable |        Obs        Mean    Std. dev.       Min        Max
-------------+---------------------------------------------------------
marriage_r~e |          1    .1428282           .    .1428282   .1428282
divorce_rate |          1    .0172918           .    .0172918   .0172918
```

The results indicate that there are no states in the Northeast and North Central regions for which `marriage_rate` exceeds 0.015, whereas there are two such states in the South and one state in the West.

◁

11.1.4 in range

The `in` *range* qualifier restricts the scope of the command to a specific observation range. A range specification takes the form $\#_1[/\#_2]$, where $\#_1$ and $\#_2$ are positive or negative integers. Negative integers are understood to mean "from the end of the data", with -1 referring to the last observation. The implied first observation must be less than or equal to the implied last observation.

The first and last observations in the dataset may be denoted by `f` and `l` (lowercase letter), respectively. `F` is allowed as a synonym for `f`, and `L` is allowed as a synonym for `l`. A range specifies absolute observation numbers within a dataset. As a result, the `in` qualifier may not be used when the command is preceded by the `by` *varlist*`:` prefix; see **[U] 11.5 by varlist: construct**.

▷ Example 5

Typing `summarize marriage_rate divorce_rate in 5/25` produces a table based on the values of `marriage_rate` and `divorce_rate` in observations 5–25:

```
. summarize marriage_rate divorce_rate in 5/25
    Variable |        Obs        Mean    Std. dev.       Min        Max
-------------+---------------------------------------------------------
marriage_r~e |         21    .0093941    .0012851   .0075757     .01293
divorce_rate |         21    .0045305    .0011273   .0029436   .0072868
```

This is, admittedly, a rather odd thing to want to do. It would not be odd, however, if we substituted `list` for `summarize`. If we wanted to see the states with the 10 lowest values of `marriage_rate`, we could type `sort marriage_rate` followed by `list marriage_rate in 1/10`.

Typing `summarize marriage_rate divorce_rate in f/l` is equivalent to typing `summarize marriage_rate divorce_rate`—all observations are summarized.

◁

▷ Example 6

Typing `summarize marriage_rate divorce_rate in 5/25 if region == "South"` produces a table based on the values of the two variables in observations 5–25 for which the value of `region` is South:

```
. summarize marriage_rate divorce_rate in 5/25 if region == "South"
    Variable |        Obs        Mean    Std. dev.       Min        Max
-------------+---------------------------------------------------------
marriage_r~e |          4    .0108187    .0016621   .0089399     .01293
divorce_rate |          4    .0051821    .0009356   .0043054   .0063596
```

The ordering of the `in` and `if` qualifiers is not significant. The command could also have been specified as `summarize marriage_rate divorce_rate if region == "South" in 5/25`.

◁

▷ Example 7

Negative `in` ranges can be useful with `sort`. For instance, we have data on automobiles and wish to list the five with the highest mileage ratings:

```
. use https://www.stata-press.com/data/r19/auto
(1978 automobile data)
. sort mpg
. list make mpg in -5/l
```

	make	mpg
70.	Toyota Corolla	31
71.	Plym. Champ	34
72.	Subaru	35
73.	Datsun 210	35
74.	VW Diesel	41

◁

11.1.5 =exp

= *exp* specifies the value to be assigned to a variable and is most often used with `generate` and `replace`. See **[U] 13 Functions and expressions** for details on expressions and [D] **generate** for details on the `generate` and `replace` commands.

Expression	Meaning
`generate newvar=oldvar+2`	creates a new variable named `newvar` equal to `oldvar`+2
`replace oldvar=oldvar+2`	changes the contents of the existing variable `oldvar`
`egen newvar=rank(oldvar)`	creates `newvar` containing the ranks of `oldvar` (see [D] **egen**)

11.1.6 weight

weight indicates the weight to be attached to each observation. The syntax of *weight* is

[*weightword*=*exp*]

where you actually type the square brackets and where *weightword* is one of

weightword	Meaning
`weight`	default treatment of weights
`fweight` *or* `frequency`	frequency weights
`pweight`	sampling weights
`aweight` *or* `cellsize`	analytic weights
`iweight`	importance weights

The underlining indicates the minimum acceptable abbreviation. Thus `weight` may be abbreviated `w` or `we`, etc.

▷ Example 8

Before explaining what the different types of weights mean, let's obtain the population-weighted mean of a variable called `median_age` from data containing observations on all 50 states of the United States. The dataset also contains a variable named `pop`, which is the total population of each state.

```
. use https://www.stata-press.com/data/r19/census12
(1980 Census data by state)
. summarize median_age [weight=pop]
(analytic weights assumed)
```

Variable	Obs	Weight	Mean	Std. dev.	Min	Max
median_age	50	225907472	30.11047	1.66933	24.2	34.7

In addition to telling us that our dataset contains 50 observations, Stata informs us that the sum of the weight is 225,907,472, which was the number of people living in the United States as of the 1980 census. The weighted mean is 30.11. We were also informed that Stata assumed that we wanted "analytic" weights.

◁

`weight` is each command's idea of what the "natural" weights are and is one of `fweight`, `pweight`, `aweight`, or `iweight`. When you specify the vague `weight`, the command informs you which kind it assumes. Not every command supports every kind of weight. A note below the syntax diagram for a command will tell you which weights the command supports.

Stata understands four kinds of weights:

1. `fweights`, or frequency weights, indicate duplicated observations. `fweights` are always integers. If the `fweight` associated with an observation is 5, that means there are really 5 such observations, each identical.
2. `pweights`, or sampling weights, denote the inverse of the probability that this observation is included in the sample because of the sampling design. A `pweight` of 100, for instance, indicates that this observation is representative of 100 subjects in the underlying population. The scale of these weights does not matter in terms of estimated parameters and standard errors, except when estimating totals and computing finite-population corrections with the `svy` commands; see [SVY] **Survey**.
3. `aweights`, or analytic weights, are inversely proportional to the variance of an observation; that is, the variance of the jth observation is assumed to be σ^2/w_j, where w_j are the weights. Typically, the observations represent averages, and the weights are the number of elements that gave rise to the average. For most Stata commands, the recorded scale of `aweights` is irrelevant; Stata internally rescales them to sum to N, the number of observations in your data, when it uses them.
4. `iweights`, or importance weights, indicate the relative "importance" of the observation. They have no formal statistical definition; this is a catch-all category. Any command that supports `iweights` will define how they are treated. They are usually intended for use by programmers who want to produce a certain computation.

See **[U] 20.24 Weighted estimation** for a thorough discussion of weights and their meaning.

❑ Technical note

When you do not specify a weight, the result is equivalent to specifying `[fweight=1]`.

❑

11.1.7 options

Many commands take command-specific options. These are described along with each command in the *Reference* manuals. Options are indicated by typing a comma at the end of the command, followed by the options you want to use.

▷ Example 9

Typing `summarize marriage_rate` produces a table of the mean, standard deviation, minimum, and maximum of the variable `marriage_rate`:

```
. summarize marriage_rate
    Variable |        Obs        Mean    Std. dev.       Min        Max
-------------+---------------------------------------------------------
marriage_r~e |         50    .0133221    .0188122    .0074654   .1428282
```

The syntax diagram for `summarize` is

`summarize` [*varlist*] [*if*] [*in*] [*weight*] [, *options*]

followed by the option table

options	Description
Main	
`detail`	display additional statistics
`meanonly`	suppress the display; calculate only the mean; programmer's option
`format`	use variable's display format
`separator(#)`	draw separator line after every # variables; default is `separator(5)`

Thus the options allowed by `summarize` are `detail` or `meanonly`, `format`, and `separator()`. The shortest allowed abbreviations for these options are `d` for `detail`, `mean` for `meanonly`, `f` for `format`, and `sep()` for `separator()`; see **[U] 11.2 Abbreviation rules**.

Typing `summarize marriage_rate, detail` produces a table that also includes selected percentiles, the four largest and four smallest values, the skewness, and the kurtosis.

```
. summarize marriage_rate, detail
                        marriage_rate
-------------------------------------------------------------
      Percentiles      Smallest
 1%     .0074654       .0074654
 5%     .0078956       .0075757
10%     .0080043       .0078956       Obs                  50
25%     .0089399       .0079079       Sum of wgt.          50

50%     .0105669                      Mean           .0133221
                       Largest        Std. dev.      .0188122
75%     .0122899       .0146266
90%     .0137832       .0153734       Variance       .0003539
95%     .0153734       .0172704       Skewness       6.718494
99%     .1428282       .1428282       Kurtosis       46.77306
```

◁

Some commands have options that are required. For instance, the `ranksum` command requires the `by(`*groupvar*`)` option, which identifies the grouping variable. *groupvar* is a specific kind of *varname*. It identifies to which group each observation belongs.

❑ Technical note

Once you have typed the *varlist* for the command, you can place options anywhere in the command. You can type `summarize marriage_rate divorce_rate if region=="West", detail`, or you can type `summarize marriage_rate divorce_rate, detail, if region=="West"`. You use a second comma to indicate a return to the command line as opposed to the option list. Leaving out the comma after the word `detail` would cause an error because Stata would attempt to interpret the phrase `if region=="West"` as an option rather than as part of the command.

You may not type an option in the middle of a *varlist*. Typing `summarize marriage_rate, detail, divorce_rate` will result in an error.

Options need not be specified contiguously. You may type `summarize marriage_rate divorce_rate, detail, if region=="South", noformat`. Both `detail` and `noformat` are options.

❑

❑ Technical note

Most options are toggles—they indicate that something either is or is not to be done. Sometimes it is difficult to remember which is the default. The following rule applies to all options: if *option* is an option, then `no`*option* is an option as well, and vice versa. Thus if we could not remember whether `detail` or `nodetail` were the default for `summarize` but we knew that we did not want the detail, we could type `summarize, nodetail`. Typing the `nodetail` option is unnecessary, but Stata will not complain.

Some options take *arguments*. The Stata `kdensity` command has an `n(#)` option that indicates the number of points at which the density estimate is to be evaluated. When an option takes an argument, the argument is enclosed in parentheses.

Some options take more than one argument. In such cases, arguments should be separated from one another by commas. For instance, you might see in a syntax diagram

`saving(`*filename*`[ , replace ])`

Here `replace` is the (optional) second argument. *Lists*, such as lists of variables (varlists) and lists of numbers (numlists), are considered to be one argument. If a syntax diagram reported

`powers(`*numlist*`)`

the list of numbers would be one argument, so the elements would not be separated by commas. You would type, for instance, `powers(1 2 3 4)`. In fact, Stata will tolerate commas here, so you could type `powers(1,2,3,4)`.

Some options take string arguments. `regress` has an `eform()` option that works this way—for instance, `eform("Exp Beta")`. To play it safe, you should type the quotes surrounding the string, although it is not required. If you do not type the quotes, any sequence of two or more consecutive blanks will be interpreted as one blank. Thus `eform(Exp beta)` would be interpreted the same as `eform(Exp beta)`.

❑

11.1.8 numlist

A *numlist* is a list of numbers. Stata allows certain shorthands to indicate ranges:

Numlist	Meaning
`2`	just one number
`1 2 3`	three numbers
`3 2 1`	three numbers in reversed order
`.5 1 1.5`	three different numbers
`1 3 -2.17 5.12`	four numbers in jumbled order
`1/3`	three numbers: 1, 2, 3
`3/1`	the same three numbers in reverse order
`5/8`	four numbers: 5, 6, 7, 8
`-8/-5`	four numbers: −8, −7, −6, −5
`-5/-8`	four numbers: −5, −6, −7, −8
`-1/2`	four numbers: −1, 0, 1, 2
`1 2 to 4`	four numbers: 1, 2, 3, 4
`4 3 to 1`	four numbers: 4, 3, 2, 1
`10 15 to 30`	five numbers: 10, 15, 20, 25, 30
`1 2:4`	same as 1 2 to 4
`4 3:1`	same as 4 3 to 1
`10 15:30`	same as 10 15 to 30
`1(1)3`	three numbers: 1, 2, 3
`1(2)9`	five numbers: 1, 3, 5, 7, 9
`1(2)10`	the same five numbers, 1, 3, 5, 7, 9
`9(-2)1`	five numbers: 9, 7, 5, 3, and 1
`-1(.5)2.5`	the numbers −1, −.5, 0, .5, 1, 1.5, 2, 2.5
`1[1]3`	same as 1(1)3
`1[2]9`	same as 1(2)9
`1[2]10`	same as 1(2)10
`9[-2]1`	same as 9(−2)1
`-1[.5]2.5`	same as −1(.5)2.5
`1 2 3/5 8(2)12`	eight numbers: 1, 2, 3, 4, 5, 8, 10, 12
`1,2,3/5,8(2)12`	the same eight numbers
`1 2 3/5 8 10 to 12`	the same eight numbers
`1,2,3/5,8,10 to 12`	the same eight numbers
`1 2 3/5 8 10:12`	the same eight numbers

`poisson`'s `constraints()` option has syntax `constraints(`*numlist*`)`. Thus you could type `constraints(2 4 to 8)`, `constraints(2(2)8)`, etc.

11.1.9 datelist

A *datelist* is a list of dates or times and is often used with graph options when the variable being graphed has a date format. For a description of how dates and times are stored and manipulated in Stata, see **[U] 25 Working with dates and times**. Calendar dates, also known as `%td` dates, are recorded in Stata as the number of days since 01jan1960, so 0 means 01jan1960, 1 means 02jan1960, and 16,541 means 15apr2005. Similarly, −1 means 31dec1959, −2 means 30dec1959, and −16,541 means 18sep1914. In such a case, a datelist is a list of dates, as in

```
15apr1973 17apr1973 20apr1973 23apr1973
```

or it is a first and last date with an increment between, as in

```
17apr1973(3)23apr1973
```

or it is a combination:

```
15apr1973 17apr1973(3)23apr1973
```

Dates specified with spaces, slashes, or commas must be bound in parentheses, as in

```
(15 apr 1973) (april 17, 1973)(3)(april 23, 1973)
```

Evenly spaced calendar dates are not especially useful, but with other time units, even spacing can be useful, such as

```
1999q1(1)2005q1
```

when %tq dates are being used. 1999q1(1)2005q1 means every quarter between 1999q1 and 2005q1. 1999q1(4)2005q1 would mean every first quarter.

To interpret a datelist, Stata first looks at the format of the related variable and then uses the corresponding date-to-numeric translation function. For instance, if the variable has a %td format, the td() function is used to translate the date; if the variable has a %tq format, the tq() function is used; and so on. See *Typing dates into expressions* in [D] **Datetime**.

11.1.10 Prefix commands

Stata has a handful of commands that are used to prefix other Stata commands. by *varlist*:, discussed in section **[U] 11.1.2 by varlist:**, is in fact an example of a prefix command. In that section, we demonstrated by using

```
by region: summarize marriage_rate divorce_rate
```

and later,

```
by region, sort: summarize marriage_rate divorce_rate
```

and although we did not, we could also have demonstrated

```
by region, sort: summarize marriage_rate divorce_rate, detail
```

Each of the above runs the summarize command separately on the data for each region.

by itself follows standard Stata syntax:

by *varlist*[, *options*]: ...

In by region, sort: summarize marriage_rate divorce_rate, detail, region is by's varlist and sort is by's option, just as marriage_rate and divorce_rate are summarize's varlist and detail is summarize's option.

by is not the only prefix command, and the full list of such commands is

Prefix command	Description
by	run command on subsets of data
collect	run command and collect results to include in a table
frame	run command on the data in a specified frame
statsby	same as by, but collect statistics from each run
rolling	run command on moving subsets and collect statistics
bayesboot	perform Bayesian bootstrap estimation of specified statistics
bootstrap	run command on bootstrap samples
jackknife	run command on jackknife subsets of data
permute	run command on random permutations
simulate	run command on manufactured data
svy	run command and adjust results for survey sampling
mi estimate	run command on multiply imputed data and adjust results for multiple imputation (MI)
bayes	fit a Bayesian regression model
fmm	fit a finite mixture model
nestreg	run command with accumulated blocks of regressors and report nested model comparison tests
stepwise	run command with stepwise variable inclusion/exclusion
xi	run command after expanding factor variables and interactions; for most commands, using factor variables is preferred to using xi (see [U] 11.4.3 Factor variables)
fp	run command with fractional polynomials of one regressor
mfp	run command with multiple fractional polynomial regressors
capture	run command and capture its return code
noisily	run command and show the output
quietly	run command and suppress the output
version	run command under specified version

The last group—capture, noisily, quietly, and version—deal with programming Stata and, for historical reasons, capture, noisily, and quietly allow you to omit the colon, so one programmer might code

```
quietly regress ...
```

and another

```
quietly: regress ...
```

All the other prefix commands require the colon. In addition to the corresponding reference manual entries, you may want to consult Baum (2016) for a richer discussion of prefix commands.

11.2 Abbreviation rules

Stata allows abbreviations. In this manual, we usually avoid abbreviating commands, variable names, and options to ensure readability:

```
. summarize myvar, detail
```

Experienced Stata users, on the other hand, tend to abbreviate the same command as

```
. sum myv, d
```

As a general rule, command, option, and variable names may be abbreviated to the shortest string of characters that uniquely identifies them.

This rule is violated if the command or option does something that cannot easily be undone; the command must then be spelled out in its entirety.

Also, a few common commands and options are allowed to have even shorter abbreviations than the general rule would allow.

The general rule is applied, without exception, to variable names.

11.2.1 Command abbreviation

The shortest allowed abbreviation for a command or option can be determined by looking at the command's syntax diagram. This minimal abbreviation is shown by underlining:

<u>g</u>enerate
<u>ap</u>pend
<u>rot</u>ate
<u>run</u>

If there is no underlining, no abbreviation is allowed. For example, `replace` may not be abbreviated, the underlying reason being that `replace` changes the data.

`rename` can be abbreviated `ren`, `rena`, or `renam`, or it can be spelled out in its entirety.

Sometimes short abbreviations are also allowed. Commands that begin with the letter *d* include `decode`, `describe`, `destring`, `dir`, `discard`, `display`, `do`, and `drop`, which suggests that the shortest allowable abbreviation for `describe` is `desc`. However, because `describe` is such a commonly used command, you may abbreviate it with the single letter `d`. You may also abbreviate the `list` command with the single letter `l`.

The other exception to the general abbreviation rule is that commands that alter or destroy data must be spelled out completely. Two commands that begin with the letter *d*, `discard` and `drop`, are destructive in the sense that, once you give one of these commands, there is no way to undo the result. Therefore, both must be spelled out.

The final exceptions to the general rule are commands implemented as ado-files. Such commands may not be abbreviated. Ado-file commands are external, and their names correspond to the names of disk files.

11.2.2 Option abbreviation

Option abbreviation follows the same logic as command abbreviation: you determine the minimum acceptable abbreviation by examining the command's syntax diagram. The syntax diagram for `summarize` reads, in part,

```
summarize ..., detail format
```

The `detail` option may be abbreviated `d`, `de`, `det`, ..., `detail`. Similarly, the `format` option may be abbreviated `f`, `fo`, ..., `format`.

The `clear` and `replace` options occur with many commands. The `clear` option indicates that even though completing this command will result in the loss of all data in memory, and even though the data in memory have changed since the data were last saved on disk, you want to continue. `clear` must be spelled out, as in `use newdata, clear`.

The `replace` option indicates that it is okay to save over an existing dataset. If you type `save mydata` and the file `mydata.dta` already exists, you will receive the message "file mydata.dta already exists", and Stata will refuse to overwrite it. To allow Stata to overwrite the dataset, you would type `save mydata, replace`. `replace` may not be abbreviated.

❑ Technical note

`replace` is a stronger modifier than `clear` and is one you should think about before using. With a mistaken `clear`, you can lose hours of work, but with a mistaken `replace`, you can lose days of work. ❑

11.2.3 Variable-name abbreviation

- Variable names may be abbreviated to the shortest string of characters that uniquely identifies them given the data currently loaded in memory.

  If your dataset contained four variables, `state`, `mrgrate`, `dvcrate`, and `dthrate`, you could refer to the variable `dvcrate` as `dvcrat`, `dvcra`, `dvcr`, `dvc`, or `dv`. You might type `list dv` to list the data on `dvcrate`. You could not refer to the variable `dvcrate` as `d`, however, because that abbreviation does not distinguish `dvcrate` from `dthrate`. If you were to type `list d`, Stata would respond with the message "ambiguous abbreviation". (If you wanted to refer to *all* variables that started with the letter *d*, you could type `list d*`; see **[U] 11.4 varname and varlists**.)

- The character ~ may be used to mean that "zero or more characters go here". For instance, `r~8` might refer to the variable `rep78`, or `rep1978`, or `repair1978`, or just `r8`. (The ~ character is similar to the `*` character in **[U] 11.4 varname and varlists**, except that it adds the restriction "and only one variable matches this specification".)

  Above, we said that you could abbreviate variables. You could type `dvcr` to refer to `dvcrate`, but, if there were more than one variable that started with the letters `dvcr`, you would receive an error. Typing `dvcr` is the same as typing `dvcr~`.

11.2.4 Abbreviations for programmers

Stata has several useful commands and functions to assist programmers with abbreviating and unabbreviating command names and variable names.

Command/function	Description
unab	expand and unabbreviate standard variable lists
tsunab	expand and unabbreviate variable lists that may contain time-series operators
fvunab	expand and unabbreviate variable lists that may contain time-series operators or factor variables
unabcmd	unabbreviate command name
novarabbrev	turn off variable abbreviation
varabbrev	turn on variable abbreviation
set varabbrev	set whether variable abbreviations are supported
abbrev(*s*,*n*)	string function that abbreviates s to n display columns
abbrev(*s*,*n*)	Mata variant of above that allows s and n to be matrices

11.3 Naming conventions

A name is a sequence of 1 to 32 letters (A–Z, a–z, and any Unicode letter), digits (0–9), and underscores (_).

Programmers: Local macro names can have no more than 31 characters in the name; see **[U] 18.3.1 Local macros**.

Stata reserves the following names:

```
alias     _n        _r_p
_all      _N        _r_se
_b        _pi       _r_ub
byte      _pred     _r_z
_coef     _r_b      _r_z_abs
_cons     _rc       _se
double    _r_ci     _skip
float     _r_cri    str#
if        _r_crlb   strL
in        _r_crub   using
int       _r_df     with
long      _r_lb
```

You may not use these reserved names for your variables.

The first character of a name must be a letter or an underscore (macro names are an exception; they may also begin with a digit). We recommend, however, that you not begin your variable names with an underscore. All of Stata's built-in variables begin with an underscore, and we reserve the right to incorporate new *_variables* freely.

Stata respects case; that is, myvar, Myvar, and MYVAR are three distinct names.

Most objects in Stata—not just variables—follow this naming convention.

11.4 varname and varlists

varlist is a list of variable names. The variable names in *varlist* refer either exclusively to new (not yet created) variables or exclusively to existing variables. *newvarlist* always refers exclusively to new (not yet created) variables. Similarly, *varname* refers to one variable, either existing or not yet created. *newvar* always refers to one new variable.

Sometimes a command will refer to a varname in another way, such as "*groupvar*". This is still a varname. The different name is used to give you an extra hint about the purpose of that variable. For example, *groupvar* is the name of a variable that defines groups within your data. Other common ways of referring to *varname* or *varlist* in Stata are

depvar, which means the dependent variable for an estimation command;

indepvars, which means *varlist* containing the independent variables for an estimation command;

xvar, which means a continuous real variable, often plotted on the x axis of a graph;

yvar, which means a variable that is a function of an *xvar*, often plotted on the y axis of a graph;

clustvar, which means a numeric variable that identifies the cluster or group to which an observation belongs;

panelvar, which means a numeric variable that identifies panels in panel data, also known as cross-sectional time-series data; and

timevar, which means a numeric variable with a `%td`, `%tc`, or `%tC` format.

11.4.1 Lists of existing variables

In lists of existing variable names, variable names may be repeated.

If you type `list state mrgrate dvcrate state`, the variable `state` will be listed twice, once in the leftmost column and again in the rightmost column of the list.

Existing variable names may be abbreviated as described in **[U] 11.2 Abbreviation rules**. You may also use "`*`" to indicate that "zero or more characters go here". For instance, if you suffix `*` to a partial variable name (for example, `sta*`), you are referring to all variable names that start with that letter combination. If you prefix `*` to a letter combination (for example, `*rate`), you are referring to all variables that end in that letter combination. If you put `*` in the middle (for example, `m*rate`), you are referring to all variables that begin and end with the specified letters. You may put more than one `*` in an abbreviation.

▷ Example 10

If the variables `poplt5`, `pop5to17`, and `pop18p` are in our dataset, we may type `pop*` as a shorthand way to refer to all three variables. For instance, `list state pop*` lists the variables `state`, `poplt5`, `pop5to17`, and `pop18p`.

If we had a dataset with variables `inc1990`, `inc1991`, …, `inc1999` along with variables `incfarm1990`, …, `incfarm1999`; `pop1990`, …, `pop1999`; and `ms1990`, …, `ms1999`, then `*1995` would be a shorthand way of referring to `inc1995`, `incfarm1995`, `pop1995`, and `ms1995`. We could type, for instance, `list *1995`.

In that same dataset, typing `list i*95` would be a shorthand way of listing `inc1995` and `incfarm1995`.

Typing `list i*f*95` would be a shorthand way of listing to `incfarm1995`.

◁

Typing ~ is an alternative to `*`, and really, it means the same thing. The difference is that ~ indicates that if more than one variable matches the specified pattern, Stata will complain rather than substituting all the variables that match the specification.

▷ Example 11

In the previous example, we could have typed `list i~f~95` to list `incfarm1995`. If, however, our dataset also included variable `infant1995`, then `list i*f*95` would list both variables and `list i~f~95` would complain that `i~f~95` is an ambiguous abbreviation.

◁

You may use `?` to specify that one character goes here. Remember, `*` means zero or more characters go here, so `?*` can be used to mean one or more characters goes here, `??*` can be used to mean two or more characters go here, and so on.

▷ Example 12

In a dataset containing variables `rep1`, `rep2`, …, `rep78`, `rep?` would refer to `rep1`, `rep2`, …, `rep9`, and `rep??` would refer to `rep10`, `rep11`, …, `rep78`.

◁

You may place a dash (`-`) between two variable names to specify all the variables stored between the two listed variables, inclusive. You can determine storage order by using `describe`; it lists variables in the order in which they are stored.

▷ Example 13

If the dataset contains the variables `state`, `mrgrate`, `dvcrate`, and `dthrate`, in that order, typing `list state-dvcrate` is equivalent to typing `list state mrgrate dvcrate`. In both cases, three variables are listed.

◁

11.4.2 Lists of new variables

In lists of *new variables*, no variable names may be repeated or abbreviated.

You may specify a dash (`-`) between two variable names that have the same letter prefix and that end in numbers. This form of the dash notation indicates a range of variable names in ascending numerical order.

For example, typing `input v1-v4` is equivalent to typing `input v1 v2 v3 v4`. Typing `infile state v1-v3 ssn using rawdata` is equivalent to typing `infile state v1 v2 v3 ssn using rawdata`.

Many commands that require a specific number of new variables also allow the new variables to be specified using the *stub*`*` notation. For example, if you are using `predict` to generate four new variables, you could type `predict pred*` to create new variables `pred1`, `pred2`, `pred3`, and `pred4`.

You may specify the storage type before the variable name to force a storage type other than the default. The numeric storage types are `byte`, `int`, `long`, `float` (the default), and `double`. The string storage types are `str#`, where # is replaced with an integer between 1 and 2045, inclusive, representing the maximum length of the string, or `strL`. See **[U] 12 Data**.

For instance, the list `var1 str8 var2 var3` specifies that `var1` and `var3` be given the default storage type and that `var2` be stored as a `str8`—a string whose maximum length is eight bytes.

The list `var1 int var2 var3` specifies that `var2` be stored as an `int`. You may use parentheses to bind a list of variable names. The list `var1 int(var2 var3)` specifies that both `var2` and `var3` be stored as `int`s. Similarly, the list `var1 str20(var2 var3)` specifies that both `var2` and `var3` be stored as `str20`s. The different storage types are listed in **[U] 12.2.2 Numeric storage types** and **[U] 12.4 Strings**.

▷ Example 14

Typing `infile str2 state str10 region v1-v5 using mydata` reads the `state` and `region` strings from the file `mydata.raw` and stores them as `str2` and `str10`, respectively, along with the variables `v1` through `v5`, which are stored as the default storage type `float` (unless we have specified a different default with the `set type` command).

Typing `infile str10(state region) v1-v5 using mydata` would achieve almost the same result, except that the `state` and `region` values recorded in the data would both be assigned to `str10` variables. (We could then use the `compress` command to shorten the strings. See [D] **compress**; it is well worth reading.)

◁

❑ Technical note

You may append a colon and a *value label name* to numeric variables. (See **[U] 12.6 Dataset, variable, and value labels** for a description of value labels.) For instance, `var1 var2:myfmt` specifies that the variable `var2` be associated with the value label stored under the name `myfmt`. This has the same effect as typing the list `var1 var2` and then subsequently giving the command `label values var2 myfmt`.

The advantage of specifying the value label association with the colon notation is that value labels can then be assigned by the current command; see [D] **input** and [D] **infile (free format)**.

❑

▷ Example 15

Typing `infile int(state:stfmt region:regfmt) v1-v5 using mydata, automatic` reads the state and region data from the file `mydata.raw` and stores them as `int`s, along with the variables `v1` through `v5`, which are stored as the default storage type.

In our previous example, both state and region were strings, so how can strings be stored in a numeric variable? See **[U] 12.6 Dataset, variable, and value labels** for the complete answer. The colon notation specifies the name of the value label, and the `automatic` option tells Stata to assign unique numeric codes to all character strings. The numeric code for state, which Stata will make up on the fly, will be stored in the `state` variable. The mapping from numeric codes to words will be stored in the value label named `stfmt`. Similarly, regions will be assigned numeric codes, which are stored in `region`, and the mapping will be stored in `regfmt`.

If we were to `list` the data, the `state` and `region` variables would look like strings. `state`, for instance, would appear to contain things like `AL`, `CA`, and `WA`, but actually it would contain only numbers like 1, 2, 3, and 4.

◁

11.4.3 Factor variables

Factor variables are extensions of varlists of existing variables. When a command allows factor variables, in addition to typing variable names from your data, you can type factor variables, which might look like

`i.`*varname*

`i.`*varname*`#i.`*varname*

`i.`*varname*`#i.`*varname*`#i.`*varname*

`i.`*varname*`##i.`*varname*

`i.`*varname*`##i.`*varname*`##i.`*varname*

Factor variables create indicator variables from categorical variables and are allowed with most estimation and postestimation commands, along with a few other commands.

Consider a variable named `group` that takes on the values 1, 2, and 3. Stata command `list` allows factor variables, so we can see how factor variables are expanded by typing

```
. list group i.group in 1/5
```

	group	1. group	2. group	3. group
1.	1	1	0	0
2.	1	1	0	0
3.	2	0	1	0
4.	2	0	1	0
5.	3	0	0	1

There are no variables named `1.group`, `2.group`, and `3.group` in our data; there is only the variable named `group`. When we type `i.group`, however, Stata acts as if the variables `1.group`, `2.group`, and `3.group` exist. `1.group`, `2.group`, and `3.group` are called virtual variables. `1.group` is a virtual variable equal to 1 when `group` $= 1$, and 0 otherwise. `2.group` is a virtual variable equal to 1 when `group` $= 2$, and 0 otherwise. `3.group` is a virtual variable equal to 1 when `group` $= 3$, and 0 otherwise.

The categorical variable to which factor-variable operators are applied must contain nonnegative integers.

❑ Technical note

We said above that `3.group` equals 1 when `group` $= 3$ and equals 0 otherwise. We should have added that `3.group` equals missing when `group` contains missing. To be precise, `3.group` equals 1 when `group` $= 3$, equals system missing (`.`) when `group` $\geq$ `.`, and equals 0 otherwise.

❑

❑ Technical note

We said above that when we typed `i.group`, Stata acts as if the variables `1.group`, `2.group`, and `3.group` exist, and that might suggest that the act of typing `i.group` somehow created the virtual variables. That is not true; the virtual variables always exist.

In fact, `i.group` is an abbreviation for `1.group`, `2.group`, and `3.group`. In any command that allows factor variables, you can specify virtual variables. Thus the listing above could equally well have been produced by typing

```
. list group 1.group 2.group 3.group in 1/5
```

#.*varname* is defined as equal to 1 when *varname* = #, equal to system missing (.) when *varname* ≥ ., and equal to 0 otherwise. Thus `4.group` is defined even when `group` takes on only the values 1, 2, and 3. `4.group` would be equal to 0 in all observations. Referring to `4.group` would not produce an error such as "virtual variable not found".

❑

When factor-variable operators are used in a regression command, one of the categories is chosen as a base category. If we type

```
. regress y i.group
```

this is equivalent to typing

```
. regress y 1b.group 2.group 3.group
```

`1b.group` is different from the other virtual variables. The `b` is a marker indicating base value. `1b.group` is a virtual variable equal to 0. We can see this by typing

```
. list group i.group in 1/5
```

	group	1. group	2. group	3. group
1.	1	1	0	0
2.	1	1	0	0
3.	2	0	1	0
4.	2	0	1	0
5.	3	0	0	1

When the `i.group` collection is included in a linear regression, virtual variable `1b.group` drops from the estimation because it does not vary; thus the coefficients on `2.group` and `3.group` would measure the change from `group` = 1. Hence, the term base value.

11.4.3.1 Factor-variable operators

`i.group` is called a factor variable, although more correctly, we should say that `group` is a categorical variable to which factor-variable operators have been applied. There are five factor-variable operators:

Operator	Description
`i.`	unary operator to specify indicators
`c.`	unary operator to treat as continuous
`o.`	unary operator to omit a variable or indicator
`#`	binary operator to specify interactions
`##`	binary operator to specify full-factorial interactions

When you type `i.group`, it forms the indicators for the distinct values of `group`. We will usually say this more briefly as `i.group` forms indicators for the levels of `group`, and sometimes we will abbreviate the statement even more and say `i.group` forms indicators for `group`.

The `c.` operator means continuous. We will get to that below.

The o. operator specifies that a continuous variable or an indicator for a level of a categorical variable should be omitted. For example, o.age means that the continuous variable age should be omitted, and o2.group means that the indicator for group = 2 should be omitted.

and ##, pronounced cross and factorial cross, are operators for use with pairs of variables.

i.group#i.sex means to form indicators for each combination of the levels of group and sex.

group#sex means the same thing, which is to say that use of # implies the i. prefix.

group#c.age (or i.group#c.age) means the interaction of the levels of group with the continuous variable age. This amounts to forming i.group and then multiplying each level by age. We already know that i.group expands to the virtual variables 1.group, 2.group, and 3.group, so group#c.age results in the collection of variables equal to 1.group*age, 2.group*age, and 3.group*age. 1.group*age will be age when group = 1, and 0 otherwise. 2.group*age will be age when group = 2, and 0 otherwise. 3.group*age will be age when group = 3, and 0 otherwise.

In a regression of y on age and group#c.age, group = 1 will again be chosen as the base value of group. Thus group#c.age expands to 1b.group*age, 2.group*age, and 3.group*age. 1b.group*age will be zero because 1b.group is zero, so it will be omitted. 2.group*age will measure the change in the age coefficient for group = 2 relative to the base group, and 3.group*age will measure the change for group = 3 relative to the base.

Here are some more examples of use of the operators:

Factor specification	Result
i.group	indicators for levels of group
i.group#i.sex	indicators for each combination of levels of group and sex, a two-way interaction
group#sex	same as i.group#i.sex
group#sex#arm	indicators for each combination of levels of group, sex, and arm, a three-way interaction
group##sex	same as i.group i.sex group#sex
group##sex##arm	same as i.group i.sex i.arm group#sex group#arm sex#arm group#sex#arm
sex#c.age	two variables—age for males and 0 elsewhere, and age for females and 0 elsewhere; if age is also in the model, one of the two virtual variables will be treated as a base
sex##c.age	same as i.sex age sex#c.age
c.age	same as age
c.age#c.age	age squared
c.age#c.age#c.age	age cubed

Several factor-variable terms are often specified in the same varlist, such as

```
. regress y  i.sex i.group sex#group age sex#c.age
```

or, equivalently,

```
. regress y  sex##group sex##c.age
```

11.4.3.2 Base levels

When we typed `i.group` in a regression command, `group` = 1 became the base level. When we do not specify otherwise, the smallest level becomes the base level.

You can specify the base level of a factor variable by using the `ib.` operator. The syntax is

Base operator[a]	Description
`ib#.`	use # as base, # = value of variable
`ib(##).`	use the #th ordered value as base[b]
`ib(first).`	use smallest value as base (default)
`ib(last).`	use largest value as base
`ib(freq).`	use most frequent value as base
`ibn.`	no base level

[a] The `i` may be omitted. For instance, you can type `ib2.group` or `b2.group`.
[b] For example, `ib(#2).` means to use the second value as the base.

Thus, if you want to use `group` = 3 as the base, you can type `ib3.group`. You can type

```
. regress y  i.sex ib3.group sex#ib3.group age sex#c.age
```

or you can type

```
. regress y  i.sex ib3.group sex#group age sex#c.age
```

That is, you only have to set the base once. If you specify the base level more than once, it must be the same base level. You will get an error if you attempt to change base levels in midsentence.

If you type `ib3.group`, the virtual variables become `1.group`, `2.group`, and `3b.group`.

Were you to type `ib(freq).group`, the virtual variables might be `1b.group`, `2.group`, and `3.group`; `1.group`, `2b.group`, and `3.group`; or `1.group`, `2.group`, and `3b.group`, depending on the most frequent group in the data.

11.4.3.3 Setting base levels permanently

You can permanently set the base level by using the `fvset` command; see [R] **fvset**. For example,

```
. fvset base 3  group
```

sets the base for `group` to be 3. The setting is recorded in the data, and if the dataset is resaved, the base level will be remembered in future sessions.

If you want to set the base group back to the default, type

```
. fvset base default  group
```

If you want to set the base levels for a group of variables to be the largest value, you can type

```
. fvset base last  group sex arm
```

See [R] **fvset** for details.

Base levels can be temporarily overridden by using the `ib.` operator regardless of whether they are set explicitly.

11.4.3.4 Selecting levels

Typing `i.group` specifies virtual variables `1b.group`, `2.group`, and `3.group`. Regardless of whether you type `i.group`, you can access those virtual variables. You can, for instance, use them in expressions and `if` statements:

```
. list if 3.group
  (output omitted)
. generate over_age = cond(3.group, age-21, 0)
```

Although throughout this section we have been typing `#.group` such as `3.group` as if it is somehow different from `i.group`, the complete, formal syntax is `i3.group`. You are allowed to omit the `i`. The point is that `i3.group` is just a special case of `i.group`; `i3.group` specifies an indicator for the third level of `group`, and `i.group` specifies the indicators for all the levels of `group`. Anyway, the above commands could be typed as

```
. list if i3.group
  (output omitted)
. generate over_age = cond(i3.group, age-21, 0)
```

Similarly, the virtual variables `1b.group`, `2.group`, and `3.group` more formally would be referred to as `i1b.group`, `i2.group`, and `i3.group`. You are allowed to omit the leading `i` whenever what appears after is a number or a `b` followed by a base specification.

You can select a range of levels—a range of virtual variables—by using the `i(`*numlist*`).`*varname*. This can be useful when specifying the model to be fit using estimation commands. You may not omit the `i` when specifying a numlist.

Examples	Description
`i2.cat`	single indicator for `cat` = 2
`2.cat`	same as `i2.cat`
`i(2 3 4).cat`	three indicators, `cat` = 2, `cat` = 3, and `cat` = 4; same as `i2.cat i3.cat i4.cat`
`i(2/4).cat`	same as `i(2 3 4).cat`
`2.cat#1.sex`	a single indicator that is 1 when `cat` = 2 and `sex` = 1 and is 0 otherwise
`i2.cat#i1.sex`	same as `2.cat#1.sex`

Rather than selecting the levels that should be included, you can specify the levels that should be omitted by using the `o.` operator. When you use `io(`*numlist*`).`*varname* in a command, indicators for the levels of *varname* other than those specified in *numlist* are included. When omitted levels are specified with the `o.` operator, the `i.` operator is implied, and the remaining indicators for the levels of *varname* will be included.

Examples	Description
`io2.cat`	indicators for levels of `cat`, omitting the indicator for `cat` = 2
`o2.cat`	same as `io2.cat`
`io(2 3 4).cat`	indicators for levels of `cat`, omitting three indicators, `cat` = 2, `cat` = 3, and `cat` = 4
`o(2 3 4).cat`	same as `io(2 3 4).cat`
`o(2/4).cat`	same as `io(2 3 4).cat`
`o2.cat#o1.sex`	indicators for each combination of the levels of `cat` and `sex`, omitting the indicator for `cat` = 2 and `sex` = 1

11.4.3.5 Applying operators to a group of variables

Factor-variable operators may be applied to groups of variables by using parentheses. You may type, for instance,

```
i.(group sex arm)
```

to mean `i.group i.sex i.arm`.

In the examples that follow, variables `group`, `sex`, `arm`, and `cat` are categorical, and variables `age`, `wt`, and `bp` are continuous:

Examples	Expansion
`i.(group sex arm)`	`i.group i.sex i.arm`
`group#(sex arm cat)`	`group#sex group#arm group#cat`
`group##(sex arm cat)`	`i.group i.sex i.arm i.cat group#sex group#arm group#cat`
`group#(c.age c.wt c.bp)`	`group#c.age group#c.wt group#c.bp`
`group#c.(age wt bp)`	same as `group#(c.age c.wt c.bp)`

Parentheses can shorten what you type and make it more readable. For instance,

```
. regress y  i.sex i.group sex#group age sex#c.age c.age#c.age sex#c.age#c.age
```

is easier to understand when written as

```
. regress y  sex##(group c.age c.age#c.age)
```

11.4.3.6 Using factor variables with time-series operators

Factor-variable operators may be combined with the `L.` and `F.` time-series operators, so you may specify lags and leads of factor variables in time-series applications. You could type `iL.group` or `Li.group`; the order of the operators does not matter. You could type `L.group#L.arm` or `L.group#c.age`.

Examples include

```
. regress y b1.sex##(i(2/4).group cL.age cL.age#cL.age)
. regress y 2.arm#(sex#i(2/4)b3.group cL.age)
. regress y 2.arm##cat##(sex##i(2/4)b3.group cL.age#c.age) c.bp
>           c.bp#c.bp c.bp#c.bp#c.bp sex##c.bp#c.age
```

11.4.3.7 Video examples

Introduction to factor variables in Stata, part 1: The basics

Introduction to factor variables in Stata, part 2: Interactions

Introduction to factor variables in Stata, part 3: More interactions

11.4.4 Time-series varlists

Time-series varlists are a variation on varlists of existing variables. When a command allows a time-series varlist, you may include time-series operators. For instance, `L.gnp` refers to the lagged value of variable gnp. The time-series operators are

Operator	Meaning
`L.`	lag x_{t-1}
`L2.`	2-period lag x_{t-2}
...	
`F.`	lead x_{t+1}
`F2.`	2-period lead x_{t+2}
...	
`D.`	difference $x_t - x_{t-1}$
`D2.`	difference of difference $x_t - x_{t-1} - (x_{t-1} - x_{t-2}) = x_t - 2x_{t-1} + x_{t-2}$
...	
`S.`	"seasonal" difference $x_t - x_{t-1}$
`S2.`	lag-2 (seasonal) difference $x_t - x_{t-2}$
...	

Time-series operators may be repeated and combined. `L3.gnp` refers to the third lag of variable gnp. So do `LLL.gnp`, `LL2.gnp`, and `L2L.gnp`. `LF.gnp` is the same as `gnp`. `DS12.gnp` refers to the one-period difference of the 12-period difference. `LDS12.gnp` refers to the same concept, lagged once.

`D1.` = `S1.`, but `D2.` ≠ `S2.`, `D3.` ≠ `S3.`, and so on. `D2.` refers to the difference of the difference. `S2.` refers to the two-period difference. If you wanted the difference of the difference of the 12-period difference of gnp, you would write `D2S12.gnp`.

Operators may be typed in uppercase or lowercase. Most users would type `d2s12.gnp` instead of `D2S12.gnp`.

You may type operators however you wish; Stata internally converts operators to their canonical form. If you typed `ld2ls12d.gnp`, Stata would present the operated variable as `L2D3S12.gnp`.

In addition to using *operator*#, Stata understands *operator*`(`*numlist*`)` to mean a set of operated variables. For instance, typing `L(1/3).gnp` in a varlist is the same as typing `L.gnp L2.gnp L3.gnp`. The operators can also be applied to a list of variables by enclosing the variables in parentheses; for example,

```
. use https://www.stata-press.com/data/r19/gxmpl1
. list year L(1/3).(gnp cpi)
```

	year	L. gnp	L2. gnp	L3. gnp	L. cpi	L2. cpi	L3. cpi
1.	1989	.	.	.	.	.	.
2.	1990	5837.9	.	.	124	.	.
3.	1991	6026.3	5837.9	.	130.7	124	.
4.	1992	6367.4	6026.3	5837.9	136.2	130.7	124
5.	1993	6689.3	6367.4	6026.3	140.3	136.2	130.7
6.	1994	7098.4	6689.3	6367.4	144.5	140.3	136.2
7.	1995	7433.4	7098.4	6689.3	148.2	144.5	140.3
8.	1996	7851.9	7433.4	7098.4	152.4	148.2	144.5

The parentheses notation may be used with any operator. Typing `D(1/3).gnp` would return the first through third differences.

The parentheses notation may be used in operator lists with multiple operators, such as `L(0/3)D2S12.gnp`.

Operator lists may include up to one set of parentheses, which may enclose a *numlist*; see **[U] 11.1.8 numlist**.

The time-series operators `L.` and `F.` may be combined with factor variables. If we want to lag the indicator variables for the levels of the factor variable `region`, we would type `iL.region`. We could also say that we are specifying the level indicator variables for the lag of the region variables. They are equivalent statements.

The numlists and parentheses notation from both factor varlists and time-series operators may be combined. For example, `iL(1/3).region` specifies the first three lags of the level indicators for `region`. If `region` has four levels, this is equivalent to typing `i1L1.region i2L1.region i3L1.region i4L1.region i1L2.region i2L2.region i3L2.region i4L2.region i1L3.region i2L3.region i3L3.region i4L3.region`. Pushing the notation further, `i(1/2)L(1/3).(region education)` specifies the first three lags of the level 1 and level 2 indicator variables for both `region` and `education`.

❑ Technical note

The `D.` and `S.` time-series operators may not be combined with factor variables because such combinations could have two meanings. `iD.a` could be the level indicators for the difference of the variable `a` from its prior period, or it could be the level indicators differenced between the two periods. These are generally not the same values, nor even the same number of indicators. Moreover, they are rarely interesting.

❑

Before you can use time-series operators in varlists, you must set the time variable by using the `tsset` command:

```
. list l.gnp
time variable not set
r(111);
. tsset time
  (output omitted)
. list l.gnp
  (output omitted)
```

See [TS] **tsset**. The time variable must take on integer values. Also, the data must be sorted on the time variable. `tsset` handles this, but later you might encounter

```
. list l.mpg
not sorted
r(5);
```

Then type `sort time` or type `tsset` to reestablish the order.

The time-series operators respect the time variable. `L2.gnp` refers to $\texttt{gnp}_{t-2}$, regardless of missing observations in the dataset. In the following dataset, the observation for 1992 is missing:

```
. use https://www.stata-press.com/data/r19/gxmpl2
. list year gnp l2.gnp, separator(0)
```

	year	gnp	L2. gnp	
1.	1989	5837.9	.	
2.	1990	6026.3	.	
3.	1991	6367.4	5837.9	
4.	1993	7098.4	6367.4	← note, filled in correctly
5.	1994	7433.4	.	
6.	1995	7851.9	7098.4	

Operated variables may be used in expressions:

```
. generate gnplag2 = l2.gnp
(3 missing values generated)
```

Stata also understands cross-sectional time-series data. If you have cross sections of time series, you indicate this when you `tsset` the data:

```
. tsset country year
```

See [TS] **tsset**. In fact, you can type that, or you can type

```
. xtset country year
```

`xtset` is how you set panel data just as `tsset` is how you set time-series data and here the two commands do the same thing. Some panel datasets are not cross-sectional time series, however, in that the second variable is not time, so `xtset` also allows

```
. xtset country
```

See [XT] **xtset**.

11.4.4.1 Video example

Time series, part 3: Time-series operators

11.5 by varlist: construct

`by` *varlist*`:` *command*

The `by` prefix causes *command* to be repeated for each distinct value or combination of values of the variables in *varlist*. *varlist* may contain numeric, string, or a mixture of numeric and string variables. (*varlist* may not contain time-series operators.)

`by` is an optional prefix to perform a Stata command separately for each group of observations where the values of the variables in the *varlist* are the same.

During each iteration, the values of the system variables _n and _N are set in relation to the first observation in the by-group; see [U] 13.7 Explicit subscripting. The in *range* qualifier cannot be used with by *varlist*: because ranges specify absolute rather than relative observation numbers.

❑ Technical note

The inability to combine in and by is not really a constraint because if provides all the functionality of in and a bit more. If you wanted to perform *command* for the first three observations in each of the by-groups, you could type

```
. by varlist: command if _n<=3
```

❑

The results of *command* would be the same as if you had formed separate datasets for each group of observations, saved them, used each separately, and issued *command*.

▷ Example 16

We provide some examples using by in [U] 11.1.2 by varlist: above. We demonstrate the effect of by on _n, _N, and explicit subscripting in [U] 13.7 Explicit subscripting.

by requires that the data first be sorted. For instance, if we had data on the average January and July temperatures in degrees Fahrenheit for 420 cities located in the Northeast and West and wanted to obtain the averages, by region, across those cities, we might type

```
. use https://www.stata-press.com/data/r19/citytemp3, clear
(City temperature data)
. by region: summarize tempjan tempjuly
not sorted
r(5);
```

Stata refused to honor our request because the data are not sorted by region. We must either sort the data by region first (see [D] sort) or specify by's sort option (which has the same effect):

```
. by region, sort: summarize tempjan tempjuly
-------------------------------------------------------------------------------
-> region = NE
    Variable |        Obs        Mean    Std. dev.       Min        Max
-------------+---------------------------------------------------------
     tempjan |        164    27.88537    3.543096        16.6       31.8
    tempjuly |        164       73.35    2.361203        66.5       76.8
-------------------------------------------------------------------------------
  (output omitted)
-------------------------------------------------------------------------------
-> region = West
    Variable |        Obs        Mean    Std. dev.       Min        Max
-------------+---------------------------------------------------------
     tempjan |        256    46.22539    11.25412          13       72.6
    tempjuly |        256    72.10859    6.483131        58.1       93.6
```

◁

▷ Example 17

Using the same data as in the example above, we estimate regressions, by `region`, of average January temperature on average July temperature. Both temperatures are specified in degrees Fahrenheit.

```
. by region: regress tempjan tempjuly
```

```
-> region = NE
      Source |       SS           df       MS      Number of obs   =       164
-------------+----------------------------------   F(1, 162)       =    479.82
       Model |  1529.74026         1  1529.74026   Prob > F        =    0.0000
    Residual |  516.484453       162  3.18817564   R-squared       =    0.7476
-------------+----------------------------------   Adj R-squared   =    0.7460
       Total |  2046.22471       163  12.5535258   Root MSE        =    1.7855

------------------------------------------------------------------------------
     tempjan |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
    tempjuly |    1.297424   .0592303    21.90   0.000     1.180461    1.414387
       _cons |   -67.28066   4.346781   -15.48   0.000    -75.86431     -58.697
------------------------------------------------------------------------------
```

(*output omitted*)

```
-> region = West
      Source |       SS           df       MS      Number of obs   =       256
-------------+----------------------------------   F(1, 254)       =      2.84
       Model |  357.161728         1  357.161728   Prob > F        =    0.0932
    Residual |  31939.9031       254  125.74765   R-squared       =    0.0111
-------------+----------------------------------   Adj R-squared   =    0.0072
       Total |  32297.0648       255  126.655156   Root MSE        =    11.214

------------------------------------------------------------------------------
     tempjan |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
    tempjuly |   .1825482   .1083166     1.69   0.093    -.0307648    .3958613
       _cons |    33.0621    7.84194     4.22   0.000     17.61859    48.5056
------------------------------------------------------------------------------
```

The regressions show that a 1-degree increase in the average July temperature in the Northeast corresponds to a 1.3-degree increase in the average January temperature. In the West, however, it corresponds to a 0.18-degree increase, which is only marginally significant.

◁

❑ Technical note

by has a second syntax that is especially useful when you want to play it safe:

by *varlist*$_1$ (*varlist*$_2$): *command*

This says that Stata is to verify that the data are sorted by *varlist*$_1$ *varlist*$_2$ and then, assuming that is true, perform *command* by *varlist*$_1$. For instance,

```
. by subject (time): generate finalval = val[_N]
```

By typing this, we want to create new variable `finalval`, which contains, in each observation, the final observed value of `val` for each subject in the data. The final value will be the last value if, within subject, the data are sorted by time. The above command verifies that the data are sorted by `subject` and `time` and then, if they are, performs

```
. by subject: generate finalval = val[_N]
```

If the data are not sorted properly, an error message will instead be issued. Of course, we could have just typed

```
. by subject: generate finalval = val[_N]
```

after verifying for ourselves that the data were sorted properly, as long as we were careful to look.

by's second syntax can be used with by's sort option, so we can also type

```
. by subject (time), sort: generate finalval = val[_N]
```

which is equivalent to

```
. sort subject time
. by subject: generate finalval = val[_N]
```

❑

See Mitchell (2020, chap. 8) for numerous examples of processing groups using the by: construct. Also see Cox (2002).

11.6 Filenaming conventions

Some commands require that you specify a *filename*. Filenames are specified in the way natural for your operating system:

Windows	Unix	Mac
`mydata`	`mydata`	`mydata`
`mydata.dta`	`mydata.dta`	`mydata.dta`
`c:mydata.dta`	`~friend/mydata.dta`	`~friend/mydata.dta`
`"my data"`	`"my data"`	`"my data"`
`"my data.dta"`	`"my data.dta"`	`"my data.dta"`
`myproj\mydata`	`myproj/mydata`	`myproj/mydata`
`"my project\my data"`	`"my project/my data"`	`"my project/my data"`
`C:\analysis\data\mydata`	`~/analysis/data/mydata`	`~/analysis/data/mydata`
`"C:\my project\my data"`	`"~/my project/my data"`	`"~/my project/my data"`
`..\data\mydata`	`../data/mydata`	`../data/mydata`
`"..\my project\my data"`	`"../my project/my data"`	`"../my project/my data"`

We strongly discourage using Unicode characters beyond plain ASCII in filenames because different operating systems use different UTF encodings for Unicode characters. For example, because Linux encodes filenames in UTF-8 and Windows encodes them in UTF-16, the file may become unusable after it has been transferred from one system to another if it contains Unicode characters beyond plain ASCII.

In most cases, where *filename* is a file that you are loading, *filename* may also be a URL. For instance, we might specify `use https://www.stata-press.com/data/r19/nlswork`.

All operating systems allow blanks in filenames, and so does Stata. However, if the filename includes a blank, you must enclose the filename in double quotes. Typing

```
. save "my data"
```

would create the file `my data.dta`. Typing

```
. save my data
```

would be an error.

Usually (the exceptions being `copy`, `dir`, `ls`, `erase`, `rm`, and `type`), Stata automatically provides a file extension if you do not supply one. For instance, if you type `use mydata`, Stata assumes that you mean `use mydata.dta` because `.dta` is the file extension Stata normally uses for data files.

Stata provides the following default file extensions that are used by various commands:

`.ado`	automatically loaded do-files
`.dct`	text data dictionary
`.do`	do-file
`.dot`	decision tree plot file
`.dta`	Stata dataset file format
`.dtas`	Stata frameset file format
`.dtasig`	`datasignature` file
`.gph`	`graph`
`.grec`	Graph Editor recording (text format)
`.irf`	impulse–response function datasets
`.log`	log file in text format
`.mata`	Mata source code
`.mlib`	Mata library
`.mmat`	Mata matrix
`.mo`	Mata object file
`.raw`	text-format data
`.smcl`	log file in SMCL format
`.stbcal`	business calendars
`.ster`	saved estimates
`.stgrf`	ancillary file to `.ster` when using the `cate` command
`.sthlp`	help file
`.stjson`	Stata collection results, labels, and styles
`.stpr`	project file
`.stptrace`	parameter-trace file; see [MI] **mi ptrace**
`.stsem`	SEM Builder file
`.stswm`	spatial weighting matrix
`.stswp`	Do-file Editor backup (swap) file
`.stxer`	ancillary file to `.ster` when using lasso commands
`.sum`	checksum files to verify network transfers

You do not have to name your data files with the `.dta` extension—if you type an explicit file extension, it will override the default. For instance, if your dataset was stored as `myfile.dat`, you could type `use myfile.dat`. If your dataset was stored as simply `myfile` with no file extension, you could type the period at the end of the filename to indicate that you are explicitly specifying the null extension. You would type `use myfile.` to use this dataset.

❑ Technical note

Stata also uses other file extensions. These files are of interest only to advanced programmers or are for Stata's internal use. They are

`.class`	class file for object-oriented programming; see [P] **class**
`.dlg`	dialog resource file
`.idlg`	dialog resource include file
`.ihlp`	help include file
`.key`	`search`'s keyword database file
`.maint`	maintenance file (for Stata's internal use only)
`.mnu`	menu file (for Stata's internal use only)
`.pkg`	user-site package file
`.plugin`	compiled addition (DLL)
`.scheme`	control file for a graph scheme
`.style`	graph style file
`.toc`	user-site description file

❑

11.6.1 A special note for Mac users

Have you seen the notation `myfolder/myfile` before? This notation is called a path and describes the location of a file or folder (also called a directory).

You do not have to use this notation if you do not like it. You could instead restrict yourself to using files only in the current folder. If that turns out to be too restricting, Stata for Mac provides enough menus and buttons that you can probably get by. You may, however, find the notation convenient. If you do, here is the rest of the definition.

The character `/` is called a path delimiter and delimits folder names and filenames in a path. If the path starts with no path delimiter, the path is relative to the current folder.

For example, the path `myfolder/myfile` refers to the file `myfile` in the folder `myfolder`, which is contained in the current folder.

The characters `..` refer to the folder containing the current folder. Thus `../myfile` refers to `myfile` in the folder containing the current folder, and `../nextdoor/myfile` refers to `myfile` in the folder `nextdoor` in the folder containing the current folder.

If a path starts with a path delimiter, the path is called an absolute path and describes a fixed location of a file or folder name, regardless of what the current folder is. The leading `/` in an absolute path refers to the root directory, which is the main hard drive from which the operating system is booted. For example, the path `/myfolder/myfile` refers to the file `myfile` in the folder `myfolder`, which is contained in the main hard drive.

11.6.2 A shortcut to your home directory

Stata understands `~` to mean your home directory. Thus, you can refer to a dataset named `mydata.dta` in a subdirectory named `mydir` within your home directory by referring to the path

```
~\mydir\mydata.dta
```

in Stata for Windows or by referring to the path

```
~/mydir/mydata.dta
```

in Stata for Mac or Stata for Unix.

11.7 References

Baum, C. F. 2016. *An Introduction to Stata Programming*. 2nd ed. College Station, TX: Stata Press.

Buis, M. L. 2020. Stata tip 135: Leaps and bounds. *Stata Journal* 20: 244–249.

Cox, N. J. 2002. Speaking Stata: How to move step by: step. *Stata Journal* 2: 86–102.

———. 2009. Stata tip 79: Optional arguments to options. *Stata Journal* 9: 504.

———. 2023. Stata tip 151: Puzzling out some logical operators. *Stata Journal* 23: 293–297.

Cox, N. J., and C. B. Schechter. 2019. Speaking Stata: How best to generate indicator or dummy variables. *Stata Journal* 19: 246–259.

———. 2023. Stata tip 152: if and if: When to use the if qualifier and when to use the if command. *Stata Journal* 23: 589–594.

Daniels, L., and N. Minot. 2020. *An Introduction to Statistics and Data Analysis Using Stata*. Thousand Oaks, CA: Sage.

Kolev, G. I. 2006. Stata tip 31: Scalar or variable? The problem of ambiguous names. *Stata Journal* 6: 279–280.

Mitchell, M. N. 2020. *Data Management Using Stata: A Practical Handbook*. 2nd ed. College Station, TX: Stata Press.

Ryan, P. 2005. Stata tip 22: Variable name abbreviation. *Stata Journal* 5: 465–466.

12 Data

Contents

12.1 Data and datasets

Data form a rectangular table of numeric and string values in which each row is an observation on all the variables and each column contains the observations on one variable. Variables are designated by *variable names*. Observations are numbered sequentially from `1` to `_N`. The following example of data contains the first five odd and first five even positive integers, along with a string variable:

```
     odd  even   name
1.     1     2   Bill
2.     3     4   Mary
3.     5     6    Pat
4.     7     8  Roger
5.     9    10   Sean
```

The observations are numbered `1` to `5`, and the variables are named `odd`, `even`, and `name`. Observations are referred to by number, and variables by name.

A *dataset* is *data* plus labelings, formats, notes, and characteristics.

All aspects of *data* and *datasets* are defined here. Long (2009) offers a long-time Stata user's hard-won advice on how to manage data in Stata to promote accurate, replicable research. Mitchell (2020) provides many examples on data management in Stata.

12.2 Numbers

A *number* may contain a sign, an integer part, a decimal point, a fraction part, an `e` or `E`, and a signed integer exponent. Numbers may *not* contain commas; for example, the number 1,024 must be typed as `1024` (or `1024.` or `1024.0`). The following are examples of valid numbers:

```
5
-5
5.2
.5
5.2e+2
5.2e-2
```

❑ Technical note

Stata also allows numbers to be represented in a hexadecimal/binary format, defined as

[`+`|`-`]`0.0`[⟨*zeros*⟩]{`X`|`x`}`-3ff`

or

[`+`|`-`]`1.`⟨*hexdigit*⟩[⟨*hexdigits*⟩]{`X`|`x`}{`+`|`-`}⟨*hexdigit*⟩[⟨*hexdigits*⟩]

The lead digit is always 0 or 1; it is 0 only when the number being expressed is zero. A maximum of 13 digits to the right of the hexadecimal point are allowed. The power ranges from `-3ff` to `+3ff`. The number is expressed in hexadecimal (base 16) digits; the number a`X+`b means $a \times 2^b$. For instance, `1.0X+3` is 2^3 or 8. `1.8X+3` is 12 because 1.8_{16} is $1 + 8/16 = 1.5$ in decimal and the number is thus $1.5 \times 2^3 = 1.5 \times 8 = 12$.

Stata can also display numbers using this format; see **[U] 12.5.1 Numeric formats**. For example,

```
. display 1.81x+2
6.015625
. display %21x 6.015625
+1.8100000000000X+002
```

This hexadecimal format is of special interest to numerical analysts.

❑

12.2.1 Missing values

A number may also take on the special value *missing*, denoted by a period (.). You specify a missing value anywhere that you may specify a number. Missing values differ from ordinary numbers in one respect: any arithmetic operation on a missing value yields a missing value.

In fact, there are 27 missing values in Stata: '.', the one just discussed, as well as .a, .b, ..., and .z, which are known as extended missing values. The missing value '.' is known as the default or system missing value. Some people use extended missing values to indicate why a certain value is unknown—the question was not asked, the person refused to answer, etc. Other people have no use for extended missing values and just use '.'.

Stata's default or system missing value will be returned when you perform an arithmetic operation on missing values or when the arithmetic operation is not defined, such as division by zero, or the logarithm of a nonpositive number.

```
. display 2/0
.
. list
```

	a
1.	.b
2.	.
3.	.a
4.	3
5.	6

```
. generate x = a + 1
(3 missing values generated)
. list
```

	a	x
1.	.b	.
2.	.	.
3.	.a	.
4.	3	4
5.	6	7

Numeric missing values are represented by "large positive values". The ordering is

$$\text{all numbers} < \texttt{.} < \texttt{.a} < \texttt{.b} < \cdots < \texttt{.z}$$

Thus the expression

$$\texttt{age} > 60$$

is true if variable age is greater than 60 or is missing. Similarly,

$$\texttt{gender} \neq 0$$

is true if gender is not zero or is missing.

To exclude missing values, you must ask whether the value is less than '.'; to detect missing values, you must ask whether the value is greater than or equal to '.'. For instance,

```
. list if age>60 & age<.
. generate agegt60 = 0 if age<=60
. replace agegt60 = 1 if age>60 & age<.
. generate agegt60 = (age>60) if age<.
```

❑ Technical note

Before Stata 8, Stata had only one representation for missing values, the period (.).

To ensure that old programs and do-files continue to work properly, when `version` is set less than 8, all missing values are treated as being the same. Thus `. == .a == .b == .z`, and so '*exp*`==.`' and '*exp*`!=.`' work just as they previously did.

❑

▷ Example 1

We have data on the income of husbands and wives recorded in the variables `hincome` and `wincome`, respectively. Typing the `list` command, we see that your data contain

```
. use https://www.stata-press.com/data/r19/gxmpl3
. list
```

	hincome	wincome
1.	32000	0
2.	35000	34000
3.	47000	.b
4.	.z	50000
5.	.a	.

The values of `wincome` in the third and fifth observations are *missing*, as distinct from the value of `wincome` in the first observation, which is known to be zero.

If we use the `generate` command to create a new variable, `income`, that is equal to the sum of `hincome` and `wincome`, three missing values would be produced.

```
. generate income = hincome + wincome
(3 missing values generated)
. list
```

	hincome	wincome	income
1.	32000	0	32000
2.	35000	34000	69000
3.	47000	.b	.
4.	.z	50000	.
5.	.a	.	.

`generate` produced a warning message that 3 missing values were created, and when we list the data, we see that 47,000 plus *missing* yields *missing*.

◁

❑ Technical note

Stata stores numeric missing values as the largest 27 numbers allowed by the particular storage type; see **[U] 12.2.2 Numeric storage types**. There are two important implications. First, if you `sort` on a variable that has missing values, the missing values will be placed last, and the sort order of any missing values will follow the rule regarding the properties of missing values stated above.

```
. sort wincome
. list wincome
```

	wincome
1.	0
2.	34000
3.	50000
4.	.
5.	.b

The second implication concerns relational operators and missing values. Do not forget that a missing value will be larger than any numeric value.

```
. list if wincome > 40000
```

	hincome	wincome	income
3.	.z	50000	.
4.	.a	.	.
5.	47000	.b	.

Observations 4 and 5 are listed because '`.`' and '`.b`' are both missing and thus are greater than 40,000. Relational operators are discussed in detail in **[U] 13.2.3 Relational operators**.

❑

▷ Example 2

In producing statistical output, Stata ignores observations with missing values. Continuing with the example above, if we request summary statistics on `hincome` and `wincome` by using the `summarize` command, we obtain

```
. summarize hincome wincome
```

Variable	Obs	Mean	Std. dev.	Min	Max
hincome	3	38000	7937.254	32000	47000
wincome	3	28000	25534.29	0	50000

Some commands discard the entire observation (known as *casewise deletion*) if one of the variables in the observation is missing. If we use the `correlate` command to obtain the correlation between `hincome` and `wincome`, for instance, we obtain

```
. correlate hincome wincome
(obs=2)
```

	hincome	wincome
hincome	1.0000	
wincome	1.0000	1.0000

The correlation coefficient is calculated over two observations.

◁

12.2.2 Numeric storage types

Numbers can be stored in one of five variable types: `byte`, `int`, `long`, `float` (the default), or `double`. `bytes` are, naturally, stored in 1 byte. `ints` are stored in 2 bytes, `longs` and `floats` in 4 bytes, and `doubles` in 8 bytes. The table below shows the minimum and maximum values for each storage type.

Storage type	Minimum	Maximum	Closest to 0 without being 0	Bytes
`byte`	-127	100	± 1	1
`int`	$-32{,}767$	32,740	± 1	2
`long`	$-2{,}147{,}483{,}647$	2,147,483,620	± 1	4
`float`	$-1.70141173319 \times 10^{38}$	$1.70141173319 \times 10^{38}$	$\pm 10^{-38}$	4
`double`	$-8.9884656743 \times 10^{307}$	$+8.9884656743 \times 10^{307}$	$\pm 10^{-323}$	8

Do not confuse the term *integer*, which is a characteristic of a number, with `int`, which is a storage type. For instance, the number 5 is an integer, no matter how it is stored; thus, if you read that an argument must be an integer, that does not mean that it must be stored as an `int`.

12.3 Dates and times

Stata has nine date, time, and date-and-time numeric encodings known collectively as `%t` variables or values. They are

`%tC`	calendar date and time, adjusted for leap seconds
`%tc`	calendar date and time, ignoring leap seconds
`%td`	calendar date
`%tw`	week
`%tm`	calendar month
`%tq`	financial quarter
`%th`	financial half-year
`%ty`	calendar year
`%tb`	business calendars

All except `%ty` and `%tb` are based on 0 = beginning of January 1960. `%tc` and `%tC` record the number of milliseconds since then. `%td` records the number of days. The others record the numbers of weeks, months, quarters, or half-years. `%ty` simply records the year, and `%tb` records a user-defined business calendar format.

For a full discussion of working with dates and times, see **[U] 25 Working with dates and times**.

12.4 Strings

This section describes the treatment of strings by Stata. The section is divided into the following subsections:

12.4.1 Overview

A string is a sequence of characters.

```
Samuel Smith
California
UK
```

Usually—but not always—strings are enclosed in double quotes.

```
"Samuel Smith"
"California"
"UK"
```

Strings typed in quotes are called *string literals*.

Strings can be stored in Stata datasets in string variables.

```
. use https://www.stata-press.com/data/r19/auto, clear
(1978 automobile data)
. describe make
Variable      Storage   Display    Value
    name         type    format    label      Variable label
------------------------------------------------------------------------------
make            str18   %-18s                 Make and model
```

The string-variable storage types are `str1`, `str2`, …, `str2045`, and `strL`. For example, variable `make` is a `str18` variable. It can contain strings of up to 18 characters long. The strings are not all 18 characters long.

```
. list make in 1/2
```

	make
1.	AMC Concord
2.	AMC Pacer

`str18` means that the variable cannot hold a string longer than 18 bytes, and even that is an unimportant detail, because Stata automatically promotes `str#` variables to be longer when required.

```
. replace make = "Mercedes Benz Gullwing" in 1
variable make was str18 now str22
(1 real change made)
```

Strings in Stata can also be stored in labels and notes that let you see information about your dataset. See **[U] 12.6 Dataset, variable, and value labels** and **[U] 12.7 Notes attached to data**. Strings in Stata programs can be stored in string scalars, macros, characteristics, and in stored results.

Stata provides a suite of string functions, such as `strlen()` and `substr()`.

```
. generate len = strlen(make)
. generate str first5 = substr(make, 1,5)
. list make len first5 in 1/2
```

	make	len	first5
1.	Mercedes Benz Gullwing	22	Merce
2.	AMC Pacer	9	AMC P

Many Stata commands can use string variables.

```
. generate str brand = word(make, 1)
. tabulate brand
```

brand	Freq.	Percent	Cum.
AMC	2	2.70	2.70
Audi	2	2.70	5.41
BMW	1	1.35	6.76
Buick	7	9.46	16.22
Cad.	3	4.05	20.27
Chev.	6	8.11	28.38
Datsun	4	5.41	33.78
Dodge	4	5.41	39.19
Fiat	1	1.35	40.54
Ford	2	2.70	43.24
Honda	2	2.70	45.95
Linc.	3	4.05	50.00
Mazda	1	1.35	51.35
Merc.	6	8.11	59.46
Mercedes	1	1.35	60.81
Olds	7	9.46	70.27
Peugeot	1	1.35	71.62
Plym.	5	6.76	78.38
Pont.	6	8.11	86.49
Renault	1	1.35	87.84
Subaru	1	1.35	89.19
Toyota	3	4.05	93.24
VW	4	5.41	98.65
Volvo	1	1.35	100.00
Total	74	100.00	

Beginning in Stata 14, text in Stata strings can include Unicode characters and is encoded as UTF-8. This means that you can use plain ASCII characters (also known as "lower ASCII" and stored as 0–127 on computers) like those shown above. You can also use the remaining Latin characters, as well as

characters from the Chinese, Cyrillic, and Japanese alphabets, among others. However, if you have characters other than ASCII in your datasets, do-files, or ado-files, you may need to take special steps. See **[U] 12.4.2 Handling Unicode strings**.

12.4.2 Handling Unicode strings

If you do not have Unicode characters beyond the plain ASCII characters, you do not need to use any special steps to work with your data. In many cases, the same is true even if you do have other Unicode characters. While it is impossible to provide a rule for every situation, there are some general guidelines that you should be aware of.

The fundamental concept to understand is the difference between characters and bytes. Characters are what you see. For example, "a", "Z", and "@" are characters. Bytes are used to encode characters, which are stored on a computer.

For plain ASCII characters, there is a one-to-one mapping between the number of bytes and the number of characters. By contrast, UTF-8 encoded Unicode characters require two, three, or four bytes. For this reason, strings containing Unicode characters require string functions that recognize whole characters; see **[U] 12.4.2.1 Unicode string functions**. Some characters from older Stata files, known as extended ASCII characters, will not display correctly and can cause unexpected results. To avoid this, you must properly convert your older datasets and text files, such as do-files, if they contain extended ASCII. See **[U] 12.4.2.6 Advice for users of Stata 13 and earlier**.

If you do have characters in your data other than plain ASCII characters, or if you write commands for others to use, you should read the following sections.

12.4.2.1 Unicode string functions

Some of Stata's string functions exist in Unicode-aware versions so they can understand the string as a sequence of Unicode characters rather than as a sequence of bytes. At times, you will need to use one of these Unicode-aware functions to return accurate results. For example, suppose that our data on `make` included a car manufactured by Clénet Coachworks.

If we wanted to know the correct string length, we would use `ustrlen()`, not `strlen()`. The former will give you the answer you expect, 17, while the latter will return the number of bytes used to store that string, 18.

There are other Unicode-aware functions. For example, to change Unicode characters to uppercase, lowercase, or titlecase, use functions `ustrupper()`, `ustrlower()`, or `ustrtitle()`. If you want to see if there is a Unicode variant of the string function you want to use, check [FN] **String functions**.

Note that Unicode-aware functions are not required just because a variable contains UTF-8 characters beyond the plain ASCII range. For example, suppose that rather than wanting the string length, we wanted to replace "Mercedes" with "Merc.". We could use `subinstr()` instead of `usubinstr()` because neither "Mercedes" nor "Merc." contains UTF-8 characters.

Other Unicode-aware functions address the display columns. These functions are primarily of interest to programmers. See **[U] 12.4.2.2 Displaying Unicode characters**.

If you are in doubt, or if you are writing code to be used in a general way by others, you should use the Unicode-aware version of a string function, if it exists. The Unicode-aware functions generally have the same names as the regular string functions, but with "u" as a prefix. See [FN] **String functions**.

12.4.2.2 Displaying Unicode characters

Stata has a concept called a display column to ensure that the fixed-width output in Stata's Results and Viewer windows continues to align properly. Stata automatically displays each character in one or two display columns.

Most users, even users with UTF-8 characters beyond the ASCII range, will find that there is no distinction between the number of characters and the number of display columns because most characters are displayed in one column. Some wider characters, however, such as Chinese, Japanese, and Korean (CJK) characters, occupy two display columns.

You may occasionally wish to account for the number of display columns that a string occupies. Just as some Stata functions understand Unicode characters, some functions understand display columns. These functions are prefixed with "ud". For example, you can obtain the number of display columns for a string with `udstrlen(`*string*`)`. If you want to extract a subset of characters from the beginning of a string and make sure it fits within 10 display columns, use `udsubstr(`*string*`,1,10)`. See [FN] **String functions** for more information.

12.4.2.3 Encodings

An encoding is the way a computer stores a given string of text. ASCII and UTF-8, which is how Stata stores all text, are examples of encodings. Plain ASCII characters are stored as a single byte, each with a value between 0 and 127. "a", "Z", and "@" are all examples of plain ASCII characters, and their respective byte values are 97, 90, and 64.

The letter "á" is also a character. In UTF-8 encoding, that single character is stored as two bytes: 195 and 161. All Unicode characters beyond the plain ASCII range are stored as two or more bytes, and each of those bytes has a value between 128 and 255. Some characters in UTF-8 encoding take three or even four bytes to store.

Not every possible combination of bytes represents a valid Unicode character. Because two or more bytes are required to encode a Unicode character, any single byte between 128 and 255 is not a valid Unicode character. Invalid Unicode characters are most likely to occur if you have extended ASCII characters in a file from a previous version of Stata; see **[U] 12.4.2.6 Advice for users of Stata 13 and earlier**.

If you have text in other encodings, including text in Stata files, you must convert it to UTF-8 for it to display properly and for some of Stata's string functions to work properly. To convert a file to UTF-8, you must know the original encoding. The most common encoding is Windows-1252. To obtain a list of other common encodings as well as a list of all possible encodings, see `unicode encoding list` and `unicode encoding alias` in [D] **unicode encoding**.

The `unicode analyze` and `unicode translate` commands help to convert text files and Stata datasets. See [D] **unicode translate** for more information. Also see **[U] 12.4.2.6 Advice for users of Stata 13 and earlier**.

12.4.2.4 Locales in Unicode

A locale identifies a community with a certain set of rules for how their language should be written. A locale can be as general as a certain language, such as "en" for English, or it can be specific to a country or region, such as "en_US" for US English and "en_HK" for Hong Kong English.

Locales use *tags* to define how specific they are to language variants; these *tags* include language, script, country, variant, and keywords. Typically the language is required and the other tags are optional. In most cases, Stata uses only the language and country tags. For example, "en_US" specifies the language as English and the country as the USA.

Certain language-specific operations require a locale to be properly carried out. For example, in English, the uppercase version of "i" is "I". In Turkish, the uppercase version of "i" is an "İ" [that is, an "I" with a dot above it (Unicode character \u0130)]. To specify how to properly convert a letter to uppercase, you can specify the locale in the `ustrupper()` function, for example, `ustrupper("i", "en_US")`.

The following Stata functions are locale-dependent: `ustrupper()`, `ustrlower()`, `ustrtitle()`, `ustrword()`, `ustrwordcount()`, `ustrcompare()`, `ustrcompareex()`, `ustrsortkey()`, and `ustrsortkeyex()`.

If you do not explicitly specify a locale when using these functions, the current Stata `locale_functions` setting will be used. You can see the current setting by typing

```
. display c(locale_functions)
```

and

```
. unicode locale list
```

to see a list of supported locales. It is unlikely, however, that you will ever need to change the `set locale_functions` setting.

See [P] **set locale_functions** for more information about setting the locale, including information about how the default value is determined.

12.4.2.5 Sorting strings containing Unicode characters

This section deals with *collation*, sorting strings that contain Unicode characters, and the special rules that apply when you do. Many users will find that they can skip this section.

If you do not have Unicode characters beyond the plain ASCII range, you can skip this section. You can also skip this section if you are interested in using `sort` only so that you can use another command or prefix. For example, suppose you have the variable `id` that contains Unicode characters and you want to type

```
. statsby id: regress y x1 x2
```

If your aim is to group the coefficients by `id` only and the exact order of `id` does not matter, then the advice in this section does not apply to you. The usual `sort` command will be sufficient.

The steps described here also do not apply to commands that require the data to be sorted or grouped. For example, suppose that you wish to perform a one-to-one `merge` for two datasets using `id` as the key variable. You can just type

```
. merge 1:1 id using ...
```

Finally, you can skip this section if you do not want to apply language-specific rules to the Unicode characters in your data. For example, if you do not particularly care that "café" is sorted before or after "cafe", but only that the two words are distinguished, then this section is not for you.

For users who wish to sort or compare strings as a human might, there are four rules that you should keep in mind.

1. Sorting is locale-specific.
2. You must generate a sort key. You cannot sort by the variable itself.
3. There are multiple options for controlling the order of Unicode strings.
4. Concatenation is required to sort by *varlist*.

Rules 1 and 3 also apply to string comparisons. We explain each of these rules in more detail below. But first, it may be helpful to review how sorting works in general.

Stata's `sort` command and Stata's logical operators $>$ and $<$ order strings based on the byte values of the characters. For example, the byte value for "a" is 97 and the byte value for "A" is 65, so "a" $>$ "A". Similarly, the byte value for "Z" is 90, so "a" $>$ "Z". This means that words starting with "Z" come before "a", which might surprise you because, in an English dictionary, words starting with "Z" would certainly come after words starting with "a".

For example, suppose we have the following data:

```
. list mystr

     +--------+
     | mystr  |
     |--------|
  1. |  Quick |
  2. |  quick |
  3. |  brown |
  4. |    Fox |
  5. |   jump |
     +--------+
```

If we `sort` these data and then `list` them, we see

```
. sort mystr
. list

     +--------+
     | mystr  |
     |--------|
  1. |    Fox |
  2. |  Quick |
  3. |  brown |
  4. |   jump |
  5. |  quick |
     +--------+
```

This probably is not the order you would have placed these values in.

To sort the values of `mystr` in a more human fashion, you can use a Unicode tool, known as the Unicode collation algorithm (UCA), for comparing and sorting strings in a language-aware manner. Given knowledge of a locale and perhaps some optional instructions about whether to consider things like case and diacritical marks, the UCA can order Unicode strings as a human (or a dictionary) would.

Stata and Mata provide access to the UCA via the `ustrcompare()`, `ustrcompareex()`, and `ustrsortkey()`, `ustrsortkeyex()` functions. Stata also provides access via the `collatorlocale()` and `collatorversion()` functions.

See http://www.unicode.org/reports/tr10/ for the formal specification of the UCA.

Rule 1: Sorting is locale-dependent.

The ordering of strings in Unicode depends on the specified language and any optional tags and keywords that are specified with the locale.

For the `ustrcompare()` and `ustrsortkey()` functions, the default rules for ordering by language (and country, if specified) are used. You can use the current Stata `locale_functions` setting or specify a different locale with these each of these functions. See **[U] 12.4.2.4 Locales in Unicode** for more information about locales, and see [D] **unicode collator** for information about locale-specific collation.

For advanced control of ordering, use the `ustrcompareex()` and `ustrsortkeyex()` functions. These functions allow you to specify a collation keyword, which is used for finer control for ordering, such as whether case-sensitivity and diacritical marks matter. For example, "pinyin" and "stroke" for the Chinese language produce different sort orders. A list of valid collation keywords and their meanings may be found http://unicode.org/repos/cldr/trunk/common/bcp47/collation.xml.

Rule 2: You must generate a sort key.

To appropriately sort your data with all the rules of the locale applied, you must generate a *sort key*. A sort key is a string created by the UCA that can be used to sort Unicode strings. You sort on the sort key rather than the Unicode string variable. The sort key is not a variable we would ever want to use for any purpose other than data management because it is not human-readable.

You can generate a sort key using either `ustrsortkey()` or `ustrsortkeyex()`. You then `sort` your data by the new variable. The following example illustrates the difference between `sort` and Unicode collation using the above functions:

```
. generate sortkey = ustrsortkey(mystr, "en")
. sort sortkey
. list mystr
```

	mystr
1.	brown
2.	Fox
3.	jump
4.	quick
5.	Quick

It is important to note that the Stata dataset is sorted by `sortkey` and not by `mystr`, even though `mystr` appears to be sorted correctly. Stata is aware of sorting only by `sortkey`. This means that if you need to perform an operation that relies on the sort order, such as `by`, you should use `sortkey` rather than `mystr`, such as

```
. by sortkey: ...
```

Also note that sort keys generated from one locale or one set of advanced options in `ustrsortkeyex()` are usually not compatible or comparable with sort keys generated from another locale or another set of options. For example, you should not compare the sort keys generated from the `"en"` locale with those generated from the `"fr"` locale.

❑ Technical note

The effective locale may be different from the requested locale. Thus, the sort keys obtained on a different machine, or even on a different user account on the same machine, may be different unless the locale is specified. You can retrieve the effective locale with the function `collatorlocale()` and then use that effective locale in future calls to the Unicode ordering functions.

❑

❑ Technical note

The Unicode standard is constantly adding more characters, and language rules are constantly changing, which means that sort keys produced by the current version of the UCA may not be compatible with sort keys of the same strings produced by future versions of the UCA.

You can use function `collatorversion()` to retrieve the current version of the collation routine and then store the result (for example, in a variable characteristic) with any saved sort keys if those keys are intended for future use.

If the current version is different from the saved sort key, then you should regenerate the sort key variables if you want them to be up-to-date with the new language rules or if you want to compare them with newly generated sort keys.

❑

Rule 3: There are multiple options for controlling the order of Unicode strings.

This may appear straightforward, but some finer points of the UCA could surprise you. Consider an example of string comparisons.

```
. display ustrcompare("café","cafe","fr")
1
```

Here we asked Stata to compare the string "café" with the string "cafe" using the French locale (`"fr"`). Stata reported `1`, which means that in this case "café" is considered to be greater than "cafe". If we were sorting our data, this means "café" would be sorted after "cafe".

Now consider

```
. display ustrcompare("café du monde","cafe new york","fr")
-1
```

It might surprise you that the result is `-1`, which means that in this case "café du monde" is considered to be less than "cafe new york", even though we already established that "café" is greater than "cafe".

The reason is that the difference between "d" and "n" in the second word of each string is considered by the UCA to be a *primary difference*, whereas the difference between "é" and "e" in the first word of each string is a diacritical mark which is considered to be a *secondary difference*. The primary difference outweighs the secondary difference even though it occurs later in the string.

The default behavior of `ustrcompare()` and `ustrsortkey()` should be sufficient for most comparison and sorting needs. For advanced control over how Unicode strings are ordered, including whether the ordering should be based on differences from primary to quaternary, use `ustrcompareex()` and `ustrsorkeyex()`. See [FN] **String functions**.

Rule 4: Concatenation is required to sort by a varlist.

An important implication of Rule 3 arises when creating sort keys for Unicode strings. Ordinarily, if you want to sort on two string variables, you can simply type

```
. sort string1 string2
```

However, to take full advantage of the UCA while sorting two or more strings, you should first concatenate them and then sort the result.

```
. generate string3 = string1 + string2
. generate sortkey = ustrsortkey(sting3, "fr")
. sort sortkey
```

If you do not do this, then primary differences that might arise in `string2` will not override any secondary differences in `string1`.

12.4.2.6 Advice for users of Stata 13 and earlier

In this section, we discuss how to use your older Stata files in modern Stata and also points you should consider when sharing your modern Stata files with users of Stata 13 and earlier.

In Stata 13 and earlier, Unicode characters were not supported. If you have only plain ASCII characters in your datasets, do-files, and ado-files, then you do not need to take any special steps to continue using these files with modern Stata. You can use `saveold` to share your dataset with users of older versions of Stata. Your do-files and ado-files can be shared directly.

If files you used with Stata 13 or earlier contain strings with extended ASCII characters, you should convert those strings to Unicode UTF-8 encoding so they will work properly with modern Stata. The `unicode analyze` command will check your files to see if they need conversion, and if so, the `unicode translate` command will convert them to UTF-8 encoding. See [D] **unicode translate**. To convert a single variable, use `ustrfrom()`.

If you have Unicode characters in your dataset and you wish to share it with a user of Stata 13 or earlier, be aware that while they can load a dataset created with the `saveold` command, their copy of Stata is not Unicode-aware and will not display Unicode characters properly. Before you use `saveold`, you can convert your string variables from the UTF-8 encoding to an extended ASCII encoding by using `ustrto()`. We recommend that you `generate` a new variable when using `ustrfrom()` or `ustrto()` so that you can review the results and make sure you are satisfied before you `replace` your existing variable. `ustrfrom()` and `ustrto()` may also be used with Mata string matrices.

12.4.3 Strings containing identifying data

String variables often contain identifying information, such as the patient's name or the name of the city or state. Such strings are typically listed but are not used directly in statistical analysis, although the data might be sorted on the string or datasets might be merged on the basis of one or more string variables.

12.4.4 Strings containing categorical data

Strings sometimes contain information to be used directly in analysis, such as the patient's sex, which might be coded "male" or "female". Stata shows a decided preference for such information to be numerically encoded and stored in numeric variables. Stata's statistical routines treat string variables as if every observation records a numeric missing value. Stata provides two commands for converting string variables into numeric codes and back again: `encode` and `decode`. See **[U] 24.2 Categorical string variables** and **[U] 11.4.3 Factor variables**.

12.4.5 Strings containing numeric data

If a string variable contains the character representation of a number, say, `myvar` contains "1", "1.2", and "−5.2", you can convert the string into a numeric value by using the `real()` function or the `destring` command. For example,

```
. generate newvar = real(myvar)
```

To convert a numeric variable to its string representation, you can use the `string()` function or the `tostring` command. For example,

```
. generate as_str = string(numvar)
```

See [FN] **String functions** and [D] **destring**.

12.4.6 String literals

A string literal is a sequence of printable characters enclosed in quotes. The quotes are not considered part of the string; they merely serve to delimit the beginning and end of the string. The following are examples of string literals:

```
"Hello, world"
"String"
"string"
" string"
"string "
""
"x/y+3"
"1.2"
```

All the strings above are distinct. Capitalization matters, as do leading and trailing spaces. Also note that `"1.2"` is a string and not a number because it is enclosed in quotes.

There is never a circumstance in which a string cannot be delimited with quotes, but there are instances where strings do not have to be delimited by quotes, such as when inputting data. In those cases, nondelimited strings are stripped of their leading and trailing spaces. Delimited strings are always accepted as is.

The list above could also be written as

```
‘"Hello, world"’
‘"String"’
‘"string"’
‘" string"’
‘"string "’
‘""’
‘"x/y+3"’
‘"1.2"’
```

`‘"` and `"’` are called compound double quotes.

Use of compound double quotes can help solve the problem of typing strings that themselves contain double quotes.

```
‘"Bob said, "Wow!" and promptly fainted."’
```

Strings in compound quotes can themselves contain compound quotes.

```
‘"The compound quotes characters are ‘" and "’"’
```

12.4.7 str1–str2045 and str

str is something generate understands. We will get to that.

str1–str2045 are known as Stata's fixed-length string storage types.

They are called that because, in your dataset, if a variable is stored as a str#, then each observation requires # bytes to store the contents of the variable. You obviously do not want # to be longer than necessary. Stata's compress command will shorten str# strings that are unnecessarily long.

```
. use https://www.stata-press.com/data/r19/auto, clear
(1978 automobile data)
. compress
  variable mpg was int now byte
  variable rep78 was int now byte
  variable trunk was int now byte
  variable turn was int now byte
  variable make was str18 now str17
  (370 bytes saved)
```

In [U] 12.4.1 Overview, we used str with generate:

```
. generate str brand = word(make, 1)
```

str is something generate understands and tells generate to create a str# variable of the minimum required length. Although you cannot tell from the output, generate created variable brand as a str7.

Stata commands automatically promote str# storage types when necessary:

```
. replace make = "Mercedes Benz Gullwing" in 1
variable make was str17 now str22
(1 real change made)
```

In fact, if the string to be stored is longer than 2,045 bytes, generate and replace will even promote to strL. We discuss strLs in the next section.

12.4.8 strL

strL variables can be 0 to 2-billion bytes long.

The "L" stands for long, and strL is often pronounced *sturl*.

strL variables are not required to be longer than 2,045 bytes.

str# variables can store strings of up to 2,045 bytes, so strL and str# overlap. This overlap is comparable to the overlap of the numeric types int and float. Any number that can be stored as an int can be stored as a float. Similarly, any string that can be stored as a str#, can be stored as a strL. The reverse is not true. In addition, strL variables can hold binary strings, whereas str# variables can only hold text strings. Thus the analogy between str#/strL and int/float is exact. There will be occasions when you will want to use strL variables in preference to str# variables, just as there are occasions when you will want to use float variables in preference to int variables.

strL variables work like str# variables. Below we repeat what we did in [U] 12.4.1 Overview using a strL variable.

```
. use https://www.stata-press.com/data/r19/auto, clear
(1978 automobile data)
. generate strL mymake = make
. describe mymake
Variable      Storage   Display    Value
    name         type    format    label      Variable label
------------------------------------------------------------------------------
mymake          strL    %9s
. list mymake in 1/2

     +-------------+
     |     mymake  |
     |-------------|
  1. | AMC Concord |
  2. |   AMC Pacer |
     +-------------+
```

We can replace strL values just as we can replace str# values:

```
. replace mymake = "Mercedes Benz Gullwing" in 1
(1 real change made)
```

We can use string functions with strL variables just as we can with str# variables:

```
. generate len = strlen(mymake)
. generate strL first5 = substr(mymake, 1, 5)
. list mymake len first5 in 1/2

     +-------------------------------------------+
     |                mymake   len   first5      |
     |-------------------------------------------|
  1. | Mercedes Benz Gullwing    22    Merce      |
  2. |             AMC Pacer     9    AMC P      |
     +-------------------------------------------+
```

We can even make tabulations:

```
. generate strL brand = word(mymake, 1)
. tabulate brand
      brand |      Freq.     Percent        Cum.
------------+-----------------------------------
        AMC |          2        2.70        2.70
       Audi |          2        2.70        5.41
        BMW |          1        1.35        6.76
  (output omitted)
      Volvo |          1        1.35      100.00
------------+-----------------------------------
      Total |         74      100.00
```

The only limitations are the following:

1. You cannot use strL variables as the matching (key) variables in a match merge of two datasets.
2. strL variables cannot be used with fillin.

strL variables are stored differently from str# variables. str# variables require # bytes per observation. strL variables require the actual number of bytes per string per observation, which means strLs require even less memory than str# when the value being stored is less than # bytes long. Most strLs, however, have an 80-byte overhead per value stored; the exception is strLs containing empty strings, in which case the overhead is 8 bytes.

Whether strL or str# requires less memory for storing the same string values depends on the string values themselves. compress can be used to figure that out:

```
. compress
  variable mpg was int now byte
  variable rep78 was int now byte
  variable trunk was int now byte
  variable turn was int now byte
  variable len was float now byte
  variable make was str18 now str17
  variable mymake was strL now str22
  variable first5 was strL now str5
  variable brand was strL now str8
  (12,420 bytes saved)
```

compress decided to demote all of our strL variables to str# to save memory.

compress, however, never promotes a str# variable to a strL, even if that would save memory. It does not do this because, as we mentioned, there are a few things you can do with str# variables that you cannot do with strL variables.

You can use recast to promote str# to strL:

```
. * variable make is currently str17
. recast strL make
. describe make
Variable      Storage   Display    Value
    name         type    format    label      Variable label
------------------------------------------------------------------------------
make            strL    %-9s                  Make and model
. compress make
  variable make was strL now str17
  (5,607 bytes saved)
```

12.4.9 strL variables and duplicated values

You would never know it, but when strL variables have the same values across observations, Stata stores only one copy of each value. This is called coalescing, and it saves memory.

Stata mostly coalesces strL variables automatically as they are created, but sometimes duplicate values escape its attention. When you type compress, however, Stata looks for coalescing opportunities. You might see

```
. compress x
x is strL now coalesced
(11,301,687 bytes saved)
```

We recommend that you type compress occasionally when strL variables are present.

12.4.10 strL variables and binary strings

strLs can hold binary strings. A binary string is, technically speaking, any string that contains binary 0. Here is an example:

```
. use https://www.stata-press.com/data/r19/auto, clear
(1978 automobile data)
. replace make = "a" + char(0) + "b" in 1
variable make was str18 now strL
(1 real change made)
. list make in 1
```

	make
1.	a\0b

list displays binary zeros as \0.

If we did this same experiment with a str# variable and include the nopromote option to prevent promotion, we would see something different:

```
. use https://www.stata-press.com/data/r19/auto, clear
(1978 automobile data)
. replace make = "a" + char(0) + "b" in 1, nopromote
(1 real change made)
. list make in 1
```

	make
1.	a

For str# strings, binary 0 indicates the end of the string, and thus the variable really does contain "a" in the first observation.

str# variables cannot contain binary 0; strL variables can.

compress knows this. If we typed compress in the first example, we would discover that compress would not demote make to be a str#. It would not do this because one of the values could not be stored in a str# variable. This is no different from compress not demoting a float variable to an int because one of the values is 1.5.

12.4.11 strL variables and files

strLs can be used to hold the contents of files. We have data on 10 patients. Some of the data have been coded from doctor notes, and those notes are stored in notes_2217.xyz, notes_2221.xyz, notes_2222.xyz, and so on. We could do the following:

```
. generate strL notes = fileread("notes_2217.xyz") in 1
. replace notes = fileread("notes_2221.xyz") in 2
. replace notes = fileread("notes_2222.xyz") in 3
. ...
```

It would be even easier for us to type

```
. generate str fname = "notes_" + string(patid) + ".xyz"
. generate strL notes = fileread(fname)
```

The original files can be re-created from the copies stored in Stata. To re-create all the files, we could type

```
. generate len = filewrite(fname, notes)
```

If we want to know whether the phrase "Diabetes Mellitus Type 1" appears in the notes and whether doctors recorded the disease as `T1DM`, we can type

```
. generate t2dm = (strpos("notes", "T1DM")) != 0
```

Of course, that depends on the `notes_*.xyz` files being either text or text-like enough so that the `T1DM` would show up as "`T1DM`".

Note that `strpos()` and all of Stata's string functions also work with binary strings.

12.4.12 String display formats

The format for strings is `%[-]#s`, such as `%18s` and `%-18s`. `#` may be up to 2,045. `#` indicates the width of the field. `%#s` specifies that the string be displayed right-aligned in the field, and `%-#s` specifies that the string is displayed left-aligned.

Stata sets good default formats for `str#` variables. The default format is `%#s`, so if a variable is `str18`, its default format is `%18s`.

Stata sets poor default formats for `strL` variables. Stata uses `%9s` in all cases. Because `strL` variables can be so long, there is no good choice for the format; the question is merely how much of the string you want to see.

When the format is too short for the length of the string, whether the string is `str#` or `strL`, Stata usually displays `#` − 2 characters of the string and adds two dots at the end. We say "usually" because a few commands are able to do something better than that.

12.4.13 How to see the full contents of a strL or a str# variable

By default, the `list` command shows only the first part of long strings, followed by two dots. How much `list` shows is determined by the width of your Results window.

`list` will show the first 2,045 bytes of long strings, whether stored as `strL`s or `str#`s, if you add the `notrim` option.

```
. list, notrim
  (output omitted)
. list mystr, notrim
  (output omitted)
. list mystr in 5, notrim
  (output omitted)
```

Another way to display long strings is to use the `display` command. With `display`, you can see the entire contents. To display the fifth observation of the variable `mystr`, you type

```
. display _asis mystr[5]
  (output omitted)
```

That one command can produce a lot of output if the string is long, even hundreds of thousands of pages! Remember that you can press *Break* to stop the listing.

To see the first 5,000 characters of the string, you type

```
. display _asis usubstr(mystr[5], 1, 5000)
```

For detailed information about displaying Unicode characters beyond plain ASCII characters, see **[U] 12.4.2.2 Displaying Unicode characters**.

Very rarely, a string variable might contain SMCL output. SMCL is Stata's text markup language. A variable might contain SMCL if you used `fileread()` to read a Stata log file into it. In that case, you can see the text correctly formatted by typing

```
. display as txt mystr[1]
  (output omitted)
```

To learn more about other features of `display`, see [R] **display**.

12.4.14 Notes for programmers

The maximum length of macros is shorter than that of `strLs`. This means the following:

1. You can use macros in string expressions without fear that results will be truncated.
2. You can enclose expanded macros in quotes—`‘"‘macname’"’`—to form string literals without fear of truncation.
3. Macros cannot hold binary strings. If you are working with binary strings, use string scalars, which are also implemented as `strLs`. See [P] **scalar**.
4. You should not assume that the result of a string expression will fit into a macro. If you are sure it will, go ahead and store the result into a macro. If you are not sure, use a string scalar, which can hold a `strL`.
5. You should not assume that the contents of a `strL` variable will fit into a macro. Use string scalars.
6. In programming, use string scalars just as you would use numeric scalars.

```
program ...
        version 19.5      // (or version 19 if you do not have StataNow)
        ...
        tempname mystr
        ...
        scalar ‘mystr’ = ...
        ...
        generate ... = ...‘mystr’...
        ...
end
```

`mystr` in the above code is a macro containing a temporary name. Thus `‘mystr’` is a reference, not an expansion, of the contents of the string scalar.

12.5 Formats: Controlling how data are displayed

Formats describe how a number or string is to be presented. For instance, how is the number 325.24 to be presented? As `325.2`, or `325.24`, or `325.240`, or `3.2524e+02`, or `3.25e+02`, or some other way? The *display format* tells Stata exactly how to present such data. You do not have to specify display formats because Stata always makes reasonable assumptions about how to display a variable, but you always have the option.

12.5.1 Numeric formats

A Stata numeric format is formed by

first type	`%`	to indicate the start of the format
then optionally type	`-`	if you want the result left-aligned
then optionally type	`0`	if you want to retain leading zeros (1)
then type	a number w	stating the width of the result
then type	`.`	
then type	a number d	stating the number of digits to follow the decimal point
then type		
either	`e`	for scientific notation, e.g., 1.00e+03
or	`f`	for fixed format, e.g., 1000.0
or	`g`	for general format; Stata chooses based on the number being displayed
then optionally type	`c`	to indicate comma format (not allowed with `e`)

(1) Specifying `0` to mean "include leading zeros" will be honored only with the `f` format.

For example,

```
%9.0g     general format, 9 columns wide
                  sqrt(2) =   1.414214
                    1,000 =       1000
               10,000,000 =   1.00e+07
%9.0gc    general format, 9 columns wide, with commas
                  sqrt(2) =   1.414214
                    1,000 =      1,000
               10,000,000 =   1.00e+07
%9.2f     fixed format, 9 columns wide, 2 decimal places
                  sqrt(2) =       1.41
                    1,000 =    1000.00
               10,000,000 = 10000000.00
%9.2fc    fixed format, 9 columns wide, 2 decimal places, with commas
                  sqrt(2) =       1.41
                    1,000 =   1,000.00
               10,000,000 = 10,000,000.00
%9.2e     exponential format, 9 columns wide
                  sqrt(2) =   1.41e+00
                    1,000 =   1.00e+03
               10,000,000 =   1.00e+07
```

Stata has three numeric format types: `e`, `f`, and `g`. The formats are denoted by a leading percent sign (%) followed by the string *w.d*, where *w* and *d* stand for two integers. The first integer, *w*, specifies the width of the format. The second integer, *d*, specifies the number of digits that are to follow the decimal point. *d* must be less than *w*. Finally, a character denotes the format type (`e`, `f`, or `g`), and a `c` may optionally be appended to that to indicate that commas are to be included in the result (`c` is not allowed with `e`).

By default, every numeric variable is given a %*w*.0g format, where *w* is large enough to display the largest number of the variable's type. The %*w*.0g format is a set of formatting rules that present the values in as readable a fashion as possible without sacrificing precision. The g format changes the number of decimal places displayed whenever it improves the readability of the current value.

The default formats for each of the numeric variable types are

```
byte     %8.0g
int      %8.0g
long    %12.0g
float    %9.0g
double  %10.0g
```

You can change the format of a variable by using the `format` *varname* %*fmt* command.

In addition to %*w*.0g, %*w*.0gc is also allowed and displays numbers with commas. "One thousand" is displayed as 1000 in %9.0g format and as 1,000 in %9.0gc format.

In addition to using %*w*.0g and %*w*.0gc, you can use %*w*.*d*g and %*w*.*d*gc, $d > 0$. For example, %9.4g and %9.4gc. The 4 means to display approximately four significant digits. For instance, the number 3.14159265 in %9.4g format is displayed as 3.142, 31.4159265 as 31.42, 314.159265 as 314.2, and 3141.59265 as 3142. The format is not exactly a significant digit format because 31415.9265 is displayed as 31416, not as 3.142e+04.

Under the f format, values are always displayed with the same number of decimal places, even if this results in a loss in the displayed precision. Thus the f format is similar to the C f format. Stata's f format is also similar to the Fortran F format, but, unlike the Fortran F format, it switches to g whenever a number is too large to be displayed in the specified f format.

In addition to %*w*.*d*f, the format %*w*.*d*fc can display numbers with commas.

The e format is similar to the C e and the Fortran E format. Every value is displayed as a leading digit (with a minus sign, if necessary), followed by a decimal point, the specified number of digits, the letter e, a plus sign or a minus sign, and the power of 10 (modified by the preceding sign) that multiplies the displayed value. When the e format is specified, the width must exceed the number of digits that follow the decimal point by at least seven to accommodate the leading sign and digit, the decimal point, the e, and the signed power of 10.

▷ Example 3

Below we have a five-observation dataset with three variables: `e_fmt`, `f_fmt`, and `g_fmt`. All three variables have the same values stored in them; only the display format varies. `describe` shows the display format to the right of the variable type.

```
. use https://www.stata-press.com/data/r19/format, clear
. describe
Contains data from https://www.stata-press.com/data/r19/format.dta
 Observations:             5
    Variables:             3                  12 Mar 2024 15:18
─────────────────────────────────────────────────────────────────────────────
Variable      Storage   Display    Value
    name         type    format    label      Variable label
─────────────────────────────────────────────────────────────────────────────
e_fmt           float   %9.2e
f_fmt           float   %10.2f
g_fmt           float   %9.0g
─────────────────────────────────────────────────────────────────────────────
Sorted by:
```

The formats for each of these variables were set by typing

```
. format e_fmt %9.2e
. format f_fmt %10.2f
```

It was not necessary to set the format for the `g_fmt` variable because Stata automatically assigned it the `%9.0g` format. Nevertheless, we could have typed `format g_fmt %9.0g`. Listing the data results in

```
. list
```

	e_fmt	f_fmt	g_fmt
1.	2.80e+00	2.80	2.801785
2.	3.96e+06	3962322.50	3962323
3.	4.85e+00	4.85	4.852834
4.	-5.60e-06	-0.00	-5.60e-06
5.	6.26e+00	6.26	6.264982

◁

❑ Technical note

The discussion above is incomplete. There is one other format available that will be of interest to numerical analysts. The `%21x` format displays base 10 numbers in a hexadecimal (base 16) format. The number is expressed in hexadecimal (base 16) digits; the number a`X+`b means $a \times 2^b$. For example,

```
. display %21x 1234.75
+1.34b0000000000X+00a
```

Thus the base 10 number 1,234.75 has a base 16 representation of `1.34bX+0a`, meaning

$$\left(1 + 3 \cdot 16^{-1} + 4 \cdot 16^{-2} + 11 \cdot 16^{-3}\right) \times 2^{10}$$

Remember, the hexadecimal–decimal equivalents are

hexadecimal	decimal
0	0
1	1
2	2
3	3
4	4
5	5
6	6
7	7
8	8
9	9
a	10
b	11
c	12
d	13
e	14
f	15

See [U] 12.2 Numbers.

❑

12.5.2 European numeric formats

The three numeric formats `e`, `f`, and `g` will use '`,`' to indicate the decimal symbol if you specify their width and depth as *w*`,`*d* rather than *w*`.`*d*. For instance, the format `%9,0g` will display what Stata would usually display as 1.5 as `1,5`.

If you use the European specification with `fc` or `gc`, the comma will be presented as a period. For instance, `%9,0gc` would display what Stata would usually display as 1,000.5 as `1.000,5`.

If this way of presenting numbers appeals to you, consider using Stata's `set dp comma` command. `set dp comma` tells Stata to interpret nearly all %*w*`.`*d*{`g`|`f`|`e`} formats as %*w*`,`*d*{`g`|`f`|`e`} formats. Most of Stata is written using a period to represent the decimal symbol, and that means that even if you set the appropriate %*w*`,`*d*{`g`|`f`|`e`} format for your data, it will affect only displays of the data. For instance, if you type `summarize` to obtain summary statistics or `regress` to obtain regression results, the decimal will still be shown as a period.

`set dp comma` changes that and affects all of Stata. With `set dp comma`, it does not matter whether your data are formatted %*w*`.`*d*{`g`|`f`|`e`} or %*w*`,`*d*{`g`|`f`|`e`}. All results will be displayed using a comma as the decimal character.

```
. use https://www.stata-press.com/data/r19/auto, clear
(1978 automobile data)
. set dp comma
. summarize mpg weight foreign
    Variable |        Obs        Mean    Std. dev.       Min        Max
-------------+---------------------------------------------------------
         mpg |         74    21,2973    5,785503         12         41
      weight |         74   3019,459    777,1936       1760       4840
     foreign |         74   ,2972973    ,4601885          0          1
. regress mpg weight foreign
      Source |       SS           df       MS      Number of obs   =        74
-------------+----------------------------------   F(2, 71)        =     69,75
       Model |  1619,2877          2  809,643849   Prob > F        =    0,0000
    Residual |  824,171761         71  11,608053   R-squared       =    0,6627
-------------+----------------------------------   Adj R-squared   =    0,6532
       Total |  2443,45946         73  33,4720474   Root MSE        =    3,4071
------------------------------------------------------------------------------
         mpg | Coefficient  Std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
      weight |  -,0065879   ,0006371   -10,34   0,000    -,0078583   -,0053175
     foreign |  -1,650029   1,075994    -1,53   0,130      -3,7955    ,4954422
       _cons |    41,6797   2,165547    19,25   0,000     37,36172    45,99768
------------------------------------------------------------------------------
```

You can switch the decimal character back to a period by typing `set dp period`.

❑ Technical note

`set dp comma` makes drastic changes inside Stata, and we mention this because some older user-written programs may not be able to deal with those changes. If you are using an older user-written program, you might `set dp comma` and then find that the program does not work and instead presents some sort of syntax error.

If, when using any program, you do get an unanticipated error, try setting `dp` back to `period`. See [D] **format** for more information.

Also understand that `set dp comma` affects how Stata outputs numbers, not how it inputs them. You must still use the period to indicate the decimal point on all input. Even with `set dp comma`, you type

```
. replace x=1.5 if x==2
```

❑

12.5.3 Date and time formats

Date and time formats are really a numeric format because Stata stores dates as the number of milliseconds, days, weeks, months, quarters, half-years, or years from 01jan1960; see **[U] 25 Working with dates and times**.

The syntax of the `%t` format is

first type	`%`	to indicate the start of the format
then optionally type	`-`	if you want the result left-aligned
then type	`t`	
then type	*character*	to indicate the units
then optionally type	*other characters*	to indicate how the date/time is to be displayed

The letter you type to specify the units is

`C`	milliseconds from 01jan1960, adjusted for leap seconds
`c`	milliseconds from 01jan1960, ignoring leap seconds
`d`	days from 01jan1960
`w`	weeks from 1960-w1
`m`	calendar months from jan1960
`q`	quarters from 1960-q1
`h`	half years from 1960-h1

There are many codes you can type after that to specify exactly how the date/time is to be displayed, but usually, you do not. Most users use the default `%tc` for date/times and `%td` for dates. See **[D] Datetime display formats** for details.

12.5.4 String formats

The syntax for a string format is

first type	`%`	to indicate the start of the format
then optionally type	`-`	if you want the result left-aligned
then type	a number	indicating the width of the result
then type	`s`	

For instance, `%10s` represents a string format with a width of 10 display columns; see **[U] 12.4.2.2 Displaying Unicode characters**.

For `str`w, the default format is `%`w`s` or `%9s`, whichever is wider. For example, a `str10` variable receives a `%10s` format. Strings are displayed right-justified in the field, unless the minus sign is coded; `%-10s` would display the string left-aligned.

▷ Example 4

Our automobile data contain a string variable called `make`.

```
. use https://www.stata-press.com/data/r19/auto
(1978 automobile data)
. describe make
Variable      Storage   Display    Value
    name         type    format    label      Variable label
------------------------------------------------------------------------------
make            str18   %-18s                 Make and model
. list make in 63/67

     +-------------------+
     |              make |
     |-------------------|
 63. | Mazda GLC         |
 64. | Peugeot 604       |
 65. | Renault Le Car    |
 66. | Subaru            |
 67. | Toyota Celica     |
     +-------------------+
```

These values are left-aligned because `make` has a display format of `%-18s`. If we want to right-align the values, we could change the format.

```
. format %18s make
. list make in 63/67

     +-------------------+
     |              make |
     |-------------------|
 63. |         Mazda GLC |
 64. |       Peugeot 604 |
 65. |    Renault Le Car |
 66. |            Subaru |
 67. |     Toyota Celica |
     +-------------------+
```

◁

12.6 Dataset, variable, and value labels

Labels are strings used to label elements in Stata, such as labels for datasets, variables, and values.

12.6.1 Dataset labels

Associated with every dataset is an 80-character *dataset label*, which is initially set to blanks. You can use the `label data "`*text*`"` command to define the dataset label.

▷ Example 5

We have just entered 1980 state data on marriage rates, divorce rates, and median ages. The `describe` command will describe the data in memory:

```
. describe
Contains data
 Observations:            50
    Variables:             4                  6 Apr 2024 15:43
-------------------------------------------------------------------------------
Variable      Storage   Display    Value
    name         type    format    label      Variable label
-------------------------------------------------------------------------------
state           str14   %14s
median_age      float   %9.2f
marriage_rate   float   %9.0g
divorce_rate    float   %9.0g
-------------------------------------------------------------------------------
Sorted by:
     Note: Dataset has changed since last saved.
```

`describe` shows that there are 50 observations on 4 variables named `state`, `median_age`, `marriage_rate`, and `divorce_rate`. `state` is stored as a `str8`; `median_age` is stored as a `float`; and `marriage_rate` and `divorce_rate` are both stored as `longs`. Each variable's display format (see **[U] 12.5 Formats: Controlling how data are displayed**) is shown. Finally, the data are not in any particular sort order, and the dataset has changed since it was last saved on disk.

We can label the data by typing `label data "1980 state data"`. We type this and then type `describe` again.

```
. label data "1980 state data"
. describe
Contains data
 Observations:            50                  1980 state data
    Variables:             4                  6 Apr 2024 15:43
-------------------------------------------------------------------------------
Variable      Storage   Display    Value
    name         type    format    label      Variable label
-------------------------------------------------------------------------------
state           str14   %14s
median_age      float   %9.2f
marriage_rate   float   %9.0g
divorce_rate    float   %9.0g
-------------------------------------------------------------------------------
Sorted by:
     Note: Dataset has changed since last saved.
```

◁

The dataset label is displayed by the `describe` and `use` commands.

12.6.2 Variable labels

In addition to the name, every variable has associated with it an 80-character *variable label*. The variable labels are initially set to blanks. You use the `label variable` *varname* "*text*" command to define a new variable label.

▷ Example 6

Continuing with the data shown above, we can associate labels with the variables by typing

```
. label variable median_age "Median age"
. label variable marriage_rate "Marriages per 100,000"
. label variable divorce_rate "Divorces per 100,000"
```

The result of `describe` will then show

```
. describe
Contains data
 Observations:            50                  1980 state data
    Variables:             4                  6 Apr 2024 15:43
-------------------------------------------------------------------------------
Variable      Storage   Display    Value
    name         type    format    label      Variable label
-------------------------------------------------------------------------------
state           str14   %14s
median_age      float   %9.2f                 Median age
marriage_rate   float   %9.0g                 Marriages per 100,000
divorce_rate    float   %9.0g                 Divorces per 100,000
-------------------------------------------------------------------------------
Sorted by:
     Note: Dataset has changed since last saved.
```

◁

Whenever Stata produces output, it will use the variable labels rather than the variable names to label the results if there is room.

12.6.3 Value labels

Value labels define a correspondence or mapping between numeric data and the words used to describe what those numeric values represent. Mappings are named and defined by the `label define` *lblname* # "*string*" # "*string*"... command. The maximum length for the *lblname* is 32 characters. # must be an integer or an extended missing value (`.a`, `.b`, ..., `.z`). The maximum length of *string* is 32,000 bytes. Named mappings are associated with variables by the `label values` *varname lblname* command.

Below, we demonstrate how to create value labels and then associate those mappings (labels) with the numeric values to which they relate. To see how to use labels in an expression in place of the numeric values with which they are associated, see **[U] 13.11 Label values**.

▷ Example 7

The definition makes value labels sound more complicated than they are in practice. We create a dataset on individuals in which we record a person's sex, coding 0 for males and 1 for females. If our dataset also contained an employee number and salary, it might resemble the following:

```
. use https://www.stata-press.com/data/r19/gxmpl4, clear
(2007 Employee data)
. describe
Contains data from https://www.stata-press.com/data/r19/gxmpl4.dta
 Observations:             7                  2007 Employee data
    Variables:             3                  11 Feb 2024 15:31
-------------------------------------------------------------------------------
Variable      Storage   Display    Value
    name         type    format    label      Variable label
-------------------------------------------------------------------------------
empno           float   %9.0g                 Employee number
sex             float   %9.0g                 Sex
salary          float   %8.0fc                Annual salary, exclusive of bonus
-------------------------------------------------------------------------------
Sorted by:
. list
```

	empno	sex	salary
1.	57213	0	34,000
2.	47229	1	37,000
3.	57323	0	34,000
4.	57401	0	34,500
5.	57802	1	37,000
6.	57805	1	34,000
7.	57824	0	32,500

We could create a mapping called `sexlabel` defining 0 as "Male" and 1 as "Female", and then associate that mapping with the variable `sex` by typing

```
. label define sexlabel 0 "Male" 1 "Female"
. label values sex sexlabel
```

From then on, our data would appear as

```
. describe
Contains data from https://www.stata-press.com/data/r19/gxmpl4.dta
 Observations:             7                  2007 Employee data
    Variables:             3                  11 Feb 2024 15:31
-------------------------------------------------------------------------------
Variable      Storage   Display    Value
    name         type    format    label      Variable label
-------------------------------------------------------------------------------
empno           float   %9.0g                 Employee number
sex             float   %9.0g      sexlabel   Sex
salary          float   %8.0fc                Annual salary, exclusive of bonus
-------------------------------------------------------------------------------
Sorted by:
     Note: Dataset has changed since last saved.
```

```
. list
```

	empno	sex	salary
1.	57213	Male	34,000
2.	47229	Female	37,000
3.	57323	Male	34,000
4.	57401	Male	34,500
5.	57802	Female	37,000
6.	57805	Female	34,000
7.	57824	Male	32,500

Notice not only that the value label is used to produce words when we `list` the data, but also that the association of the variable `sex` with the value label `sexlabel` is shown by the `describe` command.

◁

❑ Technical note

Value labels and variables may share the same name. For instance, rather than calling the value label `sexlabel` in the example above, we could just as well have named it `sex`. We would then type `label values sex sex` to associate the value label named `sex` with the variable named `sex`.

❑

▷ Example 8

Stata's `encode` and `decode` commands provide a convenient way to go from string variables to numerically coded variables and back again. Let's pretend that, in the example above, rather than coding 0 for males and 1 for females, we created a string variable recording either `"male"` or `"female"`.

```
. use https://www.stata-press.com/data/r19/gxmpl5, clear
(2007 Employee data)
. describe
Contains data from https://www.stata-press.com/data/r19/gxmpl5.dta
 Observations:             7                  2007 Employee data
    Variables:             3                  11 Feb 2024 15:37
-------------------------------------------------------------------------------
Variable      Storage   Display    Value
    name         type    format    label      Variable label
-------------------------------------------------------------------------------
empno           float   %9.0g                 Employee number
sex             str6    %9s                   Sex
salary          float   %8.0fc                Annual salary, exclusive of bonus
-------------------------------------------------------------------------------
Sorted by:
```

```
. list
```

	empno	sex	salary
1.	57213	male	34,000
2.	47229	female	37,000
3.	57323	male	34,000
4.	57401	male	34,500
5.	57802	female	37,000
6.	57805	female	34,000
7.	57824	male	32,500

We now want to create a numerically encoded variable—we will call it `gender`—from the string variable. We want to do this, say, because we typed `anova salary sex` to perform a one-way ANOVA of salary on sex, and we were told that there were "no observations". We then remembered that all of Stata's statistical commands treat string variables as if they contain nothing but missing values. The statistical commands work only with numerically coded data.

```
. encode sex, generate(gender)
. describe
Contains data from https://www.stata-press.com/data/r19/gxmpl5.dta
 Observations:             7                  2007 Employee data
    Variables:             4                  11 Feb 2024 15:37
```

Variable name	Storage type	Display format	Value label	Variable label
empno	float	%9.0g		Employee number
sex	str6	%9s		Sex
salary	float	%8.0fc		Annual salary, exclusive of bonus
gender	long	%8.0g	gender	Sex

```
Sorted by:
     Note: Dataset has changed since last saved.
```

`encode` adds a new `long` variable called `gender` to the data and defines a new value label called `gender`. The value label `gender` maps 1 to the string `male` and 2 to `female`, so if we were to `list` the data, we could not tell the difference between the `gender` and `sex` variables. However, they are different. Stata's statistical commands know how to deal with `gender` but do not understand the `sex` variable. See **[U] 24.2 Categorical string variables**.

◁

❑ Technical note

Perhaps rather than employee data, our data are on persons undergoing gender reassignment surgery. There would, therefore, be two sex variables in our data: sex before the operation and sex after the operation. Assume that the variables are named `presex` and `postsex`. We can associate the *same* value label to each variable by typing

```
. label define sexlabel 0 "Male" 1 "Female"
. label values presex sexlabel
. label values postsex sexlabel
```

❑

❑ Technical note

Stata's input commands (`input` and `infile`) can switch from the words in a value label back to the numeric codes. Remember that `encode` and `decode` can translate a string to a numeric mapping and vice versa, so we can map strings to numeric codes either at the time of input or later.

For example,

```
. label define sexlabel 0 "Male" 1 "Female"
. input empno sex:sexlabel salary, label
        empno        sex     salary
  1. 57213 Male 34000
  2. 47229 Female 37000
  3. 57323 0 34000
  4. 57401 Male 34500
  5. 57802 Female 37000
  6. 57805 Female 34000
  7. 57824 Male 32500
  8. end
```

The `label define` command defines the value label `sexlabel`. `input empno sex:sexlabel salary, label` tells Stata to input three variables from the keyboard (`empno`, `sex`, and `salary`), attach the value label `sexlabel` to the `sex` variable, and look up any words that are typed in the value label to try to convert them to numbers. To demonstrate, we `list` the data that we recently entered:

```
. list
```

	empno	sex	salary
1.	57213	Male	34000
2.	47229	Female	37000
3.	57323	Male	34000
4.	57401	Male	34500
5.	57802	Female	37000
6.	57805	Female	34000
7.	57824	Male	32500

Compare the information we typed for observation 3 with the result listed by Stata. We typed `57323 0 34000`. Thus the value of `sex` in the third observation is `0`. When Stata listed the observation, it indicated that the value is `Male` because we told Stata in our `label define` command that zero is equivalent to `Male`.

Let's now add one more observation to our data:

```
. input, label
        empno        sex     salary
  8. 67223 FEmale 33000
'FEmale' cannot be read as a number
  8. 67223 Female 33000
  9. end
```

At first we typed `67223 FEmale 33000`, and Stata responded with "'FEmale' cannot be read as a number". Remember that Stata always respects case, so `FEmale` is not the same as `Female`. Stata prompted us to type the line again, and we did so, this time correctly.

❑

❑ Technical note

Coupled with the automatic option, Stata not only can go from words to numbers but also can create the mapping. Let's input the data again, but this time, rather than typing the data, let's read the data from a file. Assume that we have a text file named employee.raw stored on our disk that contains

```
57213 Male 34000
47229 Female 37000
57323 Male 34000
57401 Male 34500
57802 Female 37000
57805 Female 34000
57824 Male 32500
```

The infile command can read these data and create the mapping automatically.

```
. label list sexlabel
value label sexlabel not found
r(111);

. infile empno sex:sexlabel salary using employee, automatic
(7 observations read)
```

Our first command, label list sexlabel, is only to prove that we had not previously defined the value label sexlabel. Stata infiled the data without complaint. We now have

```
. list
```

	empno	sex	salary
1.	57213	Male	34000
2.	47229	Female	37000
3.	57323	Male	34000
4.	57401	Male	34500
5.	57802	Female	37000
6.	57805	Female	34000
7.	57824	Male	32500

Of course, sex is just another numeric variable; it does not actually take on the values Male and Female—it takes on numeric codes that have been automatically mapped to Male and Female. We can find out what that mapping is by using the label list command.

```
. label list sexlabel
sexlabel:
             1 Male
             2 Female
```

We discover that Stata attached the codes 1 to `Male` and 2 to `Female`. Anytime we want to see what our data really look like, ignoring the value labels, we can use the `nolabel` option.

```
. list, nolabel
```

	empno	sex	salary
1.	57213	1	34000
2.	47229	2	37000
3.	57323	1	34000
4.	57401	1	34500
5.	57802	2	37000
6.	57805	2	34000
7.	57824	1	32500

❑

12.6.4 Labels in other languages

A dataset can contain labels—data, variable, and value—in up to 100 languages. To discover the languages available for the dataset in memory, type `label language`. You will see

```
. label language
Language for variable and value labels
    In this dataset, value and variable labels have been defined in only one
    language:  default
    To create new language:          . label language <name>, new
    To rename current language:      . label language <name>, rename
```

or something like the following:

```
. label language
Language for variable and value labels
    Available languages:
            default
            de
            en
            sp
    Currently set is:                . label language sp
    To select different language:    . label language <name>
    To create new language:          . label language <name>, new
    To rename current language:      . label language <name>, rename
```

Right now, the example dataset is set with sp (Spanish) labels:

```
. describe
Contains data
 Observations:            74                  Automóviles, 1978
    Variables:            12                  3 Oct 2024 13:53
-------------------------------------------------------------------------------
Variable      Storage   Display    Value
    name         type    format    label      Variable label
-------------------------------------------------------------------------------
make            str18   %-18s                 Marca y modelo
price           int     %8.0gc                Precio
mpg             int     %8.0g                 Consumo de combustible
rep78           int     %8.0g                 Historia de reparaciones
headroom        float   %6.1f                 Cabeza adelante
trunk           int     %8.0g                 Volumen del maletero
weight          int     %8.0gc                Peso
length          int     %8.0g                 Longitud
turn            int     %8.0g                 Radio de giro
displacement    int     %8.0g                 Cilindrada
gear_ratio      float   %6.2f                 Relación de cambio
foreign         byte    %8.0g                 Extranjero
-------------------------------------------------------------------------------
Sorted by: foreign
```

To create labels in more than one language, you set the new language and then define the labels in the standard way; see [D] **label language**.

12.7 Notes attached to data

A dataset may contain notes, which are nothing more than little bits of text that you define and review with the notes command. Typing note, a colon, and the text defines a note:

```
. note: Send copy to Bob once verified.
```

You can later display whatever notes you have previously defined by typing notes:

```
. notes
_dta:
  1.  Send copy to Bob once verified.
```

Notes are saved with the data, so once you save your dataset, you can replay this note in the future.

You can add more notes:

```
. note: Mary also wants a copy.
. notes
_dta:
  1.  Send copy to Bob once verified.
  2.  Mary also wants a copy.
```

The notes you have added so far are attached to the data generically, which is why Stata prefixes them with _dta when it lists them. You can attach notes to variables:

```
. note state: Verify values for Nevada.
. note state: What about the two missing values?
. notes
_dta:
  1.  Send copy to Bob once verified.
  2.  Mary also wants a copy.
state:
  1.  Verify values for Nevada.
  2.  What about the two missing values?
```

When you describe your data, you can see whether notes are attached to the dataset or to any of the variables:

```
. describe
Contains data from state
 Observations:            50                  1980 state data
    Variables:             4
                                               (_dta has notes)
-------------------------------------------------------------------------------
Variable      Storage   Display    Value
    name         type    format    label      Variable label
-------------------------------------------------------------------------------
state           str8    %9s                 *
median_age      float   %9.0g                 Median Age
marriage_rate   long    %12.0g                Marriages per 100,000
divorce_rate    long    %12.0g                Divorces per 100,000
                                             * indicated variables have notes
-------------------------------------------------------------------------------
Sorted by:
     Note: Dataset has changed since last saved.
```

See [D] **notes** for a complete description of this feature.

12.8 Characteristics

Characteristics are an arcane feature of Stata but are of great use to Stata programmers. In fact, the notes command described above was implemented using characteristics.

The dataset itself and each variable within the dataset have associated with them a set of characteristics. Characteristics are named and referred to as *varname*[*charname*], where *varname* is the name of a variable or _dta. The characteristics contain text and are stored with the data in the Stata-format .dta dataset, so they are recalled whenever the data are loaded.

How are characteristics used? The [XT] **xt** commands need to know the name of the panel variable, and some of these commands also need to know the name of the time variable. xtset is used to specify the panel variable and optionally the time variable. Users need xtset their data only once. Stata then remembers this information, even from a different Stata session. Stata does this with characteristics: _dta[iis] contains the name of the panel variable and _dta[tis] contains the name of the time variable. When an xt command is issued, the command checks these characteristics to obtain the panel and time variables' names. If this information is not found, then the data have not previously been xtset and an error message is issued. This use of characteristics is hidden from the user—no mention is made of how the commands remember the identity of the panel variable and the time variable.

As a Stata user, you need understand only how to set and clear a characteristic for the few commands that explicitly reveal their use of characteristics. You set a variable *varname*'s characteristic *charname* to *x* by typing

```
. char varname[charname] x
```

You set the data's characteristic *charname* to be *x* by typing

```
. char _dta[charname] x
```

You clear a characteristic by typing

```
. char varname[charname]
```

where *varname* is either a variable name or `_dta`. You can clear a characteristic, even if it has never been set.

The most important feature of characteristics is that Stata remembers them from one session to the next; they are saved with the data.

❑ Technical note

Programmers will want to know more. A technical description is found in [P] **char**, but for an overview, you may refer to *varname*'s *charname* characteristic by embedding its name in single quotes and typing '*varname*[*charname*]'; see **[U] 18.3.13 Referring to characteristics**.

You can fetch the names of all characteristics associated with *varname* by typing

```
. local macname : char varname[]
```

The maximum length of the contents of a characteristic is 67,784 bytes for Stata/BE, Stata/SE, and Stata/MP. The association of names with characteristics is by convention. If you, as a programmer, wish to create new characteristics for use in your ado-files, do so, but include at least one capital letter in the characteristic name. The current convention reserves all lowercase names for "official" Stata.

❑

12.9 Data Editor and Variables Manager

We have spent most of this chapter writing about data management performed from Stata's command line. However, Stata provides two powerful features in its interface to help you examine and manage your data: the Data Editor and the Variables Manager.

The Data Editor is a spreadsheet-style data editor that allows you to enter new data, edit existing data, safely browse your data in a read-only mode, and perform almost any data management task you desire in a reproducible manner using a graphical interface. To open the Data Editor, select **Data** > **Data Editor** > **Data Editor (Edit)** or **Data** > **Data Editor** > **Data Editor (Browse)**. See [GS] **6 Using the Data Editor** (GSM, GSU, or GSW) for a tutorial discussion of the Data Editor. See [D] **edit** for technical details.

The Variables Manager is a tool that lists and allows you to manage all the properties of the variables in your data. Variable properties include the name, label, storage type, format, value label, and notes. The Variables Manager allows you to sort and filter your variables; this is something that you will find to be very useful if you work with datasets containing many variables. The Variables Manager also can be used to create varlists for the Command window. To open the Variables Manager, select **Data** > **Variables Manager**. See [GS] **7 Using the Variables Manager** (GSM, GSU, or GSW) for a tutorial discussion of the Variables Manager.

Both the Data Editor and the Variables Manager submit commands to Stata to perform any changes that you request. This lets you see a log of what changes were made, and it also allows you to work interactively while still building a list of commands that you can execute later to reproduce your analysis.

12.10 Data frames

So far, we have shown you examples of using Stata with a single dataset in memory. Stata can load multiple datasets into memory at the same time, storing them in frames, also known as data frames. You can easily switch between frames, copy data or create variable aliases between them, obtain results from analyses performed on the data in them, and even link them together on key variables. See [D] **frames intro** for an overview.

12.11 References

Cox, N. J. 2006. Stata tip 33: Sweet sixteen: Hexadecimal formats and precision problems. *Stata Journal* 6: 282–283.

———. 2010a. Stata tip 84: Summing missings. *Stata Journal* 10: 157–159.

———. 2010b. Stata tip 85: Looping over nonintegers. *Stata Journal* 10: 160–163.

Cox, N. J., and C. B. Schechter. 2018. Speaking Stata: Seven steps for vexatious string variables. *Stata Journal* 18: 981–994.

Daniels, L., and N. Minot. 2020. *An Introduction to Statistics and Data Analysis Using Stata*. Thousand Oaks, CA: Sage.

Long, J. S. 2009. *The Workflow of Data Analysis Using Stata*. College Station, TX: Stata Press.

Longest, K. C. 2020. *Using Stata for Quantitative Analysis*. 3rd ed. Thousand Oaks, CA: Sage.

Mitchell, M. N. 2020. *Data Management Using Stata: A Practical Handbook*. 2nd ed. College Station, TX: Stata Press.

Rising, W. R. 2010. Stata tip 86: The missing() function. *Stata Journal* 10: 303–304.

13 Functions and expressions

Contents

If you have not read **[U] 11 Language syntax**, please do so before reading this entry.

13.1 Overview

Examples of expressions include

```
2+2
miles/gallons
myv+2/oth
(myv+2)/oth
ln(income)
age<25 & income>50000
age<25 | income>50000
age==25
name=="M Brown"
fname + " " + lname
substr(name,1,10)
val[_n-1]
L.gnp
```

Expressions like those above are allowed anywhere *exp* appears in a syntax diagram. One example is [D] **generate**:

`generate` *newvar* `=` *exp* [*if*] [*in*]

The first *exp* specifies the contents of the new variable, and the optional second expression restricts the subsample over which it is to be defined. Another is [R] **summarize**:

`summarize` [*varlist*] [*if*] [*in*]

The optional expression restricts the sample over which summary statistics are calculated.

Algebraic and string expressions are specified in a natural way using the standard rules of hierarchy. You may use parentheses freely to force a different order of evaluation.

▷ Example 1

`myv+2/oth` is interpreted as `myv+(2/oth)`. If you wanted to change the order of the evaluation, you could type `(myv+2)/oth`.

◁

13.2 Operators

Stata has four different classes of operators: arithmetic, string, relational, and logical. Each type is discussed below.

13.2.1 Arithmetic operators

The *arithmetic operators* in Stata are `+` (addition), `-` (subtraction), `*` (multiplication), `/` (division), `^` (raise to a power), and the prefix `-` (negation). Any arithmetic operation on a missing value or an impossible arithmetic operation (such as division by zero) yields a missing value.

▷ Example 2

The expression `-(x+y^(x-y))/(x*y)` denotes the formula

$$-\frac{x+y^{x-y}}{x\cdot y}$$

and evaluates to *missing* if x or y is missing or zero.

◁

13.2.2 String operators

The + and * signs are also used as string operators.

+ is used for the concatenation of two strings. Stata determines by context whether + means addition or concatenation. If + appears between two numeric values, Stata adds them. If + appears between two strings, Stata concatenates them.

▷ Example 3

The expression `"this"+"that"` results in the string `"thisthat"`, whereas the expression `2+3` results in the number `5`. Stata issues the error message "type mismatch" if the arguments on either side of the + sign are not of the same type. Thus the expression `2+"this"` is an error, as is `2+"3"`.

The expressions on either side of the + can be arbitrarily complex:

```
substr(string(20+2),1,1) + strupper(substr("rf",1+1,1))
```

The result of the above expression is the string `"2F"`. See [FN] **String functions** for a description of the `substr()`, `string()`, and `strupper()` functions.

◁

* is used to duplicate a string 0 or more times. Stata determines by context whether * means multiplication or string duplication. If * appears between two numeric values, Stata multiplies them. If * appears between a string and a numeric value, Stata duplicates the string as many times as the numeric value indicates.

▷ Example 4

The expression `"this"*3` results in the string `"thisthisthis"`, whereas the expression `2*3` results in the number `6`. Stata issues the error message "type mismatch" if the arguments on either side of the * sign are both strings. Thus the expression `"this"*"that"` is an error.

As with string concatenation above, the arguments can be arbitrarily complex.

◁

13.2.3 Relational operators

The *relational operators* are > (greater than), < (less than), >= (greater than or equal), <= (less than or equal), == (equal), and != (not equal). Observe that the relational operator for equality is a pair of equal signs. This convention distinguishes relational equality from the =*exp* assignment phrase.

❑ Technical note

You may use ~ anywhere ! would be appropriate to represent the logical operator "not". Thus the not-equal operator may also be written as ~=.

❑

Relational expressions are either *true* or *false*. Relational operators may be used on either numeric or string subexpressions; thus, the expression 3>2 is *true*, as is "zebra">"cat". In the latter case, the relation merely indicates that "zebra" comes after the word "cat" in the dictionary. All uppercase letters precede all lowercase letters in Stata's book, so "cat">"Zebra" is also *true*.

Missing values may appear in relational expressions. If x were a numeric variable, the expression x>=. is *true* if x is missing and *false* otherwise. A missing value is greater than any nonmissing value; see **[U] 12.2.1 Missing values**.

▷ Example 5

You have data on age and income and wish to list the subset of the data for persons aged 25 years or less. You could type

```
. list if age<=25
```

If you wanted to list the subset of data of persons aged exactly 25, you would type

```
. list if age==25
```

Note the double equal sign. It would be an error to type list if age=25.

◁

Although it is convenient to think of relational expressions as evaluating to *true* or *false*, they actually evaluate to numbers. A result of *true* is defined as 1 and *false* is defined as 0.

▷ Example 6

The definition of *true* and *false* makes it easy to create indicator, or dummy, variables. For instance,

```
generate incgt10k=income>10000
```

creates a variable that takes on the value 0 when income is less than or equal to $10,000, and 1 when income is greater than $10,000. Because missing values are greater than all nonmissing values, the new variable incgt10k will also take on the value 1 when income is *missing*. It would be safer to type

```
generate incgt10k=income>10000 if income<.
```

Now, observations in which income is *missing* will also contain *missing* in incgt10k. See **[U] 26 Working with categorical data and factor variables** for more examples.

◁

❑ Technical note

Although you will rarely wish to do so, because arithmetic and relational operators both evaluate to numbers, there is no reason you cannot mix the two types of operators in one expression. For instance, (2==2)+1 evaluates to 2, because 2==2 evaluates to 1, and $1 + 1$ is 2.

Relational operators are evaluated after all arithmetic operations. Thus the expression (3>2)+1 is equal to 2, whereas 3>2+1 is equal to 0. Evaluating relational operators last guarantees the *logical* (as opposed to the *numeric*) interpretation. It should make sense that 3>2+1 is *false*.

❑

13.2.4 Logical operators

The *logical operators* are & (and), | (or), and ! (not). The logical operators interpret any nonzero value (including *missing*) as *true* and zero as *false*.

▷ Example 7

If you have data on age and income and wish to list data for persons making more than $50,000 along with persons under the age of 25 making more than $30,000, you could type

```
list if income>50000 | income>30000 & age<25
```

The & takes precedence over the |. If you were unsure, however, you could have typed

```
list if income>50000 | (income>30000 & age<25)
```

In either case, the statement will also list all observations for which income is *missing*, because *missing* is greater than 50,000.

◁

❑ Technical note

Like relational operators, logical operators return 1 for *true* and 0 for *false*. For example, the expression 5 & . evaluates to 1. Logical operations, except for !, are performed after all arithmetic and relational operations; the expression 3>2 & 5>4 is interpreted as (3>2) & (5>4) and evaluates to 1.

❑

13.2.5 Order of evaluation, all operators

The order of evaluation (from first to last) of all operators is ! (or ~), ^, - (negation), /, *, - (subtraction), +, != (or ~=), >, <, <=, >=, ==, &, and |.

13.3 Functions

Stata provides mathematical functions, probability and density functions, matrix functions, string functions, functions for dealing with dates and time series, and a set of special functions for programmers. You can find all of these documented in the *Stata Functions Reference Manual*. Stata's matrix programming language, Mata, provides more functions and those are documented in the *Mata Reference Manual* or in the help documentation (type help mata functions).

Functions are merely a set of rules; you supply the function with arguments, and the function evaluates the arguments according to the rules that define the function. Because functions are essentially subroutines that evaluate arguments and cause no action on their own, functions must be used in conjunction with a Stata command. Functions are indicated by the function name, an open parenthesis, an expression or expressions separated by commas, and a close parenthesis.

For example,

```
. display sqrt(4)
2
```

or

```
. display sqrt(2+2)
2
```

demonstrates the simplest use of a function. Here we have used the mathematical function, `sqrt()`, which takes one number (or expression) as its argument and returns its square root. The function was used with the Stata command `display`. If we had simply typed

```
. sqrt(4)
```

Stata would have returned the error message

```
command sqrt is unrecognized
r(199);
```

Functions can operate on variables, as well. For example, suppose that you wanted to generate a random variable that has observations drawn from a lognormal distribution. You could type

```
. set obs 5
Number of observations (_N) was 0, now 5
. generate y = runiform()
. replace y = invnormal(y)
(5 real changes made)
. replace y = exp(y)
(5 real changes made)
. list
```

	y
1.	.686471
2.	2.380994
3.	.2814537
4.	1.215575
5.	.2920268

You could have saved yourself some typing by typing just

```
. generate y = exp(rnormal())
```

Functions accept expressions as arguments.

All functions are defined over a specified domain and return values within a specified range. Whenever an argument is outside a function's domain, the function will return a missing value or issue an error message, whichever is most appropriate. For example, if you supplied the `log()` function with an argument of zero, the `log(0)` would return a missing value because zero is outside the natural logarithm function's domain. If you supplied the `log()` function with a string argument, Stata would issue a "type mismatch" error because `log()` is a numerical function and is undefined for strings. If you supply an argument that evaluates to a value that is outside the function's range, the function will return a missing value. Whenever a function accepts a string as an argument, the string must be enclosed in double quotes, unless you provide the name of a variable that has a string storage type.

13.4 System variables (_variables)

Expressions may also contain *_variables* (pronounced "underscore variables"), which are built-in system variables that are created and updated by Stata. They are called *_variables* because their names all begin with the underscore character, "_".

The _*variables* are

_n contains the number of the current observation.

_N contains the total number of observations in the dataset or the number of observations in the current by() group.

_pi contains the value of π to machine precision.

_rc contains the value of the return code from the most recent capture command.

[*eqno*]_b[*varname*] (synonym: [*eqno*]_coef[*varname*]) contains the value (to machine precision) of the coefficient on *varname* from the most recently fitted model (such as ANOVA, regression, Cox, logit, probit, and multinomial logit). See **[U] 13.5 Accessing coefficients and standard errors** below for a complete description.

[*eqno*]_se[*varname*] contains the value (to machine precision) of the standard error of the coefficient on *varname* from the most recently fit model (such as ANOVA, regression, Cox, logit, probit, and multinomial logit). See **[U] 13.5 Accessing coefficients and standard errors** below for a complete description.

_cons is always equal to the number 1 when used directly and refers to the intercept term when used indirectly, as in _b[_cons].

[*eqno*]_r_b[*varname*] contains the value (to machine precision) of the coefficient or transformed coefficient on *varname* from the most recently fitted model.

[*eqno*]_r_se[*varname*] contains the value (to machine precision) of the standard error of the coefficient or transformed coefficient on *varname* from the most recently fit model.

[*eqno*]_r_z[*varname*] contains the value (to machine precision) of the test statistic for the coefficient on *varname* from the most recently fitted model.

[*eqno*]_r_z_abs[*varname*] contains the absolute value (to machine precision) of the test statistic for the coefficient on *varname* from the most recently fitted model.

[*eqno*]_r_df[*varname*] contains the degrees of freedom for the coefficient on *varname* from the most recently fitted model.

[*eqno*]_r_p[*varname*] contains the p-value (to machine precision) of the test statistic for the coefficient on *varname* from the most recently fitted model.

[*eqno*]_r_lb[*varname*] contains the lower-bound value (to machine precision) of the confidence interval for the coefficient or transformed coefficient on *varname* from the most recently fitted model.

[*eqno*]_r_ub[*varname*] contains the upper-bound value (to machine precision) of the confidence interval for the coefficient or transformed coefficient on *varname* from the most recently fitted model.

[*eqno*]_r_crlb[*varname*] contains the lower-bound value (to machine precision) of the credible interval for the Bayesian estimate on *varname* from the most recently fitted model.

[*eqno*]_r_crub[*varname*] contains the upper-bound value (to machine precision) of the credible interval for the Bayesian estimate on *varname* from the most recently fitted model.

13.5 Accessing coefficients and standard errors

After fitting a model, you can access the coefficients and standard errors and use them in subsequent expressions. Also see [R] **predict** (and **[U] 20 Estimation and postestimation commands**) for an easier way to obtain predictions, residuals, and the like.

13.5.1 Single-equation models

First, let's consider estimation methods that yield one estimated equation with a one-to-one correspondence between coefficients and variables such as `logit`, `ologit`, `oprobit`, `probit`, `regress`, and `tobit`. `_b[`*varname*`]` (synonym `_coef[`*varname*`]`) contains the coefficient on *varname* and `_se[`*varname*`]` contains its standard error, and both are recorded to machine precision. Thus `_b[age]` refers to the calculated coefficient on the `age` variable after typing, say, `regress response age sex`, and `_se[age]` refers to the standard error on the coefficient. `_b[_cons]` refers to the constant and `_se[_cons]` to its standard error. Thus you might type

```
. regress response age sex
. generate asif = _b[_cons] + _b[age]*age
```

13.5.2 Multiple-equation models

The syntax for referring to coefficients and standard errors in multiple-equation models is the same as in the simple-model case, except that `_b[]` and `_se[]` are preceded by an equation number in square brackets. There are, however, many alternatives in how you may type requests. The way that you are supposed to type requests is

[*eqno*]`_b[`*varname*`]`
[*eqno*]`_se[`*varname*`]`

but you may substitute `_coef[]` for `_b[]`. In fact, you may omit the `_b[]` altogether, and most Stata users do:

[*eqno*] [*varname*]

You may also omit the second pair of square brackets:

[*eqno*]*varname*

You may retain the `_b[]` or `_se[]` and insert a colon between *eqno* and *varname*:

`_b[`*eqno*`:`*varname*`]`

There are two ways to specify the equation number *eqno*: either as an absolute equation number or as an "indirect" equation number. In the absolute form, the number is preceded by a '`#`' sign. Thus `[#1]displ` refers to the coefficient on `displ` in the first equation (and `[#1]_se[displ]` refers to its standard error). You can even use this form for simple models, such as `regress`, if you prefer. `regress` estimates one equation, so `[#1]displ` refers to the coefficient on `displ`, just as `_b[displ]` does. Similarly, `[#1]_se[displ]` and `_se[displ]` are equivalent. The logic works both ways—in the multiple-equation context, `_b[displ]` refers to the coefficient on `displ` in the first equation and `_se[displ]` refers to its standard error. `_b[`*varname*`]` (`_se[`*varname*`]`) is just another way of saying `[#1]`*varname* (`[#1]_se[`*varname*`]`).

Equations may also be referred to indirectly. `[res]displ` refers to the coefficient on `displ` in the equation named `res`. Equations are often named after the corresponding dependent variable name if there is such a concept in the fitted model, so `[res]displ` might refer to the coefficient on `displ` in the equation for variable `res`.

For multinomial logit (mlogit), multinomial probit (mprobit), and similar commands, equations are named after the levels of the single dependent categorical variable. In these models, there is one dependent variable, and there is an equation corresponding to each of the outcomes (values taken on) recorded in that variable, except for the one that is taken to be the base outcome. [res]displ would be interpreted as the coefficient on displ in the equation corresponding to the outcome res. If outcome res is the base outcome, Stata treats [res]displ as zero (and Stata does the same for [res]_se[displ]).

Continuing with the multinomial outcome case: the outcome variable must be numeric. The syntax [res]displ would be understood only if there were a value label associated with the numeric outcome variable and res were one of the labels. If your data are not labeled, then you can use the usual multiple-equation syntax [##]*varname* and [##]_se[*varname*] to refer to the coefficient and standard error for variable *varname* in the #th equation.

For mlogit, if your data are not labeled, you can also use the syntax [#]*varname* and [#]_se[*varname*] (without the '#') to refer to the coefficient and standard error for *varname* in the equation for outcome #.

13.5.3 Factor variables and time-series operators

We refer to time-series–operated variables exactly as we refer to normal variables. We type the name of the variable, which for time-series–operated variables includes the operators; see **[U] 11.4.4 Time-series varlists**. You might type

```
. regress open L.close LD.volume
. display _b[L.close]
. display _b[LD.volume]
```

We cannot refer to factor variables such as i.group in expressions. Assuming that i.group has three levels, i.group represents three virtual indicator variables—1b.group, 2.group, and 3.group. We can refer to the indicator variables in expressions by typing, for example, _b[i2.group] or just _b[2.group]. That is to say, we include the operators and the levels of the factor variables when typing the indicator-variable name. Consider a regression using factor variables:

```
. use https://www.stata-press.com/data/r19/fvex, clear
(Artificial factor variables' data)
. regress y i.sex i.group sex#group age sex#c.age
```

Source	SS	df	MS	Number of obs	=	3,000
				F(7, 2992)	=	80.84
Model	221310.507	7	31615.7868	Prob > F	=	0.0000
Residual	1170122.5	2,992	391.083723	R-squared	=	0.1591
				Adj R-squared	=	0.1571
Total	1391433.01	2,999	463.965657	Root MSE	=	19.776

y	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
sex						
female	32.29378	3.782064	8.54	0.000	24.87807	39.70949
group						
2	9.477077	1.624075	5.84	0.000	6.292659	12.66149
3	18.31292	1.776337	10.31	0.000	14.82995	21.79588
sex#group						
female#2	-6.621804	2.021384	-3.28	0.001	-10.58525	-2.658361
female#3	-10.48293	3.209	-3.27	0.001	-16.775	-4.190858
age	-.212332	.0538345	-3.94	0.000	-.3178884	-.1067756
sex#c.age						
female	-.226838	.0745707	-3.04	0.002	-.3730531	-.0806229
_cons	60.48167	2.842955	21.27	0.000	54.90732	66.05601

If we want to use the coefficient for level 2 of `group` in an expression, we type `_b[2.group]`; for level 3, we type `_b[3.group]`. To refer to the coefficient of an interaction of two levels of two factor variables, we specify the interaction operator and the level of each variable. For example, to use the coefficient for `sex` = 1 (female) and `group` = 2, we type `_b[1.sex#2.group]`. (We determined that 1 was the level corresponding to female by typing `label list`.) When one of the variables in an interaction is continuous, we can make that explicit, `_b[1.sex#c.age]`, or we can leave off the `c.`, `_b[1.sex#age]`.

Referring to interactions is more challenging than referring to normal variables. It is also more challenging to refer to coefficients from estimators that use multiple equations. If you find it difficult to know what to type for a coefficient, replay your estimation results using the `coeflegend` option.

```
. regress, coeflegend
      Source |       SS           df       MS      Number of obs   =     3,000
-------------+----------------------------------   F(7, 2992)      =     80.84
       Model |  221310.507         7  31615.7868   Prob > F        =    0.0000
    Residual |  1170122.5      2,992  391.083723   R-squared       =    0.1591
-------------+----------------------------------   Adj R-squared   =    0.1571
       Total |  1391433.01     2,999  463.965657   Root MSE        =    19.776

------------------------------------------------------------------------------
           y | Coefficient  Legend
-------------+----------------------------------------------------------------
         sex |
      female |   32.29378   _b[1.sex]
             |
       group |
           2 |   9.477077   _b[2.group]
           3 |   18.31292   _b[3.group]
             |
   sex#group |
  female#2   |  -6.621804   _b[1.sex#2.group]
  female#3   |  -10.48293   _b[1.sex#3.group]
             |
         age |   -.212332   _b[age]
             |
   sex#c.age |
      female |   -.226838   _b[1.sex#c.age]
             |
       _cons |   60.48167   _b[_cons]
------------------------------------------------------------------------------
```

The Legend column shows you exactly what to type to refer to any coefficient in the estimation.

If your estimation results have both equations and factor variables, nothing changes from what we said in [U] 13.5.2 Multiple-equation models above. What you type for *varname* is just a little more complicated.

13.6 Accessing results from Stata commands

Most Stata commands—not just estimation commands—store results so that you can access them in subsequent expressions. You do that by referring to `e(`*name*`)`, `r(`*name*`)`, `s(`*name*`)`, or `c(`*name*`)`.

```
. summarize age
. generate agedev = age-r(mean)
. regress mpg weight
. display "The number of observations used is " e(N)
```

Most commands are categorized as r-class, meaning that they store results in `r()`. The returned results—such as `r(mean)`—are available immediately following the command, and if you are going to refer to them, you need to refer to them soon because the next command will probably replace what is in `r()`.

e-class commands are Stata's estimation commands—commands that fit models. Results in `e()` remain available until the next model is fit.

s-class commands are parsing commands—commands used by programmers to interpret commands you type. Few commands store anything in `s()`.

There are no c-class commands. `c()` contains values that are always available, such as `c(current_date)` (today's date), `c(pwd)` (the current directory), `c(N)` (the number of observations), and so on. There are many `c()` values and they are documented in [P] **creturn**.

Every command of Stata is designated r-class, e-class, or s-class, or, if the command stores nothing, n-class. r stands for return as in returned results, e stands for estimation as in estimation results, s stands for string, and, admittedly, this last acronym is weak, n stands for null.

You can find out what is stored where by looking in the *Stored results* section for the particular command in the *Reference* manual. If you know the class of a command—and it is easy enough to guess—you can also see what is stored by typing `return list`, `ereturn list`, or `sreturn list`:

See [R] **Stored results** and [U] **18.8 Accessing results calculated by other programs**.

13.7 Explicit subscripting

Individual observations on variables can be referred to by subscripting the variables. Explicit subscripts are specified by following a variable name with square brackets that contain an expression. The result of the subscript expression is truncated to an integer, and the value of the variable for the indicated observation is returned. If the value of the subscript expression is less than `1` or greater than `_N`, a missing value is returned.

13.7.1 Generating lags and leads

When you type something like

```
. generate y = x
```

Stata interprets it as if you typed

```
. generate y = x[_n]
```

which means that the first observation of `y` is to be assigned the value from the first observation of `x`, the second observation of `y` is to be assigned the value from the second observation on `x`, and so on. If you instead typed

```
. generate y = x[1]
```

you would set each observation of `y` equal to the first observation on `x`. If you typed

```
. generate y = x[2]
```

you would set each observation of `y` equal to the second observation on `x`. If you typed

```
. generate y = x[0]
```

Stata would merely copy a missing value into every observation of `y` because observation 0 does not exist. The same would happen if you typed

```
. generate y = x[100]
```

and you had fewer than 100 observations in your data.

When you type the square brackets, you are specifying explicit subscripts. Explicit subscripting combined with the *_variable* `_n` can be used to create lagged values on a variable. The lagged value of a variable `x` can be obtained by typing

```
. generate xlag = x[_n-1]
```

If you are really interested in lags and leads, you probably have time-series data and would be better served by using the time-series operators, such as `L.x`. Time-series operators can be used with varlists and expressions and they are safer because they account for gaps in the data; see **[U] 11.4.4 Time-series varlists** and **[U] 13.10 Time-series operators**. Even so, it is important that you understand how the above works.

The built-in underscore variable `_n` is understood by Stata to mean the observation number of the current observation. That is why

```
. generate y = x[_n]
```

results in observation 1 of `x` being copied to observation 1 of `y` and similarly for the rest of the observations. Consider

```
. generate xlag = x[_n-1]
```

`_n-1` evaluates to the observation number of the previous observation. For the first observation, `_n-1` $=$ 0 and therefore `xlag[1]` is set to missing. For the second observation, `_n-1` $=$ 1 and `xlag[2]` is set to the value of `x[1]`, and so on.

Similarly, the lead of `x` can be created by

```
. generate xlead = x[_n+1]
```

Here the last observation on the new variable `xlead` will be *missing* because `_n+1` will be greater than `_N` (`_N` is the total number of observations in the dataset).

13.7.2 Subscripting within groups

When a command is preceded by the `by` *varlist*`:` prefix, subscript expressions and the underscore variables `_n` and `_N` are evaluated relative to the subset of the data currently being processed. For example, consider the following (admittedly not very interesting) data:

```
. use https://www.stata-press.com/data/r19/gxmpl6
. list
```

	bvar	oldvar
1.	1	1.1
2.	1	2.1
3.	1	3.1
4.	2	4.1
5.	2	5.1

To see how _n, _N, and explicit subscripting work, let's create three new variables demonstrating each and then list their values:

```
. generate small_n = _n
. generate big_n = _N
. generate newvar = oldvar[1]
. list
```

	bvar	oldvar	small_n	big_n	newvar
1.	1	1.1	1	5	1.1
2.	1	2.1	2	5	1.1
3.	1	3.1	3	5	1.1
4.	2	4.1	4	5	1.1
5.	2	5.1	5	5	1.1

small_n (which is equal to _n) goes from 1 to 5, and big_n (which is equal to _N) is 5. This should not be surprising; there are 5 observations in the data, and _n is supposed to count observations, whereas _N is the total number. newvar, which we defined as oldvar[1], is 1.1. Indeed, we see that the first observation on oldvar is 1.1.

Now, let's repeat those same three steps, only this time preceding each step with the prefix by bvar:. First, we will drop the old values of small_n, big_n, and newvar so that we start fresh:

```
. drop small_n big_n newvar
. by bvar, sort: generate small_n=_n
. by bvar: generate big_n =_N
. by bvar: generate newvar=oldvar[1]
. list
```

	bvar	oldvar	small_n	big_n	newvar
1.	1	1.1	1	3	1.1
2.	1	2.1	2	3	1.1
3.	1	3.1	3	3	1.1
4.	2	4.1	1	2	4.1
5.	2	5.1	2	2	4.1

The results are different. Remember that we claimed that _n and _N are evaluated relative to the subset of data in the by-group. Thus small_n (_n) goes from 1 to 3 for bvar = 1 and from 1 to 2 for bvar = 2. big_n (_N) is 3 for the first group and 2 for the second. Finally, newvar (oldvar[1]) is 1.1 and 4.1.

You now know enough to do some amazing things.

▷ Example 8

Suppose that you have data on individual states and you have another variable in your data called region that divides the states into the four census regions. You have a variable x in your data, and you want to make a new variable called avgx to include in your regressions. This new variable is to take on the average value of x for the region in which the state is located. Thus, for California, you will have the observation on x and the observation on the average value in the region, avgx. Here is how:

```
. by region, sort: generate avgx=sum(x)/_n
. by region: replace avgx=avgx[_N]
```

First, by region, we generate avgx equal to the running sum of x divided by the number of observations so far. The , sort ensures that the data are in region order. We have, in effect, created the running average of x within region. It is the last observation of this running average, the overall average within the region, that interests us. So, by region, we replace every avgx observation in a region with the last observation within the region, avgx[_N].

Here is what we will see when we type these commands:

```
. use https://www.stata-press.com/data/r19/gxmpl7, clear
. by region, sort: generate avgx=sum(x)/_n
. by region: replace avgx=avgx[_N]
(46 real changes made)
```

In our example, there are no missing observations on x. If there had been, we would have obtained the wrong answer. When we created the running average, we typed

```
. by region, sort: generate avgx=sum(x)/_n
```

The problem is not with the sum() function. When sum() encounters a missing, it adds zero to the sum. The problem is with _n. Let's assume that the second observation in the first region has recorded a missing for x. When Stata processes the third observation in that region, it will calculate the sum of two elements (remember that one is missing) and then divide the sum by 3 when it should be divided by 2. There is an easy solution:

```
. by region: generate avgx=sum(x)/sum(x<.)
```

Rather than divide by _n, we divide by the total number of nonmissing observations seen on x so far, namely, the sum(x<.).

If our goal were simply to obtain the mean, we could have more easily accomplished it by typing egen avgx=mean(x), by(region); see [D] **egen**. egen, however, is written in Stata, and the above is how egen's mean() function works. The general principles are worth understanding.

◁

▷ Example 9

You have some patient data recording vital signs at various times during an experiment. The variables include patient, an ID number or name of the patient; time, a variable recording the date or time or epoch of the vital-sign reading; and vital, a vital sign. You probably have more than one vital sign, but one is enough to illustrate the concept. Each observation in your data represents a patient-time combination.

Let's assume that you have 1,000 patients and, for every observation on the same patient, you want to create a new variable called orig that records the patient's initial value of this vital sign.

```
. use https://www.stata-press.com/data/r19/gxmpl8, clear
. sort patient time
. by patient: generate orig=vital[1]
```

Observe that vital[1] refers not to the first reading on the first patient but to the first reading on the current patient, because we are performing the generate command by patient.

◁

▷ Example 10

Let's do one more example with these patient data. Suppose that we want to create a new dataset from our patient data that record not only the patient's identification, the time of the reading of the first vital sign, and the first vital sign reading itself, but also the time of the reading of the last vital sign and its value. We want 1 observation per patient. Here's how:

```
. sort patient time
. by patient: generate lasttime=time[_N]
. by patient: generate lastvital=vital[_N]
. by patient: drop if _n!=1
```

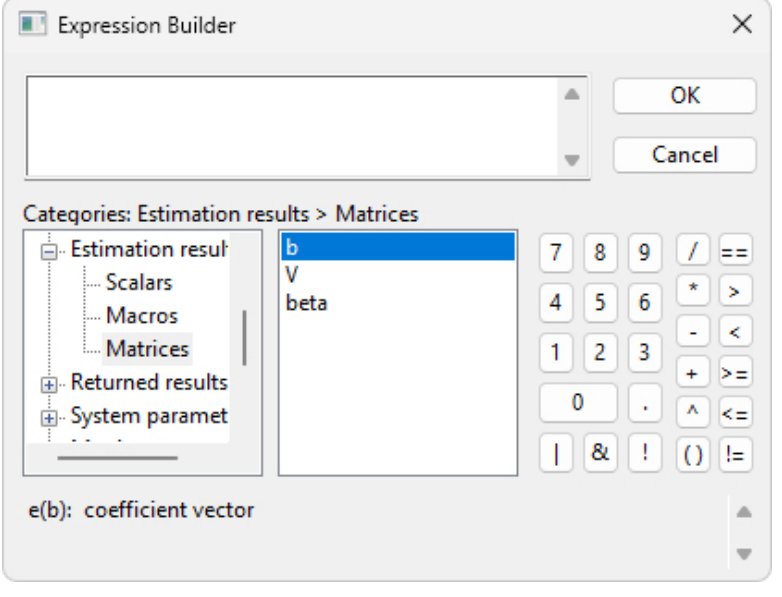
◁

See Mitchell (2020, chap. 8) for numerous examples of subscripting and subscripting within groups.

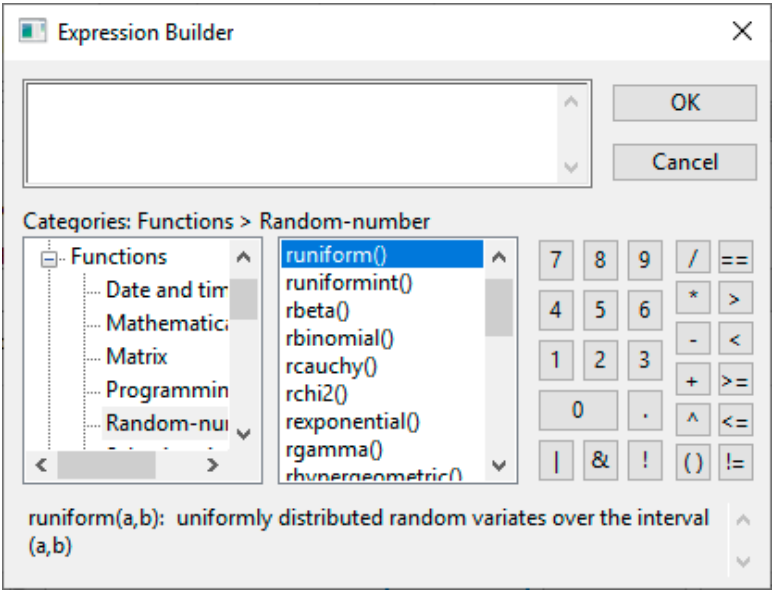
13.8 Using the Expression Builder

The Expression Builder in Stata provides a convenient way to create expressions using any of the methods described above. To access the Expression Builder, click on the **Create...** button in a dialog box of any command that allows an *exp*.

Within the Expression Builder, you can interactively browse and then select almost anything you would want to add to an expression: mathematical constants, variables, system limits, local and global macros, dataset and variable notes, and more. This is especially useful for accessing estimation results and system values when you may not immediately know the name.



You may also find the Expression Builder helpful if you want to use a function because a description of each function, as well as the order of the arguments for each function, is provided at the bottom of the dialog box when it is selected.



Watch a video example of using the Expression Builder.

13.9 Indicator values for levels of factor variables

Stata's factor-variable features let us access virtual indicator variables for categorical variables and their interactions; see **[U] 11.4.3 Factor variables** and **[U] 26 Working with categorical data and factor variables**. We can use those virtual indicator variables in expressions just as though the virtual variables existed in our data. If you have not read about factor-variable varlists in **[U] 11.4.3 Factor variables**, do so now.

If `group` is a categorical variable taking on the value 1, 2, or 3, consider the expression

```
. generate group1 = 1.group
```

We have taken the virtual indicator variable that is 1 when `group` $= 1$ and 0 when `group` $\neq 1$ and made it into a real variable—`group1`. That is strictly true only if `group` is never missing. If group can be missing, we need to add that `1.group` is missing when `group` is missing.

These virtual variables extend to interactions. If we also have a variable, `sex`, that is 0 for males and 1 for females, then

```
. generate sex0grp2 = 0.sex#2.group
```

creates the variable `sex0grp2`, which is `1` when `sex` $= 0$ and `group` $= 2$, `.` (missing) when `sex` or `group` is missing, and `0` otherwise.

Virtual indicator variables can be used in any expression, including `if` expressions.

❑ Technical note

We have been using the shorthand notation for virtual indicators that drops the `i` prefix. We have written `2.group` rather than `i2.group`. There are three cases where we cannot drop the `i` prefix—when our variable name is `e`, `d`, or `x`. These three letters can be used to construct numbers such as `1e-3`, which can also be typed `1.e-3`. If we have a variable named `e`, are we to interpret `1.e-3` as the number 0.001 or as the virtual indicator variable `1.e` with the number 3 subtracted? Because of longstanding precedent, it is interpreted as the number 0.001. If we want `1.e` interpreted as a virtual indicator, we must include the `i` prefix—`i1.e`.

❑

13.10 Time-series operators

Time-series operators allow you to refer to the lag of `gnp` by typing `L.gnp`, the second lag by typing `L2.gnp`, etc. There are also operators for lead (sometimes called forward; `F`), difference (`D`), and seasonal difference (`S`).

Time-series operators can be used with varlists and with expressions. See **[U] 11.4.4 Time-series varlists** if you have not read it already. This section has to do with using time-series operators in expressions such as with `generate`. You do not have to create new variables; you can use the time-series operated variables directly.

13.10.1 Generating lags, leads, and differences

In a time-series context, referring to `L2.gnp` is better than referring to `gnp[_n-2]` because there might be missing observations. Pretend that observation 4 contains data for $t = 25$ and observation 5 data for $t = 27$. `L2.gnp` will still produce correct answers; `L2.gnp` for observation 5 will be the value from observation 4 because the time-series operators look at t to find the relevant observation. The more mechanical `gnp[_n-2]` just goes 2 observations back, which, here, would not produce the desired result.

This same idea holds for differences. In our example, `D.gnp` will produce a missing value in observation 5 ($t = 27$) because there is no data recorded for $t = 26$, and therefore there is no first difference for $t = 27$.

Time-series operators can be used with varlists or with expressions, so you can type

```
. regress val L.gnp r
```

or

```
. generate gnplagged = L.gnp
. regress val gnplagged
```

Before you can type either one, however, you must use the `tsset` command to tell Stata the identity of the time variable; see [TS] **tsset**. Once you have `tsset` the data, anyplace you see an *exp* in a syntax diagram, you may type time series–operated variables, so you can type

```
. summarize r if F.gnp < gnp
```

or

```
. generate grew = 1 if gnp > L.gnp & L.gnp < .
. replace grew = 0 if grew >= . & L.gnp < .
```

or

```
. generate grew = (gnp > L.gnp) if L.gnp < .
```

13.10.2 Time-series operators and factor variables

As with varlists, factor variables may be combined with the `L.` (lag) and `F.` (lead) time-series operators in expressions. We can generate a variable containing the lag of the level 2 indicator of `group` (`group` = 2) by typing

```
. generate lag2group = 2L.group
```

The operators can be combined anywhere expressions are allowed. We can select observations for which the lag of the second level of group is 1 by typing `if i2L.group`.

They can be combined in interactions. We can generate the lag of the interaction of `sex` = 1 with `group` = 3 by typing

```
. generate lag1sexX3grp = 1L.sex#2L.group
```

See **[U] 11.4.3.6 Using factor variables with time-series operators** and **[U] 11.4.4 Time-series varlists** for more on factor variables and time-series operators.

13.10.3 Operators within groups

Stata also understands panel or cross-sectional time-series data. For instance, if you type

```
. tsset country time
```

you are declaring that you have time-series data. The time variable is `time`, and you have time-series data for separate countries.

Once you have `tsset` both cross-sectional and time identifiers, you proceed just as you would if you had a simple time series.

```
. generate grew = (gnp > L.gnp) if L.gnp < .
```

would produce correct results. The `L.` operator will not confuse the observation at the end of one panel with the beginning of the next.

13.10.4 Video example

Time series, part 3: Time-series operators

13.11 Label values

If you have not read **[U] 12.6 Dataset, variable, and value labels**, please do so. You may use labels in an expression in place of the numeric values with which they are associated. To use a label in this way, type the label in double quotes followed by a colon and the name of the value label.

▷ Example 11

If the value label `yesno` associates the label `yes` with 1 and `no` with 0, then `"yes":yesno` (said aloud as the value of `yes` under `yesno`) is evaluated as 1. If the double-quoted label is not defined in the indicated value label, or if the value label itself is not found, a missing value is returned. Thus the expression `"maybe":yesno` is evaluated as *missing*.

```
. use https://www.stata-press.com/data/r19/gxmpl9, clear
. list
```

	name	answer
1.	Mikulin	no
2.	Gaines	no
3.	Hilbe	yes
4.	DeLeon	no
5.	Cain	no
6.	Wann	yes
7.	Schroeder	no
8.	Cox	no
9.	Bishop	no
10.	Hardin	yes
11.	Lancaster	yes
12.	Poole	no

```
. list if answer=="yes":yesno
```

	name	answer
3.	Hilbe	yes
6.	Wann	yes
10.	Hardin	yes
11.	Lancaster	yes

In the above example, the variable `answer` is not a string variable; it is a numeric variable that has the associated value label `yesno`. Because `yesno` associates `yes` with 1 and `no` with 0, we could have typed `list if answer==1` instead of what we did type. We could not have typed `list if answer=="yes"` because `answer` is not a string variable. If we had, we would have received the error message "type mismatch".

◁

13.12 Precision and problems therein

Examine the following short Stata session:

```
. drop _all
. input x y
            x          y
  1. 1 1.1
  2. 2 1.2
  3. 3 1.3
  4. end
. count if x==1
      1
. count if y==1.1
      0
```

```
. list
```

	x	y
1.	1	1.1
2.	2	1.2
3.	3	1.3

We created a dataset containing two variables, x and y. The first observation has x equal to 1 and y equal to 1.1. When we asked Stata to `count` the number of times that the variable x took on the value 1, we were told that it occurred once. Yet when we asked Stata to `count` the number of times y took on the value 1.1, we were told zero—meaning that it never occurred. What has gone wrong? When we `list` the data, we see that the first observation has y equal to 1.1.

Despite appearances, Stata has not made a mistake. Stata stores numbers internally in binary form, and the number 1.1 has no exact binary representation—that is, there is no finite string of binary digits that is equal to 1.1.

❑ Technical note

The number 1.1 in binary form is 1.0001100110011 …, where the period represents the binary point. The problem binary computers have with storing numbers like 1/10 is much like the problem we base-10 users have in precisely writing 1/11, which is 0.0909090909 ….

For detailed information about precision on binary computers and how Stata stores binary floating-point numbers, see Gould (2011a).

❑

The number that appears as 1.1 in the listing above is actually 1.1000000238419, which is off by roughly 2 parts in 10^8. Unless we tell Stata otherwise, it stores all numbers as `floats`, which are also known as *single-precision* or *4-byte reals*. On the other hand, Stata performs all internal calculations in `doubles`, which are also known as *double-precision* or *8-byte reals*. This is what leads to the difficulty.

In the above example, we compared the number 1.1, stored as a `float`, with the number 1.1 stored as a `double`. The double-precision representation of 1.1 is more accurate than the single-precision representation, but it is also different. Those two numbers are not equal.

There are several ways around this problem. The problem with 1.1 apparently not equaling 1.1 would never arise if the storage precision and the precision of the internal calculations were the same. Thus you could store all your data as `doubles`. This takes more computer memory, however, and it is unlikely that your data are really that accurate and the extra digits would meaningfully affect any calculated result, even if the data were that accurate.

❑ Technical note

This is unlikely to affect any calculated result because Stata performs all internal calculations in double precision. This is all rather ironic, because the problem would also not arise if we had designed Stata to use single precision for its internal calculations. Stata would be less accurate, but the problem would have been completely disguised from the user, making this entry unnecessary.

❑

Another solution is to use the `float()` function. `float(`*x*`)` rounds *x* to its `float` representation. If we had typed `count if y==float(1.1)` in the above example, we would have been informed that there is one such value.

13.13 References

Cox, N. J. 2006. Stata tip 33: Sweet sixteen: Hexadecimal formats and precision problems. *Stata Journal* 6: 282–283.

———. 2011a. Speaking Stata: Compared with …. *Stata Journal* 11: 305–314.

———. 2011b. Speaking Stata: Fun and fluency with functions. *Stata Journal* 11: 460–471.

———. 2011c. Stata tip 96: Cube roots. *Stata Journal* 11: 149–154.

Cox, N. J., and C. B. Schechter. 2019. Speaking Stata: How best to generate indicator or dummy variables. *Stata Journal* 19: 246–259.

Crow, K. 2012. Building complicated expressions the easy way. *The Stata Blog: Not Elsewhere Classified.* https://blog.stata.com/2012/02/07/building-complicated-expressions-the-easy-way/.

Gould, W. W. 2006. Mata Matters: Precision. *Stata Journal* 6: 550–560.

———. 2011a. How to read the %21x format, part 2. *The Stata Blog: Not Elsewhere Classified.* https://blog.stata.com/2011/02/10/how-to-read-the-percent-21x-format-part-2/.

———. 2011b. Precision (yet again), Part I. *The Stata Blog: Not Elsewhere Classified.* https://blog.stata.com/2011/06/17/precision-yet-again-part-i/.

———. 2011c. Precision (yet again), Part II. *The Stata Blog: Not Elsewhere Classified.* https://blog.stata.com/2011/06/23/precision-yet-again-part-ii/.

———. 2012. The penultimate guide to precision. *The Stata Blog: Not Elsewhere Classified.* https://blog.stata.com/2012/04/02/the-penultimate-guide-to-precision/.

Linhart, J. M. 2008. Mata Matters: Overflow, underflow and the IEEE floating-point format. *Stata Journal* 8: 255–268.

Mitchell, M. N. 2020. *Data Management Using Stata: A Practical Handbook*. 2nd ed. College Station, TX: Stata Press.

Weiss, M. 2009. Stata tip 80: Constructing a group variable with specified group sizes. *Stata Journal* 9: 640–642.

14 Matrix expressions

Contents

14.1 Overview

Stata has two matrix programming languages, one that might be called Stata's older matrix language and another that is called Mata. Stata's Mata is the new one, and there is an uneasy relationship between the two.

Below we discuss Stata's older language and leave the newer one to another manual—the [M] *Mata Reference Manual*—or you can learn about the newer one by typing `help mata`.

We admit that the newer language is better in almost every way than the older language, but the older one still has a use because it is the one that Stata truly and deeply understands. Even when Mata wants to talk to Stata, matrixwise, it is the older language that Mata must use, so you must learn to use the older language as well as the new.

This is not nearly as difficult, or messy, as you might imagine because Stata's older language is remarkably easy to use, and really, there is not much to learn. Just remember that for heavy-duty programming, it will be worth your time to learn Mata, too.

14.1.1 Definition of a matrix

Stata's definition of a matrix includes a few details that go beyond the mathematics. To Stata, a matrix is a named entity containing an $r \times c$ rectangular array of double-precision numbers (including missing values) that is bordered by a row and a column of names. For the dimensions of a matrix, see [R] **Limits**.

```
. matrix list A
A[3,2]
    c1  c2
r1   1   2
r2   3   4
r3   5   6
```

Here we have a 3×2 matrix named `A` containing elements 1, 2, 3, 4, 5, and 6. Row 1, column 2 (written $A_{1,2}$ in math and `A[1,2]` in Stata) contains 2. The columns are named `c1` and `c2` and the rows, `r1`, `r2`, and `r3`. These are the default names Stata comes up with when it cannot do better. The names do not play a role in the mathematics, but they are of great help when it comes to labeling the output.

The names are operated on just as the numbers are. For instance,

```
. matrix B=A'*A
. matrix list B
symmetric B[2,2]
    c1  c2
c1  35
c2  44  56
```

We defined $\mathbf{B} = \mathbf{A}'\mathbf{A}$. The row and column names of $\mathbf{B}$ are the same. Multiplication is defined for any $a \times b$ and $b \times c$ matrices, the result being $a \times c$. Thus the row and column names of the result are the row names of the first matrix and the column names of the second matrix. We formed $\mathbf{A}'\mathbf{A}$, using the transpose of $\mathbf{A}$ for the first matrix—which also interchanged the names—and so obtained the names shown.

14.2 Row and column names

Matrix rows and columns always have names. Stata is smart about setting these names when the matrix is created, and the matrix commands and operators manipulate these names throughout calculations, so the names typically are set correctly at the conclusion of matrix calculations.

For instance, consider the matrix calculation $\mathbf{b} = (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{y}$ performed on real data:

```
. use https://www.stata-press.com/data/r19/auto
(1978 automobile data)
. matrix accum XprimeX = weight foreign
(obs=74)
. matrix vecaccum yprimeX = mpg weight foreign
. matrix b = invsym(XprimeX)*yprimeX'
. matrix list b
b[3,1]
                mpg
 weight  -.00658789
foreign  -1.6500291
  _cons   41.679702
```

These names were produced without our ever having given a special command to place the names on the result. When we formed matrix `XprimeX`, Stata produced the result

```
. matrix list XprimeX
symmetric XprimeX[3,3]
            weight    foreign      _cons
 weight  7.188e+08
foreign      50950         22
  _cons     223440         22         74
```

`matrix accum` forms $\mathbf{X}'\mathbf{X}$ matrices from data and sets the row and column names to the variable names used. The names are correct in the sense that, for instance, the (1,1) element is the sum across the observations of squares of `weight` and the (2,1) element is the sum of the product of `weight` and `foreign`.

Similarly, `matrix vecaccum` forms $\mathbf{y}'\mathbf{X}$ matrices, and it sets the row and column names to the variable names used, so `matrix vecaccum yprimeX = mpg weight foreign` resulted in

```
. matrix list yprimeX
yprimeX[1,3]
      weight  foreign    _cons
mpg  4493720      545     1576
```

The final step, `matrix b = invsym(XprimeX)*yprimeX'`, manipulated the names, and, if you think carefully, you can derive the rules for yourself. `invsym()` (inversion) is much like transposition, so row and column names must be swapped. Here, however, the matrix was symmetric, so that amounted to leaving the names as they were. Multiplication amounts to taking the column names of the first matrix and the row names of the second. The final result is

```
. matrix list b
b[3,1]
                mpg
 weight  -.00658789
foreign  -1.6500291
  _cons   41.679702
```

and the interpretation is $\texttt{mpg} = -0.00659\,\texttt{weight} - 1.65\,\texttt{foreign} + 41.68 + e$.

Researchers realized long ago that using matrix notation simplifies the description of complex calculations. What they may not have realized is that, corresponding to each mathematical definition of a matrix operator, there is a definition of the operator's effect on the names that can be used to carry the names forward through long and complex matrix calculations.

14.2.1 The purpose of row and column names

Mostly, matrices in Stata are used in programming estimators, and Stata uses row and column names to produce pretty output. Say that we wrote code—interactively or in a program—that produced the following coefficient vector `b` and covariance matrix `V`:

```
. matrix list b
b[1,3]
          weight  displacement         _cons
y1    -.00656711     .00528078     40.084522
. matrix list V
symmetric V[3,3]
                    weight  displacement         _cons
      weight     1.360e-06
displacement     -.0000103     .00009741
       _cons    -.00207455     .01188356     4.0808455
```

We could now produce standard estimation output by coding two more lines:

```
. ereturn post b V
. ereturn display
```

	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
weight	-.0065671	.0011662	-5.63	0.000	-.0088529	-.0042813
displacement	.0052808	.0098696	0.54	0.593	-.0140632	.0246248
_cons	40.08452	2.02011	19.84	0.000	36.12518	44.04387

Stata's `ereturn` command knew to produce this output because of the row and column names on the coefficient vector and variance matrix. Moreover, we usually do nothing special in our code that produces `b` and `V` to set the row and column names because, given how matrix names work, they work themselves out.

Also, sometimes row and column names help us detect programming errors. Assume that we wrote code to produce matrices `b` and `V` but made a mistake. Sometimes our mistake will result in the wrong row and column names. Rather than the `b` vector we previously showed you, we might produce

```
. matrix list b
b[1,3]
        weight          c2       _cons
y1  -.00656711       42.23   40.084522
```

If we `post`ed our estimation results now, Stata would refuse because it can tell by the names that there is a problem:

```
. ereturn post b V
name conflict
r(507);
```

Understand, however, that Stata follows the standard rules of matrix algebra; the names are just along for the ride. Matrices are summed by position, meaning that a directive to form $\mathbf{C} = \mathbf{A} + \mathbf{B}$ results in $C_{11} = A_{11} + B_{11}$, regardless of the names, and it is not an error to sum matrices with different names:

```
. matrix list a
symmetric a[3,3]
              c1          c2          c3
   mpg      14419
weight    1221120   1.219e+08
 _cons        545       50950          22
. matrix list b
symmetric b[3,3]
                  c1        c2        c3
displacement  3211055
         mpg   227102     22249
       _cons    12153      1041        52
. matrix c = a + b
. matrix list c
symmetric c[3,3]
                    c1          c2          c3
displacement    3225474
         mpg    1448222   1.219e+08
       _cons      12698       51991          74
```

Matrix row and column names are used to label output; they do not affect how matrix algebra is performed.

14.2.2 Two-part names

Row and column names have two parts separated by a colon: *equation_name*:*opvarname*.

In the examples shown so far, the *equation_name* has been blank and the *opvarname*s have been simple variable names without factor-variable or time-series operators. A blank *equation_name* is typical. Run any single-equation model (such as `regress`, `probit`, or `logistic`), and if you fetch the resulting matrices, you will find that they have row and column names that use only *opvarname*s.

Those who work with time-series data will find matrices with row and column names of the form *opvarname*. For time-series variables, *opvarname* is the variable name prefixed by a time-series operator such as `L.`, `D.`, or `L2D.`; see **[U] 11.4.4 Time-series varlists**. For example,

```
. matrix list example1
symmetric example1[3,3]
                            L.
              rate        rate       _cons
  rate   3.0952534
L.rate    .0096504   .00007742
 _cons  -2.8413483  -.01821928   4.8578916
```

We obtained this matrix by running a linear regression on `rate` and `L.rate` and then fetching the covariance matrix. Think of the row and column name `L.rate` no differently from how you think of `rate` or, in the previous examples, `r1`, `r2`, `c1`, `c2`, `weight`, and `foreign`.

Those who work with factor variables will also find row and column names of the *opvarname* form. For factor variables, *opvarname* is any factor-variable construct that references a single virtual indicator variable. For example, `3.group` refers to the virtual variable that is `1` when `group` $= 3$ and is `0` otherwise, `1.sex#3.group` refers to the virtual variable that is `1` when `sex` $= 1$ and `group` $= 3$ and is `0` otherwise, and `1.sex#c.age` refers to the virtual variable that takes on the values of `age` when `sex` $= 1$ and is `0` otherwise. For example,

```
. matrix list example2
symmetric example2[5,5]
                    0b.          1.     0b.sex#      1.sex#
                   sex         sex       c.age       c.age       _cons
     0b.sex          0
      1.sex          0   7.7785864
0b.sex#c.age         0    .08350827   .00231307
 1.sex#c.age         0  -.09705697   5.606e-17    .00223195
      _cons          0  -3.2868185  -.08350827  -2.131e-15   3.2868185
```

`1.sex#c.age` is a row name and column name just like `rate` or `L.rate` in the prior example. For details on factor variables and valid factor-variable constructs see **[U] 11.4.3 Factor variables**, **[U] 26 Working with categorical data and factor variables**, **[U] 13.9 Indicator values for levels of factor variables**, and **[U] 20.12 Accessing estimated coefficients**.

Factor-variable operators may be combined with the time-series operators `L.` and `F.`, leading to *opvarnames* such as `1L.sex` (the first lag of the level 1 indicator of `sex`) and `3L2.group` (the second lag of the level 3 indicator of `group`).

Equation names are used to label partitioned matrices and, in estimation, occur in the context of multiple equations. Here is a matrix with *equation_names* and simple (unoperated) *opvarnames*.

```
. matrix list example3
symmetric example2[5,5]
                     mpg:        mpg:        mpg:        mpg:        mpg:
                 foreign       displ       _cons     foreign       _cons
   mpg:foreign   1.6483972
     mpg:displ     .004747   .00003876
     mpg:_cons  -1.4266352  -.00905773   2.4341021
weight:foreign  -51.208454  -4.665e-19   15.224135   24997.727
  weight:_cons   15.224135   2.077e-17  -15.224135  -7431.7565   7431.7565
```

Here is an example with *equation_names* and operated variable names:

```
. matrix list example4
symmetric example3[5,5]
                     val:        val:        val:     weight:     weight:
                                   L.
                    rate        rate       _cons     foreign       _cons
      val:rate   2.2947268
    val:L.rate   .00385216    .0000309
     val:_cons  -1.4533912   -.0072726   2.2583357
weight:foreign  -163.86684   7.796e-17   49.384526   25351.696
  weight:_cons   49.384526  -1.566e-16  -49.384526   -7640.237    7640.237
```

`val:L.rate` is a column name, just as, in the previous section, `c2` and `foreign` were column names.

Say that this last matrix is the variance matrix produced by a program we wrote and that our program also produced a coefficient vector, `b`:

```
. matrix list b
b[1,5]
           val:        val:        val:     weight:     weight:
                         L.
          rate        rate       _cons     foreign       _cons
y1   4.5366753  -.00316923    20.68421  -1008.7968   3324.7059
```

Here is the result of posting and displaying the results:

```
. ereturn post b example4
. ereturn display
```

	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
val						
rate						
—	4.536675	1.514836	2.995	0.003	1.567652	7.505698
L1	-.0031692	.0055591	-0.570	0.569	-.0140648	.0077264
_cons	20.68421	1.502776	13.764	0.000	17.73882	23.6296
weight						
foreign	-1008.797	159.2222	-6.336	0.000	-1320.866	-696.7271
_cons	3324.706	87.40845	38.036	0.000	3153.388	3496.023

We have been using `matrix list` to see the row and column names on our matrices because `matrix list` works on all matrices. There is a better way to see the names when we are working with estimation results because estimation results have the same names on the rows and columns of the variance matrix, and those same names are also the column names for the coefficient vector. That better way is the `coeflegend` display option available on almost every estimation command. For example,

```
. use https://www.stata-press.com/data/r19/fvex
(Artificial factor variables' data)
. generate t = _n
. tsset t
  (output omitted)
. sureg (y = sex##group) (distance = d.age il2.sex)
  (output omitted)
. sureg, coeflegend
Seemingly unrelated regression
```

Equation	Obs	Params	RMSE	"R-squared"	chi2	P>chi2
y	2,998	5	20.03657	0.1343	464.08	0.0000
distance	2,998	2	181.3797	0.0005	0.92	0.6314

	Coefficient	Legend
y		
sex		
female	21.59726	_b[y:1.sex]
group		
2	11.42832	_b[y:2.group]
3	21.6461	_b[y:3.group]
sex#group		
female#2	-4.892653	_b[y:1.sex#2.group]
female#3	-6.220653	_b[y:1.sex#3.group]
_cons	50.5957	_b[y:_cons]
distance		
age		
D1.	.2230927	_b[distance:D.age]
L2.sex		
female	1.300898	_b[distance:1L2.sex]
_cons	57.96172	_b[distance:_cons]

We could have used `matrix list e(V)` or `matrix list e(b)` to see the names, but the limited space available to `matrix list` to write the names would have made the names more difficult to read. With `coeflegend`, the names are neatly arrayed in their own Legend column. One difference between `matrix list` and the `coeflegend` option is that `coeflegend` brackets the names with `_b[]`. That is because `coeflegend`'s primary use is to show us how to type coefficients in expressions and postestimation commands; see **[U] 13.5 Accessing coefficients and standard errors** and **[U] 20.12 Accessing estimated coefficients**. There the `_b[]` is required.

14.2.3 Setting row and column names

You reset row and column names by using the `matrix rownames` and `matrix colnames` commands.

Before resetting the names, use `matrix list` to verify that the names are not set correctly; often, they already are. When you enter a matrix by hand, however, the row names are unimaginatively set to `r1`, `r2`, ..., and the column names to `c1`, `c2`, ...

```
. matrix a = (1,2,3\4,5,6)
. matrix list a
a[2,3]
    c1  c2  c3
r1   1   2   3
r2   4   5   6
```

Regardless of the current row and column names, `matrix rownames` and `matrix colnames` reset them:

```
. matrix colnames a = foreign alpha _cons
. matrix rownames a = one two
. matrix list a
a[2,3]
     foreign    alpha    _cons
one        1        2        3
two        4        5        6
```

You may set the *operator* as part of the *opvarname*,

```
. matrix colnames a = foreign l.rate _cons
. matrix list a
a[2,3]
                   L.
     foreign     rate    _cons
one        1        2        3
two        4        5        6
```

The names you specify may be any virtual factor-variable indicators, and those names may include the base (`b.`) and omitted (`o.`) operators,

```
. matrix colnames b = 0b.sex 2o.arm 1.sex#c.age 1.sex#3.group#2.arm
. matrix list b
b[2,4]
                                        1.sex#
           0b.       2o.     1.sex#  3.group#
          sex       arm      c.age     2.arm
one         1         2          3         3
two         5         6          7         8
```

See **[U] 11.4.3 Factor variables** for more about factor-variable operators.

You may set equation names:

```
. matrix colnames a = this:foreign this:l.rate that:_cons
. matrix list a
a[2,3]
        this:    this:    that:
                    L.
     foreign     rate    _cons
one        1        2        3
two        4        5        6
```

See [P] **matrix rownames** for more information.

14.2.4 Obtaining row and column names

`matrix list` displays the matrix with its row and column names. In a programming context, you can fetch the row and column names into a macro using

```
local ... : rowfullnames matname
local ... : colfullnames matname
local ... : rownames matname
local ... : colnames matname
local ... : roweq matname
local ... : coleq matname
```

`rowfullnames` and `colfullnames` return the full names (*equation_name*:*opvarnames*) listed one after the other.

`rownames` and `colnames` omit the equations and return *opvarnames*, listed one after the other.

`roweq` and `coleq` return the equation names, listed one after the other.

See [P] **macro** and [P] **matrix define** for more information.

14.3 Vectors and scalars

Stata does not have vectors as such—they are considered special cases of matrices and are handled by the `matrix` command.

Stata does have scalars, although they are not strictly necessary because they, too, could be handled as special cases. See [P] **scalar** for a description of scalars.

14.4 Inputting matrices by hand

You input matrices using

`matrix input` *matname* `= (...)`

or

`matrix` *matname* `= (...)`

In either case, you enter the matrices by row. You separate one element from the next by using commas (,) and one row from the next by using backslashes (\). If you omit the word `input`, you are using the expression parser to input the matrix:

```
. matrix a = (1,2\3,4)
. matrix list a
a[2,2]
    c1  c2
r1   1   2
r2   3   4
```

This has the advantage that you can use expressions for any of the elements:

```
. matrix b = (1, 2+3/2 \ cos(_pi), _pi)
. matrix list b
b[2,2]
           c1         c2
r1          1        3.5
r2         -1  3.1415927
```

The disadvantage is that the matrix must be small, say, no more than 50 elements.

`matrix input` has no such restriction, but you may not use subexpressions for the elements:

```
. matrix input c  = (1,2\3,4)
. matrix input d = (1, 2+3/2 \ cos(_pi), _pi)
invalid syntax
r(198);
```

Either way, after inputting the matrix, you will probably want to set the row and column names; see [U] **14.2.3 Setting row and column names** above.

For small matrices, you may prefer entering them in a dialog box. Launch the dialog box from the menu **Data > Matrices, ado language > Input matrix by hand**, or by typing `db matrix_input`. The dialog box is particularly convenient for small symmetric matrices.

14.5 Accessing matrices created by Stata commands

Some Stata commands—including all estimation commands—leave behind matrices that you can subsequently use. After executing an estimation command, type `ereturn list` to see what is available:

```
. use https://www.stata-press.com/data/r19/auto
(1978 automobile data)
. probit foreign mpg weight
  (output omitted)
. ereturn list
scalars:
               e(rank) =  3
                  e(N) =  74
                 e(ic) =  5
                  e(k) =  3
               e(k_eq) =  1
               e(k_dv) =  1
          e(converged) =  1
                 e(rc) =  0
                 e(ll) =  -26.84418900579869
         e(k_eq_model) =  1
               e(ll_0) =  -45.03320955699139
```

```
                e(df_m) =  2
                e(chi2) =  36.3780411023854
                   e(p) =  1.26069126402e-08
              e(N_cdf) =  0
              e(N_cds) =  0
               e(r2_p) =  .4039023807124771

macros:
            e(cmdline) : "probit foreign mpg weight"
                e(cmd) : "probit"
          e(estat_cmd) : "probit_estat"
            e(predict) : "probit_p"
          e(marginsok) : "default Pr"
       e(marginsnotok) : "stdp DEviance SCore"
              e(title) : "Probit regression"
           e(chi2type) : "LR"
  e(deriv_useminbound) : "off"
                e(opt) : "moptimize"
                e(vce) : "oim"
               e(user) : "mopt__probit_d2()"
          e(ml_method) : "d2"
          e(technique) : "nr"
              e(which) : "max"
             e(depvar) : "foreign"
         e(properties) : "b V"

matrices:
                  e(b) :  1 x 3
                  e(V) :  3 x 3
               e(mns) :  1 x 3
              e(rules) :  1 x 4
               e(ilog) :  1 x 20
           e(gradient) :  1 x 3

functions:
             e(sample)
```

Most estimation commands leave behind `e(b)` (the coefficient vector) and `e(V)` (the variance–covariance matrix of the estimator):

```
. matrix list e(b)

e(b)[1,3]
       foreign:    foreign:    foreign:
           mpg      weight       _cons
y1  -.10395033  -.00233554    8.275464
```

You can refer to `e(b)` and `e(V)` in any matrix expression:

```
. matrix myb = e(b)

. matrix list myb

myb[1,3]
       foreign:    foreign:    foreign:
           mpg      weight       _cons
y1  -.10395033  -.00233554    8.275464

. matrix c = e(b)*invsym(e(V))*e(b)'

. matrix list c

symmetric c[1,1]
           y1
y1  22.440542
```

14.6 Creating matrices by accumulating data

In programming estimators, matrices of the form $\mathbf{X}'\mathbf{X}$, $\mathbf{X}'\mathbf{Z}$, $\mathbf{X}'\mathbf{W}\mathbf{X}$, and $\mathbf{X}'\mathbf{W}\mathbf{Z}$ often occur, where $\mathbf{X}$ and $\mathbf{Z}$ are data matrices. `matrix accum`, `matrix glsaccum`, `matrix vecaccum`, and `matrix opaccum` produce such matrices; see [P] **matrix accum**.

We recommend that you not load the data into a matrix and use the expression parser directly to form such matrices, although see [P] **matrix mkmat** if that is your interest. If that is your interest, be sure to read the technical note at the end of [P] **matrix mkmat**. There is much to recommend learning how to use the `matrix accum` commands.

14.7 Matrix operators

You can create new matrices or replace existing matrices by typing

`matrix` *matname* = *matrix_expression*

For instance,

```
. matrix A = invsym(R*V*R')
. matrix IAR = I(rowsof(A)) - A*R
. matrix beta = b*IAR' + r*A'
. matrix C = -C'
. matrix D = (A, B \ B', A)
. matrix E = (A+B)*C'
. matrix S = (S+S')/2
```

The following operators are provided:

Operator	Symbol
Unary operators	
negation	-
transposition	'
Binary operators	
(lowest precedence)	
row join	\
column join	,
addition	+
subtraction	-
multiplication	*
division by scalar	/
Kronecker product	#
(highest precedence)	

Parentheses may be used to change the order of evaluation.

Note in particular that , and \ are operators; `(1,2)` creates a 1×2 matrix (vector), and `(A,B)` creates a `rowsof(A)` $\times$ `colsof(A)+colsof(B)` matrix, where `rowsof(A)` $=$ `rowsof(B)`. `(1\2)` creates a 2×1 matrix (vector), and `(A\B)` creates a `rowsof(A)+rowsof(B)` $\times$ `colsof(A)` matrix, where `colsof(A)` $=$ `colsof(B)`. Thus expressions of the form

```
matrix R = (A,B)*Vinv*(A,B)'
```

are allowed.

14.8 Matrix functions

In addition to the functions listed below, see [P] **matrix svd** for singular value decomposition, [P] **matrix symeigen** for eigenvalues and eigenvectors of symmetric matrices, and see [P] **matrix eigenvalues** for eigenvalues of nonsymmetric matrices. For a full description of the matrix functions, see [FN] **Matrix functions**.

Matrix functions returning matrices:

`cholesky(`M`)`	`I(`n`)`	`nullmat(`*matname*`)`
`corr(`M`)`	`inv(`M`)`	`sweep(`M`,`i`)`
`diag(`v`)`	`invsym(`M`)`	`vec(`M`)`
`get(`*systemname*`)`	`J(`r`,`c`,`z`)`	`vecdiag(`M`)`
`hadamard(`M`,`N`)`	`matuniform(`r`,`c`)`	

Matrix functions returning scalars:

`coleqnumb(`M`,`s`)`	`diag0cnt(`M`)`	`roweqnumb(`M`,`s`)`
`colnfreeparms(`M`)`	`el(`M`,`i`,`j`)`	`rownfreeparms(`M`)`
`colnumb(`M`,`s`)`	`issymmetric(`M`)`	`rownumb(`M`,`s`)`
`colsof(`M`)`	`matmissing(`M`)`	`rowsof(`M`)`
`det(`M`)`	`mreldif(`X`,`Y`)`	`trace(`M`)`

14.9 Subscripting

1. In matrix and scalar expressions, you may refer to *matname*`[`r`,`c`]`, where r and c are scalar expressions, to obtain one element of *matname* as a scalar.

   Examples:
   ```
   matrix A = A / A[1,1]
   generate newvar = oldvar / A[2,2]
   ```

2. In matrix expressions, you may refer to *matname*`[`s_r`,`s_c`]`, where s_r and s_c are string expressions, to obtain a submatrix with one element. The element returned is based on searching the row and column names.

   Examples:
   ```
   matrix B = V["price","price"]
   generate sdif = dif / sqrt(V["price","price"])
   ```

3. In matrix expressions, you may mix these two syntaxes and refer to *matname*`[`r`,`s_c`]` or to *matname*`[`s_r`,`c`]`.

   Example:
   ```
   matrix b = b * R[1,"price"]
   ```

4. In matrix expressions, you may use *matname*`[`r_1`..`r_2`,`c_1`..`c_2`]` to refer to submatrices; r_1, r_2, c_1, and c_2 may be scalar expressions. If r_2 evaluates to missing, it is taken as referring to the last row of *matname*; if c_2 evaluates to missing, it is taken as referring to the last column of *matname*. Thus *matname*`[`r_1`...,`c_1`...]` is allowed.

   Examples:
   ```
   matrix S = Z[1..4, 1..4]
   matrix R = Z[5..., 5...]
   ```

5. In matrix expressions, you may refer to *matname*[s_{r1}..s_{r2},s_{c1}..s_{c2}] to refer to submatrices where s_{r1}, s_{r2}, s_{c1}, and s_{c2}, are string expressions. The matrix returned is based on looking up the row and column names.

   If the string evaluates to an equation name only, all the rows or columns for the equation are returned.

   Examples:
```
matrix S = Z["price".."weight", "price".."weight"]
matrix L = D["mpg:price".."mpg:weight", "mpg:price".."mpg:weight"]
matrix T1 = C["mpg:", "mpg:"]
matrix T2 = C["mpg:", "price:"]
```

6. In matrix expressions, any of the above syntaxes may be combined.

   Examples:
```
matrix T1 = C["mpg:", "price:weight".."price:displ"]
matrix T2 = C["mpg:", "price:weight"...]
matrix T3 = C["mpg:price", 2..5]
matrix T4 = C["mpg:price", 2]
```

7. When defining an element of a matrix, use

   `matrix` *matname*`[`i`,`j`] =` *expression*

   where i and j are scalar expressions. The matrix *matname* must already exist.

   Example:
```
matrix A = J(2,2,0)
matrix A[1,2] = sqrt(2)
```

8. To replace a submatrix within a matrix, use the same syntax. If the expression on the right evaluates to a scalar or 1×1 matrix, the element is replaced. If it evaluates to a matrix, the submatrix with top-left element at (i, j) is replaced. The matrix *matname* must already exist.

   Example:
```
matrix A = J(4,4,0)
matrix A[2,2] = C'*C
```

14.10 Using matrices in scalar expressions

Scalar expressions are documented as *exp* in the Stata manuals:

`generate` *newvar* `=` *exp* `if` *exp* ...
`replace` *newvar* `=` *exp* `if` *exp* ...
`regress` ... `if` *exp* ...
`if` *exp* `{`...`}`
`while` *exp* `{`...`}`

Most importantly, scalar expressions occur in `generate` and `replace`, in the `if` *exp* qualifier allowed on the end of many commands, and in the `if` and `while` commands for program control.

You will rarely need to refer to a matrix in any of these situations except when using the `if` qualifier and the `while` command.

In any case, you may refer to matrices in any of these situations, but the expression cannot require evaluation of matrix expressions returning matrices. Thus you could refer to `trace(A)` but not to `trace(A+B)`.

It can be difficult to predict when an evaluation of an expression requires evaluating a matrix; even experienced users can be surprised. If you get the error message "matrix operators that return matrices not allowed in this context", r(509), you have encountered such a situation.

The solution is to split the line in two. For instance, you would change

```
if trace(A+B)==0 {
        ...
}
```

to

```
matrix AplusB = A+B
if trace(AplusB)==0 {
        ...
}
```

or even to

```
matrix Trace = trace(A+B)
if Trace[1,1]==0 {
        ...
}
```

14.11 Reference

Miura, H. 2012. Stata graph library for network analysis. *Stata Journal* 12: 94–129.

15 Saving and printing output—log files

Contents

15.1 Overview

Stata can record your session into a file called a log file but does not start a log automatically; you must tell Stata to record your session. By default, the resulting log file contains what you type and what Stata produces in response, recorded in a format called Stata Markup and Control Language (SMCL); see [P] **smcl**. The file can be printed or converted to plain text for incorporation into documents you create with your word processor.

To start a log:	`. log using` *filename*
Your session is now being recorded in file *filename*`.smcl`.	
To temporarily stop logging:	
Temporarily stop:	`. log off`
Resume:	`. log on`
To stop logging and close the file:	`. log close`
You can now print *filename*`.smcl` or type: to create *filename*`.log` that you can load into your word processor.	`. translate` *filename*`.smcl` *filename*`.log`
You can also create a PDF of *filename*`.smcl` on Windows or Mac:	`. translate` *filename*`.smcl` *filename*`.pdf`
Alternative ways to start logging:	
append to an existing log:	`. log using` *filename*`, append`
replace an existing log:	`. log using` *filename*`, replace`
Using the GUI:	
To start a log:	click on the **Log** button
To temporarily stop logging:	click on the **Log** button, and choose **Suspend**
To resume:	click on the **Log** button, and choose **Resume**
To stop logging and close the file:	click on the **Log** button, and choose **Close**
To print previous or current log:	select **File > View...**, choose file, right-click on the Viewer, and select **Print**

Also, `cmdlog` will produce logs containing solely what you typed—logs that, although not containing your results, are sufficient to re-create the session.

To start a command-only log:	`. cmdlog using` *filename*
To stop logging and close the file:	`. cmdlog close`
To re-create your session:	`. do` *filename*`.txt`

15.1.1 Starting and closing logs

With great foresight, you begin working in Stata and type `log using session` (or click on the **Log** button) before starting your work:

```
. log using session
-------------------------------------------------------------------------------
      name:  <unnamed>
       log:  C:\example\session.smcl
  log type:  smcl
 opened on:  17 Mar 2025, 12:35:08

. use https://www.stata-press.com/data/r19/census5
(1980 Census data by state)

. tabulate region [fweight=pop]

    Census |
    region |      Freq.     Percent        Cum.
-----------+-----------------------------------
        NE |  49,135,283       21.75       21.75
   N Cntrl |  58,865,670       26.06       47.81
     South |  74,734,029       33.08       80.89
      West |  43,172,490       19.11      100.00
-----------+-----------------------------------
     Total | 225,907,472      100.00

. summarize median_age
    Variable |        Obs        Mean    Std. dev.       Min        Max
-------------+---------------------------------------------------------
  median_age |         50       29.54    1.693445       24.2       34.7

. log close
      name:  <unnamed>
       log:  C:\example\session.smcl
  log type:  smcl
 closed on:  17 Mar 2025, 12:35:38
-------------------------------------------------------------------------------
```

There is now a file named `session.smcl` on your disk. If you were to look at it in a text editor or word processor, you would see something like this:

```
{smcl}
{com}{sf}{ul off}{txt}{.-}
      name:  {res}<unnamed>
       {txt}log:  {res}C:\example\session.smcl
  {txt}log type:  {res}smcl
 {txt}opened on:  {res}17 Mar 2025, 12:35:08

{com}. use https://www.stata-press.com/data/r19/census5
{txt}(1980 Census data by state)

{com}. tabulate region [fweight=pop]

     {txt}Census {c |}
     region {c |}      Freq.     Percent        Cum.
{hline 12}{c +}{hline 35}
         NE {c |}{res} 49,135,283       21.75       21.75
{txt}    N Cntrl {c |}{res} 58,865,670       26.06       47.81
  (output omitted)
```

What you are seeing is SMCL, which Stata understands. Here is the result of typing the file using Stata's `type` command:

```
. type session.smcl
-------------------------------------------------------------------------------
      name:  <unnamed>
       log:  C:\example\session.smcl
  log type:  smcl
 opened on:  17 Mar 2025, 12:35:08

. use https://www.stata-press.com/data/r19/census5
(1980 Census data by state)

. tabulate region [fweight=pop]

    Census
    region |      Freq.     Percent        Cum.
-----------+-----------------------------------
        NE |  49,135,283       21.75       21.75
    N Cntrl |  58,865,670       26.06       47.81
     South |  74,734,029       33.08       80.89
      West |  43,172,490       19.11      100.00
-----------+-----------------------------------
     Total | 225,907,472      100.00

. summarize median_age

    Variable |        Obs        Mean    Std. dev.       Min        Max
-------------+---------------------------------------------------------
  median_age |         50       29.54    1.693445       24.2       34.7

. log close
      name:  <unnamed>
       log:  C:\example\session.smcl
  log type:  smcl
 closed on:  17 Mar 2025, 12:35:38
-------------------------------------------------------------------------------

. _
```

What you will see is a perfect copy of what you previously saw. If you use Stata to print the file, you will get a perfect printed copy, too.

SMCL files can be translated to plain text, which is a format more useful for inclusion into a word processing document. If you type `translate` *filename*`.smcl` *filename*`.log`, Stata will translate *filename*`.smcl` to text and store the result in *filename*`.log`:

```
. translate session.smcl session.log
```

The resulting file `session.log` looks like this:

```
-------------------------------------------------------------------------------
      name:  <unnamed>
       log:  C:\example\session.smcl
  log type:  smcl
 opened on:  17 Mar 2025, 12:35:08

. use https://www.stata-press.com/data/r19/census5
(1980 Census data by state)

. tabulate region [fweight=pop]

    Census |
    region |      Freq.     Percent        Cum.
-----------+-----------------------------------
        NE |  49,135,283       21.75       21.75
    N Cntrl |  58,865,670       26.06       47.81
     South |  74,734,029       33.08       80.89
  (output omitted)
```

When you use `translate` to create *filename*`.log` from *filename*`.smcl`, *filename*`.log` must not already exist:

```
. translate session.smcl session.log
file session.log already exists
r(602);
```

If the file does already exist and you wish to overwrite the existing copy, you can specify the `replace` option:

```
. translate session.smcl session.log, replace
```

See [R] **translate** for more information.

On Windows and Mac, you can also convert your SMCL file to a PDF to share it more easily with others:

```
. translate session.smcl session.pdf
```

See [R] **translate** for more information.

If you prefer, you can skip the SMCL and create text logs directly, either by specifying that you want the log in `text` format,

```
. log using session, text
```

or by specifying that the file to be created be a `.log` file:

```
. log using session.log
```

If you wish to suppress the header and footer information `log` usually displays when you open and close a log, you can specify the `nomsg` option with `log using` and `log close`. Alternatively, to request that these messages always be suppressed, specify `set logmsg off`. See [R] **log**.

15.1.2 Appending to an existing log

Stata never lets you accidentally write over an existing log file. If you have an existing log file and you want to continue logging, you have three choices:

- create a new log file
- append the new log onto the existing log file by typing `log using` *logname*`, append`
- replace the existing log file by typing `log using` *logname*`, replace`

For example, if you have an existing log file named `session.smcl`, you might type

```
. log using session, append
```

to append the new log to the end of the existing log file, `session.smcl`.

15.1.3 Suspending and resuming logging

Once you have started logging your session, you can turn logging on and off. When you turn logging off, Stata temporarily stops recording your session but leaves the log file open. When you turn logging back on, Stata continues to record your session, appending the additional record to the end of the file.

Say that the first time something interesting happens, you type `log using results` (or click on **Log** and open `results.smcl`). You then retype the command that produced the interesting result (or double-click on the command in the History window, or use the *PgUp* key to retrieve the command; see **[U] 10 Keyboard use**). You now have a copy of the interesting result saved in the log file.

You are now reasonably sure that nothing interesting will occur, at least for a while. Rather than type `log close`, however, you type `log off`, or you click on **Log** and choose **Suspend**. From now on, nothing goes into the file. The next time something interesting happens, you type `log on` (or click on **Log** and choose **Resume**) and reissue the (interesting) command. After that, you type `log off`. You keep working like this—toggling the log on and off.

15.2 Placing comments in logs

Stata treats lines starting with a "`*`" as comments and ignores them. Thus, if you are working interactively and wish to make a comment, you can type "`*`" followed by your comment:

```
. * check that all the spells are completed
. _
```

Stata ignores your comment, but if you have a log going the comment now appears in the file.

❑ Technical note

`log` can be combined with `#review` (see **[U] 10 Keyboard use**) to bail you out when you have not adequately planned ahead. Say that you have been working in front of your computer, and you now realize that you have done what you wanted to do. Unfortunately, you are not sure exactly what it is you have done. Did you make a mistake? Could you reproduce the result? Unfortunately, you have not been logging your output. Typing `#review` will allow you to look over what commands you have issued, and, combined with `log`, will allow you to make a record. You can also see the commands that you have issued in the History window. You can save those commands to a file by selecting the commands to save, right-clicking on the History window, and selecting **Save selected...**.

Type `log using` *filename*. Type `#review 100`. Stata will list the last 100 commands you gave, or however many it has stored. Because `log` is making a record, that list will also be stored in the file. Finally, type `log close`.

❑

15.3 Logging only what you type

Log files record everything that happens during a session, both what you type and what Stata produces in response.

Stata can also produce command log files—files that contain only what you type. These files are perfect for later going back and creating a Stata do-file.

`cmdlog` creates command log files, and its basic syntax is

`cmdlog using` *filename* [`, append replace`]	creates *filename*`.txt`
`cmdlog off`	temporarily suspends command logging
`cmdlog on`	resumes command logging
`cmdlog close`	closes the command log file

See **[R] log** for all the details.

Command logs are plain text files. If you typed

```
. cmdlog using session
(cmdlog C:\example\session.txt opened)
. use https://www.stata-press.com/data/r19/census5
(Census Data)
. tabulate region [fweight=pop]
  (output omitted)
. summarize median_age
  (output omitted)
. cmdlog close
(cmdlog C:\example\session.txt closed)
```

file `mycmds.txt` would contain

```
use https://www.stata-press.com/data/r19/census5
tabulate region [fweight=pop]
summarize median_age
```

You can create both kinds of logs—full session logs and command logs—simultaneously, if you wish. A command log file can later be used as a do-file; see [R] **do**.

15.4 The log-button alternative

The capabilities of the `log` command (but not the `cmdlog` command) are available from Stata's GUI interface; just click on the **Log** button or select **Log** from the **File** menu.

You can use the Viewer to view logs, even logs that are in the process of being created. Just select **File > View...**. If you are currently logging, the filename to view will already be filled in with the current log file, and all you need to do is click on **OK**. Periodically, you can click on the **Refresh** button to bring the Viewer up to date.

You can also use the Viewer to view previous logs.

You can access the Viewer by selecting **File > View...**, or you can use the `view` command:

```
. view myoldlog.smcl
```

15.5 Printing logs

You print logs from the Viewer. Select **File > View...**, or type `view` *logfilename* from the command line to load the log into the Viewer, and then right-click on the Viewer and select **Print**.

You can also print logs by other means; see [R] **translate**.

15.6 Creating multiple log files for simultaneous use

Programmers or advanced users may want to create more than one log file for simultaneous use. For example, you may want a log file of your whole session but want a separate log file for part of your session.

You can create multiple logs by using `log`'s `name()` option; see [R] **log**.

16 Do-files

Contents

16.1 Description

Rather than typing commands at the keyboard, you can create a text file containing commands and instruct Stata to execute the commands stored in that file. Such files are called *do-files* because the command that causes them to be executed is `do`.

A do-file is a standard text file that is executed by Stata when you type `do` *filename*. You can use any text editor or the built-in Do-file Editor to create do-files; see **[GSW] 13 Using the Do-file Editor—automating Stata**. Using do-files rather than typing commands with the keyboard or using dialog boxes offers several advantages. By writing the steps you take to manage and analyze your data in the form of a do-file, you can reproduce your work later. Also, writing a do-file makes the inevitable debugging process much easier. If you decide to change one part of your analysis, changing the relevant commands in your do-file is much easier than having to start back at square one, as is often necessary when working interactively. In this chapter, we describe the mechanics of do-files. Long (2009) cogently argues that do-files should be used in all research projects and offers an abundance of time-tested advice in how to manage data and statistical analysis.

▷ Example 1

You can use do-files to create a batchlike environment in which you place all the commands you want to perform in a file and then instruct Stata to `do` that file. Assume that you use your text editor or word processor to create a file called `myjob.do` that contains these three lines:

begin `myjob.do`

```
use https://www.stata-press.com/data/r19/census5
tabulate region
summarize marriage_rate divorce_rate median_age if state!="Nevada"
```

end `myjob.do`

You then enter Stata and instruct Stata to do the file:

```
. do myjob

. use https://www.stata-press.com/data/r19/census5
(1980 Census data by state)

. tabulate region
```

Census region	Freq.	Percent	Cum.
NE	9	18.00	18.00
N Cntrl	12	24.00	42.00
South	16	32.00	74.00
West	13	26.00	100.00
Total	50	100.00	

```
. summarize marriage_rate divorce_rate median_age if state !="Nevada"
```

Variable	Obs	Mean	Std. dev.	Min	Max
marriage_r~e	49	.0106791	.0021746	.0074654	.0172704
divorce_rate	49	.0054268	.0015104	.0029436	.008752
median_age	49	29.52653	1.708286	24.2	34.7

You typed only `do myjob` to produce this output. Because you did not specify the file extension, Stata assumed you meant `do myjob.do`; see **[U] 11.6 Filenaming conventions**.

◁

16.1.1 Version

We recommend that the first line in your do-file declare the Stata release you used when you wrote the do-file; `myjob.do` would read better as

begin myjob.do

```
version 19.5      // (or version 19 if you do not have StataNow)
use https://www.stata-press.com/data/r19/census5
tabulate region
summarize marriage_rate divorce_rate median_age if state!="Nevada"
```

end myjob.do

We admit that we do not always follow our own advice, as you will see many examples in this manual that do not include the `version` line. (In the above, the text that follows two forward slashes, `//`, is a comment; see **[U] 16.1.2 Comments and blank lines in do-files**.)

If you intend to keep the do-file, however, you should include this line because it ensures that your do-file will continue to work with future versions of Stata. Stata is under continual development, and sometimes things change in surprising ways.

For instance, in Stata 3.0, a new syntax for specifying the weights was introduced. If you had an old do-file written for Stata 2.1 that analyzed weighted data and did not have `version 2.1` at the top, you would find that today's Stata would flag some of the file's lines as syntax errors. If you had the `version 2.1` line, it would work just as it used to.

Skipping ahead to Stata 10, we introduced `xtset` and declared that, to use the `xt` commands, you must `xtset` your data first. Previously, you specified options on the end of each `xt` command that identified the group and, optionally, the time variables. Despite this change, if you include `version 9` or earlier at the top of your do-file, the `xt` commands will continue to work the old way.

For an overview of versioning and an up-to-date list of the issues that versioning does not address automatically, see `help version`.

When running an old do-file that includes a `version` statement, you need not worry about setting the version back after it has completed. Stata automatically restores the previous value of `version` when the do-file completes.

See **[U] 12.4.2.6 Advice for users of Stata 13 and earlier** for information about sharing your Stata 19 files with users of Stata 13 or earlier.

16.1.2 Comments and blank lines in do-files

You may freely include blank lines in your do-file. In the previous example, the do-file could just as well have read

```
begin myjob.do
version 19.5      // (or version 19 if you do not have StataNow)

use https://www.stata-press.com/data/r19/census5
tabulate region
summarize marriage_rate divorce_rate median_age if state!="Nevada"
end myjob.do
```

There are four ways to include comments in a do-file.

1. Begin the line with a '`*`'; Stata ignores such lines. `*` cannot be used within Mata.
2. Place the comment in `/* */` delimiters.
3. Place the comment after two forward slashes, that is, `//`. Everything after the `//` to the end of the current line is considered a comment (unless the `//` is part of `https://...`). We used this type of comment on the first line of the do-file above.
4. Place the comment after three forward slashes, that is, `///`. Everything after the `///` to the end of the current line is considered a comment. However, when you use `///`, the next line joins with the current line. `///` lets you split long lines across multiple lines in the do-file.

Note that a whitespace character must separate any of the four comment methods from surrounding text.

❑ Technical note

The `/* */`, `//`, and `///` comment indicators can be used in do-files and ado-files only; you may not use them interactively. You can, however, use the '`*`' comment indicator interactively.

❑

`myjob.do` then might read

```
begin myjob.do
* a sample analysis job
version 19.5      // (or version 19 if you do not have StataNow)

use https://www.stata-press.com/data/r19/census5

/* obtain the summary statistics: */
tabulate region
summarize marriage_rate divorce_rate median_age if state!="Nevada"
end myjob.do
```

or equivalently,

```
begin myjob.do
// a sample analysis job
version 19.5      // (or version 19 if you do not have StataNow)
use https://www.stata-press.com/data/r19/census5
// obtain the summary statistics:
tabulate region
summarize marriage_rate divorce_rate median_age if state!="Nevada"
end myjob.do
```

The style of comment indicator you use is up to you. One advantage of the `/* */` method is that it can be put at the end of lines:

```
begin myjob.do
* a sample analysis job
version 19.5      // (or version 19 if you do not have StataNow)
use https://www.stata-press.com/data/r19/census5
tabulate region                   /* obtain summary statistics */
summarize marriage_rate divorce_rate median_age if state!="Nevada"
end myjob.do
```

In fact, `/* */` can be put anywhere, even in the middle of a line:

```
begin myjob.do
* a sample analysis job
version 19.5      // (or version 19 if you do not have StataNow)
use /* confirm this is latest */ https://www.stata-press.com/data/r19/census5
tabulate region                   /* obtain summary statistics */
summarize marriage_rate divorce_rate median_age if state!="Nevada"
end myjob.do
```

You can achieve the same results with the `//` and `///` methods:

```
begin myjob.do
// a sample analysis job
version 19.5      // (or version 19 if you do not have StataNow)
use https://www.stata-press.com/data/r19/census5
tabulate region                   // obtain summary statistics
summarize marriage_rate divorce_rate median_age if state!="Nevada"
end myjob.do
```

or

```
begin myjob.do
// a sample analysis job
version 19.5      // (or version 19 if you do not have StataNow)
use /// confirm this is latest
https://www.stata-press.com/data/r19/census5
tabulate region                   // obtain summary statistics
summarize marriage_rate divorce_rate median_age if state!="Nevada"
end myjob.do
```

16.1.3 Long lines in do-files

When you use Stata interactively, you press *Enter* to end a line and tell Stata to execute it. If you need to type a line that is wider than the screen, you simply do it, letting it wrap or scroll.

You can follow the same procedure in do-files—if your editor or word processor will let you—but you can do better. You can change the end-of-line delimiter to ';' by using `#delimit`, you can comment out the line break by using `/* */` comment delimiters, or you can use the `///` line-join indicator.

▷ Example 2

In the following fragment of a do-file, we temporarily change the end-of-line delimiter:

fragment of `example.do`

```
use mydata
#delimit ;
summarize weight price displ headroom rep78 length turn gear_ratio
          if substr(company,1,4)=="Ford" |
             substr(company,1,2)=="GM", detail ;
generate byte ford = substr(company,1,4)=="Ford" ;
#delimit cr
generate byte gm = substr(company,1,2)=="GM"
```

fragment of `example.do`

Once we change the line delimiter to semicolon, all lines, even short ones, must end in semicolons. Stata treats carriage returns as no different from blanks. We can change the delimiter back to carriage return by typing `#delimit cr`.

The `#delimit` command is allowed only in do-files—it is not allowed interactively. You need not remember to set the delimiter back to carriage return at the end of a do-file because Stata will reset it automatically.

◁

▷ Example 3

The other way around long lines is to comment out the carriage return by using `/* */` comment brackets or to use the `///` line-join indicator. Thus our code fragment could also read

fragment of example.do

```
use mydata
summarize weight price displ headroom rep78 length turn gear_ratio /*
      */  if substr(company,1,4)=="Ford" |    /*
      */     substr(company,1,2)=="GM", detail
generate byte ford = substr(company,1,4)=="Ford"
generate byte gm = substr(company,1,2)=="GM"
```

fragment of example.do

or

fragment of example.do

```
use mydata
summarize weight price displ headroom rep78 length turn gear_ratio ///
        if substr(company,1,4)=="Ford" |    ///
           substr(company,1,2)=="GM", detail
generate byte ford = substr(company,1,4)=="Ford"
generate byte gm = substr(company,1,2)=="GM"
```

fragment of example.do

◁

16.1.4 Error handling in do-files

A do-file stops executing when the end of the file is reached, an `exit` is executed, or an error (nonzero *return code*) occurs. If an error occurs, the remaining commands in the do-file are not executed.

If you press *Break* while executing a do-file, Stata responds as though an error has occurred, stopping the do-file. This happens because the return code is nonzero; see **[U] 8 Error messages and return codes** for an explanation of return codes.

▷ Example 4

Here is what happens when we execute a do-file and then press *Break*:

```
. do myjob2
. version 19.5      // (or version 19 if you do not have StataNow)
. use census
(Census data)
. tabulate region
     Census |
     region |      Freq.     Percent        Cum.
——Break——
r(1);
end of do-file
——Break——
r(1);
. _
```

When we pressed *Break*, Stata responded by typing —Break— and showed a return code of 1. Stata seemingly repeated itself, typing first "end of do-file", and then —Break— and the return code of 1 again. Do not worry about the repeated messages. The first message indicates that Stata was stopping the `tabulate` because you pressed *Break*, and the second message indicates that Stata is stopping the do-file for the same reason.

◁

▷ Example 5

Let's try our example again, but this time, let's introduce an error. We change the file `myjob2.do` to read

```
——————————————————————————————————————————————— begin myjob2.do ———————
version 19.5      // (or version 19 if you do not have StataNow)
use censas
tabulate region
summarize marriage_rate divorce_rate median_age if state!="Nevada"
——————————————————————————————————————————————— end myjob2.do —————————
```

To introduce a subtle typographical error, we typed `use censas` when we meant `use census5`. We assume that there is no file called `censas.dta`, so now we have an error. Here is what happens when you instruct Stata to `do` the file:

```
. do myjob2
. version 19.5      // (or version 19 if you do not have StataNow)
. use censas
file censas.dta not found
r(601);
end of do-file
r(601);
. _
```

When Stata was told to `use censas`, it responded with "file censas.dta not found" and a return code of 601. Stata then typed "end of do-file" and repeated the return code of 601. The repeated message occurred for the same reason it did when we pressed *Break* in the previous example. The `use` resulted in a return code of 601, so the do-file itself resulted in the same return code. The important thing to understand is that Stata stopped executing the file because there was an error.

◁

❑ Technical note

We can tell Stata to continue executing the file even if there are errors by typing `do` *filename*`, nostop`. Here is the result:

```
. do myjob2, nostop
. version 19.5      // (or version 19 if you do not have StataNow)
. use censas
file censas.dta not found
r(601);
. tabulate region
no variables defined
r(111);
summarize marriage_rate divorce_rate median_age if state!="Nevada"
no variables defined
r(111);
end of do-file
. _
```

None of the commands worked because the do-file's first command failed. That is why Stata ordinarily stops. However, if our file had contained anything that could work, it would have worked. In general, we do not recommend coding in this manner, as unintended consequences can result when errors do not stop execution.

❑

16.1.5 Logging the output of do-files

You log the output of do-files just as you would an interactive session; see **[U] 15 Saving and printing output—log files**.

Many users include the commands to start and stop the logging in the do-file itself:

```
begin myjob3.do
version 19.5      // (or version 19 if you do not have StataNow)
log using myjob3, replace
* a sample analysis job
use census
tabulate region                   // obtain summary statistics
summarize marriage_rate divorce_rate median_age if state!="Nevada"
log close
end myjob3.do
```

We chose to open with `log using myjob3, replace`, the important part being the `replace` option. Had we omitted the option, we could not easily rerun our do-file. If `myjob3.smcl` had already existed and `log` was not told that it is okay to replace the file, the do-file would have stopped and instead reported that "file myjob3.smcl already exists". We could get around that, of course, by erasing the log file before running the do-file.

16.1.6 Preventing —more— conditions

Stata has —more— turned off by default; see **[U] 7 –more– conditions**.

If you have `set more on` for interactive use, Stata's feature of pausing every time the screen is full will probably be an irritation when you are running a do-file and logging the output.

The way around this is to include the line `set more off` in your do-file, which prevents Stata from issuing —more—. The previous `set more` setting will automatically be restored when the do-file is finished.

16.2 Calling other do-files

Do-files may call other do-files. Say that you wrote `makedata.do`, which infiles your data, generates a few variables, and saves `step1.dta`. Say that you wrote `anlstep1.do`, which performed a little analysis on `step1.dta`. You could then create a third do-file,

```
begin master.do
version 19.5      // (or version 19 if you do not have StataNow)
do makedata
do anlstep1
end master.do
```

and so in effect combine the two do-files.

Do-files may call other do-files, which, in turn, call other do-files, and so on. Stata allows do-files to be nested 64 deep.

Be not confused: `master.do` above could call 1,000 do-files one after the other, and still the level of nesting would be only two.

16.3 Creating and running do-files

16.3.1 Creating and running do-files for Windows

1. You can execute do-files by typing `do` followed by the filename, as we did above.
2. You can execute do-files by selecting **File > Do...**.
3. You can use the Do-file Editor to compose, save, and execute do-files; see **[GSW] 13 Using the Do-file Editor—automating Stata**. To use the Do-file Editor, click on the **Do-file Editor** button, or type `doedit` in the Command window. Stata also has a Project Manager for managing collections of do-files and other files. See [P] **Project Manager**.
4. You can double-click on the icon for the do-file to launch Stata and open the do-file in the Do-file Editor.
5. You can run the do-file in batch mode. See **[GSW] B.5 Stata batch mode** for details, but the short explanation is that you open a Window command window and type

   ```
   C:\data> "C:\Program Files\Stata19\Stata" /s do myjob
   ```

   or

   ```
   C:\data> "C:\Program Files\Stata19\Stata" /b do myjob
   ```

   to run in batch mode, assuming that you have installed Stata in the folder `C:\Program Files\Stata19`. `/b` and `/s` determine the kind of log produced, but put that aside for a second. When you start Stata in these ways, Stata will run in the background. When the do-file completes, the Stata icon on the taskbar will flash. You can then click on it to close Stata. If you want to stop the do-file before it completes, click on the Stata icon on the taskbar, and Stata will ask you if you want to cancel the job. If you want Stata to exit when the do-file is complete rather than flashing on the taskbar, also specify `/e` on the command line.

To log the output, you can start the log before executing the do-file or you can include the `log using` and `log close` in your do-file.

When you run Stata in these ways, Stata takes the following actions:

a. Stata automatically opens a log. If you specified `/s`, Stata will open a SMCL log; if you specified `/b`, Stata will open a plain text log. If your do-file is named *xyz*`.do`, the log will be called *xyz*`.smcl` (`/s`) or *xyz*`.log` (`/b`) in the same directory.

b. If your do-file explicitly opens another log, Stata will save two copies of the output.

c. Stata ignores —`more`— conditions and anything else that would cause the do-file to stop were it running interactively.

16.3.2 Creating and running do-files for Mac

1. You can execute do-files by typing `do` followed by the filename, as we did above.
2. You can execute do-files by selecting **File > Do...**.
3. You can use the Do-file Editor to compose, save, and execute do-files; see **[GSM] 13 Using the Do-file Editor—automating Stata**. Click on the **Do-file Editor** button, or type `doedit` in the Command window. Stata also has a Project Manager for managing collections of do-files and other files. See [P] **Project Manager**.

4. You can double-click on the icon for the do-file to open the do-file in the Do-file Editor.
5. Double-clicking on the icon for a do-file named `Stata.do` will launch Stata if it is not already running and set the current working directory to the location of the do-file.
6. You can run the do-file in batch mode. See [GSM] **B.3 Stata batch mode** for details, but the short explanation is that you open a Terminal window and type

   ```
   % /Applications/Stata/Stata.app/Contents/MacOS/Stata -s do myjob
   ```

   or

   ```
   % /Applications/Stata/Stata.app/Contents/MacOS/Stata -b do myjob
   ```

   to run in batch mode, assuming that you have installed Stata/BE in the folder `/Applications/Stata`. `-b` and `-s` determine the kind of log produced, but put that aside for a second. When you start Stata in these ways, Stata will run in the background. When the do-file completes, the Stata icon on the Dock will bounce until you put Stata into the foreground. You can then exit Stata. If you want to stop the do-file before it completes, right-click on the Stata icon on the Dock, and select **Quit**.

To log the output, you can start the log before executing the do-file or you can include the `log using` and `log close` in your do-file.

When you run Stata in these ways, Stata takes the following actions:

a. Stata automatically opens a log. If you specified `-s`, Stata will open a SMCL log; if you specified `-b`, Stata will open a plain text log. If your do-file is named *xyz*`.do`, the log will be called *xyz*`.smcl` (`-s`) or *xyz*`.log` (`-b`) in the same directory.

b. If your do-file explicitly opens another log, Stata will save two copies of the output.

c. Stata ignores —`more`— conditions and anything else that would cause the do-file to stop were it running interactively.

16.3.3 Creating and running do-files for Unix

1. You can execute do-files by typing `do` followed by the filename, as we did above.
2. You can execute do-files by selecting **File > Do...**.
3. You can use the Do-file Editor to compose, save, and execute do-files; see [GSU] **13 Using the Do-file Editor—automating Stata**. Click on the **Do-file Editor** button, or type `doedit` in the Command window. Stata also has a Project Manager for managing collections of do-files and other files. See [P] **Project Manager**.
4. At the Unix prompt, you can type

   $ `xstata do` *filename*

   or

   $ `stata do` *filename*

   to launch Stata and run the do-file. When the do-file completes, Stata will prompt you for the next command just as if you had started Stata the normal way. If you want Stata to exit instead, include `exit, STATA clear` as the last line of your do-file.

To log the output, you can start the log before executing the do-file or you can include the `log using` and `log close` in your do-file.

5. At the Unix prompt, you can type

   $ stata -s do *filename* &

   or

   $ stata -b do *filename* &

   to run the do-file in the background. The above two examples both involve the use of stata, not xstata. Type stata, even if you usually use the GUI version of Stata, xstata. The examples differ only in that one specifies the -s option and the other, the -b option, which determines the kind of log that will be produced. In the above examples, Stata takes the following actions:

   a. Stata automatically opens a log. If you specified -s, Stata will open a SMCL log; if you specified -b, Stata will open a plain text log. If your do-file is named *xyz*.do, the log will be called *xyz*.smcl (-s) or *xyz*.log (-b) in the current directory (the directory from which you issued the stata command).

   b. If your do-file explicitly opens another log, Stata will save two copies of the output.

   c. Stata ignores —more— conditions and anything else that would cause the do-file to stop were it running interactively.

To reiterate: one way to run a do-file in the background and obtain a text log is by typing

```
$ stata -b do myfile &
```

Another way uses standard redirection:

```
$ stata < myfile.do > myfile.log &
```

The first way is slightly more efficient. Either way, Stata knows it is in the background and ignores —more— conditions and anything else that would cause the do-file to stop if it were running interactively. However, if your do-file contains either the #delimit command or the comment characters (/* at the end of one line and */ at the beginning of the next), the second method will not work. We recommend that you use the first method: stata -b do myfile &.

The choice between stata -b do myfile & and stata -s do myfile & is more personal. We prefer obtaining SMCL logs (-s) because they look better when printed, and, in any case, they can always be converted to text format with translate; see [R] **translate**.

16.4 Programming with do-files

This is an advanced topic, and we are going to refer to concepts not yet explained; see **[U] 18 Programming Stata** for more information.

16.4.1 Argument passing

Do-files accept arguments, just as Stata programs do; this is described in **[U] 18 Programming Stata** and **[U] 18.4 Program arguments**. In fact, the logic Stata follows when invoking a do-file is the same as when invoking a program: the local macros are stored, and new ones are defined. Arguments are stored in the local macros `1', `2', and so on. When the do-file completes, the previous definitions are restored, just as with programs.

Thus, if you wanted your do-file to

1. use a dataset of your choosing,
2. tabulate a variable named region, and

3. summarize variables marriage_rate and divorce_rate,

you could write the do-file

```
begin myxmpl.do
use '1'
tabulate region
summarize marriage_rate divorce_rate
end myxmpl.do
```

and you could run this do-file by typing, for instance,

```
. do myxmpl census
  (output omitted)
```

The first command—use '1'—would be interpreted as use census5 because census5 was the first argument you typed after do myxmpl.

An even better version of the do-file would read

```
begin myxmpl.do
args dsname
use 'dsname'
tabulate region
summarize marriage_rate divorce_rate
end myxmpl.do
```

The args command merely assigns a better name to the argument passed. args dsname does not verify that what we type following do myxmpl is a filename—we would have to use the syntax command if we wanted to do that—but substituting 'dsname' for '1' does make the code more readable.

If our program were to receive two arguments, we could refer to them as '1' and '2', or we could put an 'args dsname other' at the top of our do-file and then refer to 'dsname' and 'other'.

To learn more about argument passing, see **[U] 18.4 Program arguments**. Baum (2016) provides many examples and tips related to do-files.

16.4.2 Suppressing output

There is an alternative to typing do *filename*; it is run *filename*. run works in the same way as do, except that neither the instructions in the file nor any of the output caused by those instructions is shown on the screen or in the log file.

For instance, with the above myxmpl.do, typing run myxmpl census5 results in

```
. run myxmpl census
. _
```

All the instructions were executed, but none of the output was shown.

This is not useful here, but if the do-file contained only the definitions of Stata programs—see **[U] 18 Programming Stata**—and you merely wanted to load the programs without seeing the code, run would be useful.

16.5 References

Baum, C. F. 2016. *An Introduction to Stata Programming*. 2nd ed. College Station, TX: Stata Press.

Long, J. S. 2009. *The Workflow of Data Analysis Using Stata*. College Station, TX: Stata Press.

Wiggins, V. L. 2018. How to automate common tasks. *The Stata Blog: Not Elsewhere Classified*. https://blog.stata.com/2018/10/09/how-to-automate-common-tasks/.

17 Ado-files

Contents

17.1 Description

Stata is programmable, and even if you never write a Stata program, Stata's programmability is still important. Many of Stata's features are implemented as Stata programs, and new features are implemented every day, both by StataCorp and by others.

1. You can obtain additions from the *Stata Journal*. You subscribe to the printed journal, but the software additions are available free over the internet.
2. You can obtain additions from the Stata forum, Statalist, where an active group of users advise each other on how to use Stata, and often, in the process, trade programs. Visit the Statalist website, https://www.statalist.org, for instructions on how to participate.
3. The Boston College Statistical Software Components (SSC) Archive is a distributed database making available a large and constantly growing number of Stata programs. You can browse and search the archive, and you can find links to the archive from https://www.stata.com. Importantly, Stata knows how to access the archive and other places, as well. You can search for additions by using Stata's `search, net` command; see [R] **search**. You can immediately install materials you find with `search, net` by using the hyperlinks that will be displayed by `search` in the Results window or by using the `net` command. A specialized command, `ssc`, has several options available to help you find and install the community-contributed commands that are available from this site; see [R] **ssc**.
4. You can write your own additions to Stata.

This chapter is written for people who want to use ado-files. All users should read it. If you later decide you want to write ado-files, see **[U] 18.11 Ado-files**.

17.2 What is an ado-file?

An ado-file defines a Stata command, but not all Stata commands are defined by ado-files.

When you type `summarize` to obtain summary statistics, you are using a command built into Stata.

When you type ci to obtain confidence intervals, you are running an ado-file. The results of using a built-in command or an ado-file are indistinguishable.

An ado-file is a text file that contains a Stata program. When you type a command that Stata does not know, it looks in certain places for an ado-file of that name. If Stata finds it, Stata loads and executes it, so it appears to you as if the ado-command is just another command built into Stata.

We just told you that Stata's ci command is implemented as an ado-file. That means that, somewhere, there is a file named ci.ado.

Ado-files usually come with help files. When you type help ci (or select **Help > Stata command...**, and type ci), Stata looks for ci.sthlp, just as it looks for ci.ado when you use the ci command. A help file is also a text file that tells Stata's help system what to display.

17.3 How can I tell if a command is built in or an ado-file?

You can use the which command to determine whether a file is built in or implemented as an ado-file. For instance, logistic is an ado-file, and here is what happens when you type which logistic:

```
. which logistic
C:\Program Files\Stata19\ado\base\l\logistic.ado
*! version 3.5.4  28feb2017
```

summarize is a built-in command:

```
. which summarize
built-in command:  summarize
```

17.4 How can I look at an ado-file?

When you type which followed by an ado-command, Stata reports where the file is stored:

```
. which logistic
C:\Program Files\Stata19\ado\base\l\logistic.ado
*! version 3.5.4  28feb2017
```

Ado-files are just text files containing the Stata program. You can view them in Stata's Viewer window (or even look at them in your editor or word processor) by typing

```
. type "C:\Program Files\Stata19\ado\base\l\logistic.ado"
*! version 3.5.4  28feb2017
program define logistic, eclass prop(or svyb svyj svyr swml mi bayes) ///
                                 byable(onecall)
        version 6.0, missing
  (output omitted)
end
```

or

```
. viewsource logistic.ado
  (output omitted)
```

The type command displays the contents of a file. The viewsource command searches for a file along the ado-directories and displays the file in the Viewer. You can also look at the corresponding help file in raw form if you wish. If there is a help file, it is stored in the same place as the ado-file:

```
. type "C:\Program Files\Stata19\ado\base\l\logistic.sthlp", asis
{smcl}
{* *! version 1.4.6  23feb2022}{...}
{viewerdialog logistic "dialog logistic"}{...}
```
(*output omitted*)

or

```
. viewsource logistic.sthlp
```
(*output omitted*)

17.5 Where does Stata look for ado-files?

Stata looks for ado-files in seven places, which can be categorized in three ways:

I. The official ado-directory:
   1. (BASE), the official directory containing the ado-files shipped with your version of Stata and any updated ado-files that have been made available since then

II. Your personal ado-directories:
   2. (SITE), the directory for ado-files your site might have installed
   3. (PLUS), the directory for ado-files you personally might have installed
   4. (PERSONAL), the directory for ado-files you might have written
   5. (OLDPLACE), the directory where Stata users used to save their personally written ado-files

III. The current directory:
   6. (.), the ado-files you have written just this instant or for just this project

The location of these directories varies from computer to computer, but Stata's sysdir command will tell you where they are on your computer:

```
. sysdir
   STATA:  C:\Program Files\Stata19\
    BASE:  C:\Program Files\Stata19\ado\base\
    SITE:  C:\Program Files\Stata19\ado\site\
    PLUS:  C:\ado\plus\
PERSONAL:  C:\ado\personal\
OLDPLACE:  C:\ado\
```

17.5.1 Where is the official ado-directory?

This is the directory listed as BASE by sysdir:

```
. sysdir
   STATA:  C:\Program Files\Stata19\
    BASE:  C:\Program Files\Stata19\ado\base\
    SITE:  C:\Program Files\Stata19\ado\site\
    PLUS:  C:\ado\plus\
PERSONAL:  C:\ado\personal\
OLDPLACE:  C:\ado\
```

1. BASE contains the ado-files we originally shipped to you and any updates you might have installed since then. You can install updates by using the update command or by selecting **Help > Check for updates**; see [U] 17.8 How do I install official updates?.

17.5.2 Where is my personal ado-directory?

These are the directories listed as PERSONAL, PLUS, SITE, and OLDPLACE by sysdir:

```
. sysdir
   STATA:  C:\Program Files\Stata19\
    BASE:  C:\Program Files\Stata19\ado\base\
    SITE:  C:\Program Files\Stata19\ado\site\
    PLUS:  C:\ado\plus\
PERSONAL:  C:\ado\personal\
OLDPLACE:  C:\ado\
```

1. PERSONAL is for ado-files you have written. Store your private ado-files here; see **[U] 17.7 How do I add my own ado-files?**.
2. PLUS is for ado-files you personally installed but did not write. Such ado-files are usually obtained from the SJ or the SSC Archive, but they are sometimes found in other places, too. You find and install such files by using Stata's net command, or you can select **Help > SJ and community-contributed features**; see **[U] 17.6 How do I install an addition?**.
3. SITE is really the opposite of a personal ado-directory—it is a public directory corresponding to PLUS. If you are on a networked computer, the site administrator can install ado-files here, and all Stata users will then be able to use them just as if they all found and installed them in their PLUS directory for themselves. Site administrators find and install the ado-files just as you would, using Stata's net command, but they specify an option when they install something that tells Stata to write the files into SITE rather than PLUS; see [R] **net**.
4. OLDPLACE is for old-time Stata users. Prior to Stata 6, all "personal" ado-files, whether personally written or just personally installed, were written in the same directory—OLDPLACE. So that the old-time Stata users do not have to go back and rearrange what they have already done, Stata still looks in OLDPLACE.

17.6 How do I install an addition?

Additions come in four types:

1. Community-contributed additions, which you might find in the SJ, etc.
2. Updates to community-contributed additions
   See **[U] 17.9 How do I install updates to community-contributed additions?**.
3. Ado-files you have written
   See **[U] 17.7 How do I add my own ado-files?** If you have an ado-file obtained from the Stata forum or a friend, treat it as belonging to this case.
4. Official updates provided by StataCorp
   See **[U] 17.8 How do I install official updates?**.

Community-contributed additions you might find in the *Stata Journal* (SJ), etc., are obtained over the internet. To access them on the internet,

1. select **Help > SJ and community-contributed features**, and click on one of the links

or

2. type net from https://www.stata.com.

What to do next will be obvious, but, in case it is not, see [GSM] 19 Updating and extending Stata—internet functionality, [GSU] 19 Updating and extending Stata—internet functionality, or [GSW] 19 Updating and extending Stata—internet functionality. Also see [U] 29 Using the internet to keep up to date, [R] net, and [R] ado update.

17.7 How do I add my own ado-files?

You write a Stata program (see [U] 18 Programming Stata), store it in a file ending in `.ado`, perhaps write a help file, and copy everything to the directory `sysdir` lists as `PERSONAL`:

```
. sysdir
   STATA:  C:\Program Files\Stata19\
    BASE:  C:\Program Files\Stata19\ado\base\
    SITE:  C:\Program Files\Stata19\ado\site\
    PLUS:  C:\ado\plus\
PERSONAL:  C:\ado\personal\
OLDPLACE:  C:\ado\
```

Here we would copy the files to `C:\ado\personal`.

While you are writing your ado-file, it is sometimes convenient to store the pieces in the current directory. Do that if you wish; you can move them to your personal ado-directory when the program is debugged.

17.8 How do I install official updates?

Updates are available over the internet:

1. select **Help > Check for updates**, and then click on **https://www.stata.com**

or

2. type `update query`.

What to do next should be obvious, but in case it is not, see [GSM] 19 Updating and extending Stata—internet functionality, [GSU] 19 Updating and extending Stata—internet functionality, or [GSW] 19 Updating and extending Stata—internet functionality. Also see [U] 29 Using the internet to keep up to date and [R] net.

The official updates include bug fixes and new features but do not change the syntax of an existing command or change the way Stata works.

Once you have installed the updates, you can enter Stata and type `help whatsnew` (or select **Help > What's new?**) to learn about what has changed.

17.9 How do I install updates to community-contributed additions?

If you have previously installed community-contributed additions, you can check for updates to them by typing `adoupdate`. If updates are available, you can install them by typing `ado update, update`. See [R] ado update.

17.10 References

Cox, N. J. 2006. Stata tip 30: May the source be with you. *Stata Journal* 6: 149–150.

Wiggins, V. L. 2018. How to automate common tasks. *The Stata Blog: Not Elsewhere Classified*. https://blog.stata.com/2018/10/09/how-to-automate-common-tasks/.

18 Programming Stata

Contents

Stata programming is an advanced topic. Some Stata users live productive lives without ever programming Stata. After all, you do not need to know how to program Stata to import data, create new variables, and fit models. On the other hand, programming Stata is not difficult—at least if the problem is not difficult—and Stata's programmability is one of its best features. The real power of Stata is not revealed until you program it.

Stata has two programming languages. One, known informally as "ado", is the focus of this chapter. It is based on Stata's commands, and you can write scripts and programs to automate reproducible analyses and to add new features to Stata.

The other language, Mata, is a byte-compiled language with syntax similar to C/C++, but with extensive matrix capabilities. The two languages can interact with each other. You can call Mata functions from ado-programs, and you can call ado-programs from Mata functions. You can learn all about Mata in the *Mata Reference Manual*.

Stata also has a Project Manager to help you manage large collections of Stata scripts, programs, and other files. See [P] **Project Manager**.

If you are uncertain whether to read this chapter, we recommend that you start reading and then bail out when it gets too arcane for you. You will learn things about Stata that you may find useful even if you never write a Stata program.

If you want even more, we offer courses over the internet on Stata programming; see **[U] 3.6.2 NetCourses**. Baum (2016) provides a wealth of practical knowledge related to Stata programming.

18.1 Description

When you type a command that Stata does not recognize, Stata first looks in its memory for a program of that name. If Stata finds it, Stata executes the program.

There is no Stata command named `hello`,

```
. hello
command hello is unrecognized
r(199);
```

but there could be if you defined a program named `hello`, and after that, the following might happen when you typed `hello`:

```
. hello
hi there

. _
```

This would happen if, beforehand, you had typed

```
. program hello
  1. display "hi there"
  2. end

. _
```

That is how programming works in Stata. A program is defined by

```
program progname
        Stata commands
end
```

and it is executed by typing *progname* at Stata's dot prompt.

18.2 Relationship between a program and a do-file

Stata treats programs the same way it treats do-files. Below we will discuss passing arguments, consuming results from Stata commands, and other topics, but everything we say applies equally to do-files and programs.

Programs and do-files differ in the following ways:

1. You invoke a do-file by typing `do` *filename*. You invoke a program by simply typing the program's name.
2. Programs must be defined (loaded) before they are used, whereas all that is required to run a do-file is that the file exist. There are ways to make programs load automatically, however, so this difference is of little importance.
3. When you type `do` *filename*, Stata displays the commands it is executing and the results. When you type *progname*, Stata shows only the results, not the display of the underlying commands. This is an important difference in outlook: in a do-file, how it does something is as important as what it does. In a program, the how is no longer important. You might think of a program as a new feature of Stata.

Let's now mention some of the similarities:

1. Arguments are passed to programs and do-files in the same way.
2. Programs and do-files both contain Stata commands. Any Stata command you put in a do-file can be put in a program.
3. Programs may call other programs. Do-files may call other do-files. Programs may call do-files (this rarely happens), and do-files may call programs (this often happens). Stata allows programs (and do-files) to be nested up to 64 deep.

Now here is the interesting thing: programs are typically defined in do-files (or in a variant of do-files called ado-files; we will get to that later).

You can define a program interactively, and that is useful for pedagogical purposes, but in real applications, you will compose your program in a text editor and store its definition in a do-file.

You have already seen your first program:

```
program hello
        display "hi there"
end
```

You could type those commands interactively, but if the body of the program were more complicated, that would be inconvenient. So instead, suppose that you typed the commands into a do-file:

begin `hello.do`

```
program hello
        display "hi there"
end
```

end `hello.do`

Now returning to Stata, you type

```
. do hello

. program hello
  1.         display "hi there"
  2. end

.
end of do-file
```

Do you see that typing `do hello` did nothing but load the program? Typing `do hello` is the same as typing out the program's definition because that is all the do-file contains. The do-file was executed, but the statements in the do-file only defined the program `hello`; they did not execute it. Now that the program is loaded, we can execute it interactively:

```
. hello
hi there
```

So, that is one way you could use do-files and programs together. If you wanted to create new commands for interactive use, you could

1. Write the command as a `program` . . . `end` in a do-file.
2. `do` the do-file before you use the new command.
3. Use the new command during the rest of the session.

There are more convenient ways to do this that would automatically load the do-file, but put that aside. The above method would work.

Another way we could use do-files and programs together is to put the definition of the program and its execution together into a do-file:

begin `hello.do`

```
program hello
        display "hi there"
end
hello
```

end `hello.do`

Here is what would happen if we executed this do-file:

```
. do hello

. program hello
  1.         display "hi there"
  2. end

. hello
hi there

.
end of do-file
```

Do-files and programs are often used in such combinations. Why? Say that program `hello` is long and complicated and you have a problem where you need to do it twice. That would be a good reason to write a program. Moreover, you may wish to carry forth this procedure as a step of your analysis and, being cautious, do not want to perform this analysis interactively. You never intended program `hello` to be used interactively—it was just something you needed in the midst of a do-file—so you defined the program and used it there.

Anyway, there are many variations on this theme, but few people actually sit in front of Stata and interactively type `program` and then compose a program. They instead do that in front of their text editor. They compose the program in a do-file and then execute the do-file.

There is one other (minor) thing to know: once a program is defined, Stata does not allow you to redefine it:

```
. program hello
program hello already defined
r(110);
```

Thus, in our most recent do-file that defines and executes `hello`, we could not rerun it in the same Stata session:

```
. do hello

. program hello
program hello already defined
r(110);

end of do-file
r(110);
```

That problem is solved by typing `program drop hello` before redefining it. We could do that interactively, or we could modify our do-file:

begin hello.do

```
program drop hello
program hello
        display "hi there"
end
hello
```

end hello.do

There is a problem with this solution. We can now rerun our do-file, but the first time we tried to run it in a Stata session, it would fail:

```
. do hello

. program drop hello
hello not found
r(111);

end of do-file
r(111);
```

The way around this conundrum is to modify the do-file:

begin hello.do

```
capture program drop hello
program hello
        display "hi there"
end
hello
```

end hello.do

`capture` in front of a command makes Stata indifferent to whether the command works; see [P] **capture**. In real do-files containing programs, you will often see `capture program drop` before the program's definition.

To learn about the `program` command itself, see [P] **program**. It manipulates programs. `program` can define programs, drop programs, and show you a directory of programs that you have defined.

A program can contain any Stata command, but certain Stata commands are of special interest to program writers; see the *Programming* heading in the subject table of contents in the *Stata Index*.

18.3 Macros

Before we can begin programming, we must discuss macros, which are the variables of Stata programs.

A *macro* is a string of characters, called the *macroname*, that stands for another string of characters, called the *macro contents*.

Macros can be local or global. We will start with local macros because they are the most commonly used, but nothing really distinguishes one from the other at this stage.

18.3.1 Local macros

Local macro names can be up to 31 (not 32) characters long.

One sets the contents of a local macro with the `local` command. In fact, we can do this interactively. We will begin by experimenting with macros in this way to learn about them. If we type

```
. local shortcut "myvar thisvar thatvar"
```

then `‘shortcut’` is a synonym for "`myvar thisvar thatvar`". Note the single quotes around `shortcut`. We said that sentence exactly the way we meant to because

if you type	`‘shortcut’`,
i.e.,	left-single-quote `shortcut` right-single-quote,
Stata hears	`myvar thisvar thatvar`.

To access the contents of the macro, we use a left single quote (located at the upper left on most keyboards), the macro name, and a right single quote (located under the " on the right side of most keyboards).

The single quotes bracketing the macroname `shortcut` are called the macro-substitution characters. `shortcut` means `shortcut`. `‘shortcut’` means `myvar thisvar thatvar`.

So, if you typed

```
. list ‘shortcut’
```

the effect would be exactly as if you typed

```
. list myvar thisvar thatvar
```

Macros can be used anywhere in Stata. For instance, if we also defined

```
. local cmd "list"
```

we could type

```
. ‘cmd’ ‘shortcut’
```

to mean `list myvar thisvar thatvar`.

For another example, consider the definitions

```
. local prefix "my"
. local suffix "var"
```

Then

```
. ‘cmd’ ‘prefix’‘suffix’
```

would mean `list myvar`.

One other important note is on the way we use left and right single quotes within Stata, which you will especially deal with when working with macros (see **[U] 18.3 Macros**). Single quotes (and double quotes, for that matter) may look different on your keyboard, your monitor, and our printed documentation, making it difficult to determine which key to press on your keyboard to replicate what we have shown you.

For the left single quote, we use the grave accent, which occupies a key by itself on most computer keyboards. On US keyboards, the grave accent is located at the top left, next to the numeral 1. On some non-US keyboards, the grave accent is produced by a dead key. For example, pressing the grave accent dead key followed by the letter a would produce à; to get the grave accent by itself, you would press the grave accent dead key followed by a space. This accent mark appears in our printed documentation as `‘`.

For the right single quote, we use the standard single quote, or apostrophe. On US keyboards, the single quote is located on the same key as the double quote, on the right side of the keyboard next to the *Enter* key.

18.3.2 Global macros

Let’s put aside why Stata has two kinds of macros—local and global—and focus right now on how global macros work.

Global macros can have names that are up to 32 (not 31) characters long. You set the contents of a global macro by using the `global` rather than the `local` command:

```
. global shortcut "alpha beta"
```

You obtain the contents of a global macro by prefixing its name with a dollar sign: `$shortcut` is equivalent to “`alpha beta`”.

In the previous section, we defined a local macro named `shortcut`, which is a different macro. `‘shortcut’` is still “`myvar thisvar thatvar`”.

Local and global macros may have the same names, but even if they do, they are unrelated and are still distinguishable.

Global macros are just like local macros except that you set their contents with `global` rather than `local`, and you substitute their contents by prefixing them with a `$` rather than enclosing them in `‘’`.

18.3.3 The difference between local and global macros

The difference between local and global macros is that local macros are private and global macros are public.

Say that you have written a program

```
program myprog
        code using local macro alpha
end
```

The local macro `alpha` in `myprog` is private in that no other program can modify or even look at `alpha`’s contents. To make this point absolutely clear, assume that your program looks like this:

```
program myprog
        code using local macro alpha
        mysub
        more code using local macro alpha
end
program mysub
        code using local macro alpha
end
```

myprog calls mysub, and both programs use a local macro named alpha. Even so, the local macros in each program are different. mysub's alpha macro may contain one thing, but that has nothing to do with what myprog's alpha macro contains. Even when mysub begins execution, its alpha macro is different from myprog's. It is not that mysub's inherits myprog's alpha macro contents but is then free to change it. It is that myprog's alpha and mysub's alpha are entirely different things.

When you write a program using local macros, you need not worry that some other program has been written using local macros with the same names. Local macros are just that: local to your program.

Global macros, on the other hand, are available to all programs. If both myprog and mysub use the global macro beta, they are using the same macro. Whatever the contents of $beta are when mysub is invoked, those are the contents when mysub begins execution, and, whatever the contents of $beta are when mysub completes, those are the contents when myprog regains control.

18.3.4 Macros and expressions

From now on, we are going to use local and global macros according to whichever is convenient; whatever is said about one applies to the other.

Consider the definitions

```
. local one 2+2
. local two = 2+2
```

(which we could just as well have illustrated using the global command). In any case, note the equal sign in the second macro definition and the lack of the equal sign in the first. Formally, the first should be

```
. local one "2+2"
```

but Stata does not mind if we omit the double quotes in the local (global) statement.

local one 2+2 (with or without double quotes) copies the string 2+2 into the macro named one.

local two = 2+2 evaluates the expression 2+2, producing 4, and stores 4 in the macro named two.

That is, you type

local *macname contents*

if you want to copy *contents* to *macname*, and you type

local *macname* = *expression*

if you want to evaluate *expression* and store the result in *macname*.

In the second form, *expression* can be numeric or string. 2+2 is a numeric expression. As an example of a string expression,

```
. local res = substr("this",1,2) + "at"
```

stores that in res.

Because the expression can be either numeric or string, what is the difference between the following statements?

```
. local a "example"
. local b = "example"
```

Both statements store `example` in their respective macros. The first does so by a simple copy operation, whereas the second evaluates the expression `"example"`, which is a string expression because of the double quotes that, here, evaluates to itself. You could put a more complicated expression to be evaluated on the right-hand side of the second syntax.

There are some other issues of using macros and expressions that look a little strange to programmers coming from other languages, at least the first time they see them. Say that the macro `‘i’` contains `5`. How would you increment `i` so that it contains $5 + 1 = 6$? The answer is

```
local i = ‘i’ + 1
```

Do you see why the single quotes are on the right but not the left? Remember, `‘i’` refers to the contents of the local macro named `i`, which, we just said, is `5`. Thus, after expansion, the line reads

```
local i = 5 + 1
```

which is the desired result.

There is a another way to increment local macros that will be more familiar to some programmers, especially C programmers:

```
local ++i
```

As C programmers would expect, `local ++i` is more efficient (executes more quickly) than `local i = i+1`, but in terms of outcome, it is equivalent. You can decrement a local macro by using

```
local --i
```

`local -i` is equivalent to `local i = i-1` but executes more quickly. Finally,

```
local i++
```

will *not* increment the local macro `i` but instead redefines the local macro `i` to contain `++`. There is, however, a context in which `i++` (and `i-`) do work as expected; see **[U] 18.3.7 Macro increment and decrement functions**.

18.3.5 Double quotes

Consider another local macro, `‘answ’`, which might contain `yes` or `no`. In a program that was supposed to do something different on the basis of `answ`’s content, you might code

```
if "‘answ’" == "yes" {
        ...
}
else {
        ...
}
```

Note the odd-looking `"‘answ’"`, and now think about the line after substitution. The line reads either

```
if "yes" == "yes" {
```

or

```
if "no" == "yes" {
```

either of which is the desired result. Had we omitted the double quotes, the line would have read

```
if no == "yes" {
```

(assuming `‘answ’` contains `no`), and that is not at all the desired result. As the line reads now, `no` would not be a string but would be interpreted as a variable in the data.

The key to all of this is to think of the line after substitution.

Double quotes are used to enclose strings: `"yes"`, `"no"`, `"my dir\my file"`, `"‘answ’"` (meaning that the contents of local macro `answ`, treated as a string), and so on. Double quotes are used with macros,

```
local a "example"
if "‘answ’" == "yes" {
        ...
}
```

and double quotes are used by many Stata commands:

```
. regress lnwage age ed if sex=="female"
. generate outa = outcome if drug=="A"
. use "person file"
```

Do not omit the double quotes just because you are using a “quoted” macro:

```
. regress lnwage age ed if sex=="‘x’"
. generate outa = outcome if drug=="‘firstdrug’"
. use "‘filename’"
```

Stata has two sets of double-quote characters, of which `""` is one. The other is `‘""’`. They both work the same way:

```
. regress lnwage age ed if sex==‘"female"’
. generate outa = outcome if drug==‘"A"’
. use ‘"person file"’
```

No rational user would use `‘""’` (called compound double quotes) instead of `""` (called simple double quotes), but smart programmers do use them:

```
local a ‘"example"’
if ‘"‘answ’"’ == ‘"yes"’ {
        ...
}
```

Why is `‘"example"’` better than `"example"`, `‘"‘answ’"’` better than `"‘answ’"`, and `‘"yes"’` better than `"yes"`? The answer is that only `‘"‘answ’"’` is better than `"‘answ’"`; `‘"example"’` and `‘"yes"’` are no better—and no worse—than `"example"` and `"yes"`.

`‘"‘answ’"’` is better than `"‘answ’"` because the macro `answ` might itself contain (simple or compound) double quotes. The really great thing about compound double quotes is that they nest. Say that `‘answ’` contained the string “`I "think" so`”. Then,

Stata would find	`if "‘answ’"=="yes"`
confusing because it would expand to	`if "I "think" so"=="yes"`
Stata would not find	`if ‘"‘answ’"’==‘"yes"’`
confusing because it would expand to	`if ‘"I "think" so"’==‘"yes"’`

Open and close double quote in the simple form look the same; open quote is `"` and so is close quote. Open and close double quote in the compound form are distinguishable; open quote is `‘"` and close quote is `"’`, and so Stata can pair the close with the corresponding open double quote. `‘"I "think" so"’` is easy for Stata to understand, whereas `"I "think" so"` is a hopeless mishmash. (If you disagree, consider what `"A"B"C"` might mean. Is it the quoted string `A"B"C`, or is it quoted string `A`, followed by `B`, followed by quoted string `C`?)

Because Stata can distinguish open from close quotes, even nested compound double quotes are understandable: `‘"I ‘"think"’ so"’`. (What does `"A"B"C"` mean? Either it means `‘"A‘"B"’C"’` or it means `‘"A"’B‘"C"’`.)

Yes, compound double quotes make you think that your vision is stuttering, especially when combined with the macro substitution `‘’` characters. That is why we rarely use them, even when writing programs. You do not have to use exclusively one or the other style of quotes. It is perfectly acceptable to code

```
local a "example"
if ‘"‘answ’"’ == "yes" {
        ...
}
```

using compound double quotes where it might be necessary (`‘"‘answ’"’`) and using simple double quotes in other places (such as `"yes"`). It is also acceptable to use simple double quotes around macros (for example, `"‘answ’"`) if you are certain that the macros themselves do not contain double quotes or (more likely) if you do not care what happens if they do.

Sometimes careful programmers should use compound double quotes. Later you will learn that Stata's `syntax` command interprets standard Stata syntax and so makes it easy to write programs that understand things like

```
. myprog mpg weight if strpos(make,"VW")!=0
```

`syntax` works—we are getting ahead of ourselves—by placing the `if` *exp* typed by the user in the local macro `if`. Thus `‘if’` will contain "`if strpos(make,"VW")!=0`" here. Now say that you are at a point in your program where you want to know whether the user specified an `if` *exp*. It would be natural to code

```
if ‘"‘if’"’ != "" {
        // the if exp was specified
        ...
}
else {
        // it was not
        ...
}
```

We used compound double quotes around the macro `‘if’`. The local macro `‘if’` might contain double quotes, so we placed compound double quotes around it.

18.3.6 Macro functions

In addition to allowing `=`*exp*, `local` and `global` provide *macro functions*. The use of a macro function is denoted by a colon (`:`) following the macro name, as in

```
local       lbl : variable label myvar
local filenames : dir "." files "*.dta"
local        xi : word ‘i’ of ‘list’
```

Some macro functions access a piece of information. In the first example, the variable label associated with variable `myvar` will be stored in macro `lbl`. Other macro functions perform operations to gather the information. In the second example, macro `filenames` will contain the names of all the `.dta` datasets in the current directory. Still other macro functions perform an operation on their arguments and return the result. In the third example, `xi` will contain the `‘i’`th word (element) of `‘list’`. See [P] **macro** for a list of the macro functions.

Another useful source of information is `c()`, documented in [P] **creturn**:

```
local  today "‘c(current_date)’"
local curdir "‘c(pwd)’"
local   newn = c(N)+1
```

`c()` refers to a prerecorded list of values, which may be used directly in expressions or which may be quoted and the result substituted anywhere. `c(current_date)` returns today's date in the form "*dd MON yyyy*". Thus the first example stores in macro `today` that date. `c(pwd)` returns the current directory, such as `C:\data\proj`. Thus the second example stores in macro `curdir` the current directory. `c(N)` returns the number of observations of the data in memory. Thus the third example stores in macro `newn` that number, plus one.

Note the use of quotes with `c()`. We could just as well have coded the first two examples as

```
local  today = c(current_date)
local curdir = c(pwd)
```

`c()` is a Stata function in the same sense that `sqrt()` is a Stata function. Thus we can use `c()` directly in expressions. It is a special property of macro expansion, however, that you may use the `c()` function inside macro-expansion quotes. The same is not true of `sqrt()`.

In any case, whenever you need a piece of information, whether it be about the dataset or about the environment, look in [P] **macro** and [P] **creturn**. It is likely to be in one place or the other, and sometimes, it is in both. You can obtain the current directory by using

```
local curdir = c(pwd)
```

or by using

```
local curdir : pwd
```

When information is in both, it does not matter which source you use.

18.3.7 Macro increment and decrement functions

We mentioned incrementing macros in **[U] 18.3.4 Macros and expressions**. The construct

```
command that makes reference to ‘i’
local ++i
```

occurs so commonly in Stata programs that it is convenient (and faster when executed) to collapse both lines of code into one and to increment (or decrement) `i` at the same time that it is referred to. Stata allows this:

```
while (‘++i’ < 1000) {
        ...
}
while (‘i++’ < 1000) {
        ...
}
while (‘--i’ > 0) {
        ...
}
while (‘i--’ > 0) {
        ...
}
```

Above we have chosen to illustrate this by using Stata's `while` command, but `++` and `--` can be used anyplace in any context, just so long as it is enclosed in macro-substitution quotes.

When the `++` or `--` appears before the name, the macro is first incremented or decremented, and then the result is substituted.

When the `++` or `--` appears after the name, the current value of the macro is substituted and then the macro is incremented or decremented.

❑ Technical note

Do not use the inline `++` or `--` operators when a part of the line might not be executed. Consider

```
if (‘i’==0) local j = ‘k++’
```

versus

```
if (‘i’==0) {
        local j = ‘k++’
}
```

The first will not do what you expect because macros are expanded before the line is interpreted. Thus the first will result in `k` always being incremented, whereas the second increments `k` only when `‘i’==0`.

❑

18.3.8 Macro expressions

Typing

command that makes reference to ‘=exp’

is equivalent to

`local` *macroname* `=` *exp*
command that makes reference to ‘macroname’

although the former runs faster and is easier to type. When you use *‘=exp’* within some larger command, *exp* is evaluated by Stata's expression evaluator, and the results are inserted as a literal string into the larger command. Then the command is executed. For example,

```
summarize u4
summarize u‘=2+2’
summarize u‘=4*(cos(0)==1)’
```

all do the same thing. *exp* can be any valid Stata expression and thus may include references to variables, matrices, scalars, or even other macros. In the last case, just remember to enclose the submacros in quotes:

```
replace `var' = `group'[`=`j'+1']
```

Also, typing

command that makes reference to `` `:*macro function*' ``

is equivalent to

```
local macroname : macro function
command that makes reference to `macroname'
```

Thus one might code

```
format y `:format x'
```

to assign to variable y the same format as the variable x.

❑ Technical note

There is another macro expansion operator, . (called dot), which is used in conjunction with Stata's class system; see [P] **class** for more information.

There is also a macro expansion function, `macval()`, which is for use when expanding a macro—`` `macval(*name*)' ``—which confines the macro expansion to the first level of *name*, thereby suppressing the expansion of any embedded references to macros within *name*. Only a few Stata users have or will ever need this, but, if you suspect you are one of them, see [P] **macro** and then see [P] **file** for an example.

❑

18.3.9 Advanced local macro manipulation

This section is really an aside to help test your understanding of macro substitution. The tricky examples illustrated below sometimes occur in real programs.

1. Say that you have macros x1, x2, x3, and so on. Obviously, `` `x1' `` refers to the contents of x1, `` `x2' `` to the contents of x2, etc. What does `` `x`i'' `` refer to? Suppose that `` `i' `` contains 6.

   The rule is to expand the inside first:

`` `x`i'' ``	expands to	`` `x6' ``
`` `x6' ``	expands to	the contents of local macro x6

   So, there you have a vector of macros.

2. We have already shown adjoining expansions: `` `alpha'`beta' `` expands to myvar if `` `alpha' `` contains my and `` `beta' `` contains var. What does `` `alpha'`gamma'`beta' `` expand to when gamma is undefined?

   Stata does not mind if you refer to a nonexistent macro. A nonexistent macro is treated as a macro with no contents. If local macro gamma does not exist, then

`` `gamma' ``	expands to	nothing

   It is not an error. Thus `` `alpha'`gamma'`beta' `` expands to myvar.

3. You clear a local macro by setting its contents to nothing:

   ```
   local macname
   or local macname ""
   or local macname = ""
   ```

18.3.10 Advanced global macro manipulation

Global macros are rarely used, and when they are used, it is typically for communication between programs. You should never use a global macro where a local macro would suffice.

1. Constructions like `$x$i` are expanded sequentially. If `$x` contained `this` and `$i` `6`, then `$x$i` expands to `this6`. If `$x` was undefined, then `$x$i` is just `6` because undefined global macros, like undefined local macros, are treated as containing nothing.
2. You can nest macro expansion by including braces, so if `$i` contains `6`, `${x$i}` expands to `${x6}`, which expands to the contents of `$x6` (which would be nothing if `$x6` is undefined).
3. You can mix global and local macros. Assume that local macro `j` contains `7`. Then, `${x`j'}` expands to the contents of `$x7`.
4. You also use braces to force the contents of global macros to run up against the succeeding text. For instance, assume that the macro `drive` contains "`b:`". If `drive` were a local macro, you could type

   ```
   `drive'myfile.dta
   ```

   to obtain `b:myfile.dta`. Because `drive` is a global macro, however, you must type

   ```
   ${drive}myfile.dta
   ```

   You could not type

   ```
   $drive myfile.dta
   ```

   because that would expand to `b: myfile.dta`. You could not type

   ```
   $drivemyfile.dta
   ```

   because that would expand to `.dta`.
5. Because Stata uses $ to mark global-macro expansion, printing a real $ is sometimes tricky. To display the string $22.15 with the `display` command, you can type `display "\$22.15"`, although you can get away with `display "$22.15"` because Stata is rather smart. Stata would not be smart about `display "$this"` if you really wanted to display `$this` and not the contents of the macro `this`. You would have to type `display "\$this"`. Another alternative would be to use the SMCL code for a dollar sign when you wanted to display it: `display "{c S|}this"`; see [P] **smcl**.
6. Real dollar signs can also be placed into the contents of macros, thus postponing substitution. First, let's understand what happens when we do not postpone substitution; consider the following definitions:

   ```
   global baseset "myvar thatvar"
   global bigset "$baseset thisvar"
   ```

   `$bigset` is equivalent to "`myvar thatvar thisvar`". Now say that we redefine the macro `baseset`:

   ```
   global baseset "myvar thatvar othvar"
   ```

   The definition of `bigset` has not changed—it is still equivalent to "`myvar thatvar thisvar`". It has not changed because `bigset` used the definition of `baseset` that was current at the time it was defined. `bigset` no longer knows that its contents are supposed to have any relation to `baseset`.

Instead, let's assume that we had defined `bigset` as

```
global bigset "\$baseset thisvar"
```

at the outset. Then `$bigset` is equivalent to "`$baseset thisvar`", which in turn is equivalent to "`myvar thatvar othvar thisvar`". Because `bigset` explicitly depends upon `baseset`, anytime we change the definition of `baseset`, we will automatically change the definition of `bigset` as well.

18.3.11 Constructing Windows filenames by using macros

Stata uses the \ character to tell its parser not to expand macros.

Windows uses the \ character as the directory path separator.

Mostly, there is no problem using a \ in a filename. However, if you are writing a program that contains a Windows path in macro `path` and a filename in `fname`, do not assemble the final result as

```
`path'\`fname'
```

because Stata will interpret the \ as an instruction to not expand `` `fname' ``. Instead, assemble the final result as

```
`path'/`fname'
```

Stata understands / as a directory separator on all platforms.

18.3.12 Accessing system values

Stata programs often need access to system parameters and settings, such as the value of π, the current date and time, or the current working directory.

System values are accessed via Stata's c-class values. The syntax works much the same as if you were referring to a local macro. For example, a reference to the c-class value for π, `` `c(pi)' ``, will expand to a literal string containing `3.141592653589793` and could be used to do

```
. display sqrt(2*`c(pi)')
2.5066283
```

You could also access the current time

```
. display "`c(current_time)'"
11:34:57
```

C-class values are designed to provide one all-encompassing way to access system parameters and settings, including system directories, system limits, string limits, memory settings, properties of the data currently in memory, output settings, efficiency settings, network settings, and debugging settings.

See [P] **creturn** for a detailed list of what is available. Typing

```
. creturn list
```

will give you the list of current settings.

18.3.13 Referring to characteristics

Characteristics—see **[U] 12.8 Characteristics**—are like macros associated with variables. They have names of the form *varname*[*charname*]—such as `mpg[comment]`—and you quote their names just as you do macro names to obtain their contents:

To substitute the value of *varname*[*charname*], type	`` `varname[charname]' ``
For example,	`` `mpg[comment]' ``

You set the contents using the `char` command:

`char` *varname*`[`*charname*`]` [`["`]*text*[`"`]]

This is similar to the `local` and `global` commands, except that there is no `=`*exp* variation. You clear a characteristic by setting its contents to nothing just as you would with a macro:

Type	`char` *varname*`[`*charname*`]`
or	`char` *varname*`[`*charname*`] ""`

What is unique about characteristics is that they are saved with the data, meaning that their contents survive from one session to the next, and they are associated with variables in the data, so if you ever drop a variable, the associated characteristics disappear, too. (Also, `_dta[`*charname*`]` is associated with the data but not with any variable in particular.)

All the standard rules apply: characteristics may be referred to by quotation in any context, and the characteristic's contents are substituted for the quoted characteristic name. As with macros, referring to a nonexistent characteristic is not an error; it merely substitutes to nothing.

18.4 Program arguments

When you invoke a program or do-file, what you type following the program or do-file name are the arguments. For instance, if you have a program called `xyz` and type

```
. xyz mpg weight
```

then `mpg` and `weight` are the program's arguments, `mpg` being the first argument and `weight` the second.

Program arguments are passed to programs via local macros:

Macro	Contents
`` `0' ``	what the user typed exactly as the user typed it, odd spacing, double quotes, and all
`` `1' ``	the first argument (first word of `` `0' ``)
`` `2' ``	the second argument (second word of `` `0' ``)
`` `3' ``	the third argument (third word of `` `0' ``)
...	...
`` `*' ``	the arguments `` `1' ``, `` `2' ``, `` `3' ``, ..., listed one after the other and with one blank in between; similar to but different from `` `0' `` because odd spacing and double quotes are removed

That is, what the user types is passed to you in three different ways:

1. It is passed in `‘0’` exactly as the user typed it, meaning quotes, odd spacing, and all.
2. It is passed in `‘1’`, `‘2’`, . . . broken out into arguments on the basis of blanks (but with quotes used to force binding; we will get to that).
3. It is passed in `‘*’` as "`‘1’ ‘2’ ‘3’ . . .`", which is a crudely cleaned up version of `‘0’`.

You will probably not use all three forms in one program.

We recommend that you ignore `‘*’`, at least for receiving arguments; it is included so that old Stata programs will continue to work.

Operating directly with `‘0’` takes considerable programming sophistication, although Stata's `syntax` command makes interpreting `‘0’` according to standard Stata syntax easy. That will be covered in **[U] 18.4.4 Parsing standard Stata syntax** below.

The easiest way to receive arguments, however, is to deal with the positional macros `‘1’`, `‘2’`, ...

At the start of this section, we imagined an `xyz` program invoked by typing `xyz mpg weight`. Then `‘1’` would contain `mpg`, `‘2’` would contain `weight`, and `‘3’` would contain nothing.

Let's write a program to report the correlation between two variables. Of course, Stata already has a command that can do this—`correlate`—and, in fact, we will implement our program in terms of `correlate`. It is silly, but all we want to accomplish right now is to show how Stata passes arguments to a program.

Here is our program:

```
program xyz
        correlate ‘1’ ‘2’
end
```

Once the program is defined, we can try it:

```
. use https://www.stata-press.com/data/r19/auto
(1978 automobile data)

. xyz mpg weight
(obs=74)
```

	mpg	weight
mpg	1.0000	
weight	-0.8072	1.0000

See how this works? We typed `xyz mpg weight`, which invoked our `xyz` program with `‘1’` being `mpg` and `‘2’` being `weight`. Our program gave the command `correlate ‘1’ ‘2’`, and that expanded to `correlate mpg weight`.

Stylistically, this is not a good example of the use of positional arguments, but realistically, there is nothing wrong with it. The stylistic problem is that if `xyz` is really to report the correlation between two variables, it ought to allow standard Stata syntax, and that is not a difficult thing to do. Realistically, the program works.

Positional arguments, however, play an important role, even for programmers who care about style. When we write a subroutine—a program to be called by another program and not intended for direct human use—we often pass information by using positional arguments.

Stata forms the positional arguments `‘1’`, `‘2’`, . . . by taking what the user typed following the command (or do-file), parsing it on white space with double quotes used to force binding, and stripping the quotes. The arguments are formed on the basis of words, but double-quoted strings are kept together as one argument but with the quotes removed.

Let’s create a program to illustrate these concepts. Although we would not normally define programs interactively, this program is short enough that we will:

```
. program listargs
  1.  display "The 1st argument you typed is:  ‘1’"
  2.  display "The 2nd argument you typed is:  ‘2’"
  3.  display "The 3rd argument you typed is:  ‘3’"
  4.  display "The 4th argument you typed is:  ‘4’"
  5.  end
```

The `display` command simply types the double-quoted string following it; see [P] **display**.

Let’s try our program:

```
. listargs
The 1st argument you typed is:
The 2nd argument you typed is:
The 3rd argument you typed is:
The 4th argument you typed is:
```

We type `listargs`, and the result shows us what we already know—we typed nothing after the word `listargs`. There are no arguments. Let’s try it again, this time adding `this is a test`:

```
. listargs this is a test
The 1st argument you typed is:  this
The 2nd argument you typed is:  is
The 3rd argument you typed is:  a
The 4th argument you typed is:  test
```

We learn that the first argument is ‘`this`’, the second is ‘`is`’, and so on. Blanks always separate arguments. You can, however, override this feature by placing double quotes around what you type:

```
. listargs "this is a test"
The 1st argument you typed is:  this is a test
The 2nd argument you typed is:
The 3rd argument you typed is:
The 4th argument you typed is:
```

This time we typed only one argument, ‘`this is a test`’. When we place double quotes around what we type, Stata interprets whatever we type inside the quotes to be one argument. Here `‘1’` contains ‘`this is a test`’ (the double quotes were removed).

We can use double quotes more than once:

```
. listargs "this is" "a test"
The 1st argument you typed is:  this is
The 2nd argument you typed is:  a test
The 3rd argument you typed is:
The 4th argument you typed is:
```

The first argument is ‘`this is`’ and the second argument is ‘`a test`’.

18.4.1 Named positional arguments

Positional arguments can be named: in your code, you do not have to refer to `‘1’`, `‘2’`, `‘3’`, …; you can instead refer to more meaningful names, such as `n`, `a`, and `b`; `numb`, `alpha`, and `beta`; or whatever else you find convenient. You want to do this because programs coded in terms of `‘1’`, `‘2’`, … are hard to read and therefore are more likely to contain errors.

You obtain better-named positional arguments by using the `args` command:

```
program progname
        args argnames
        ...
end
```

For instance, if your program received four positional arguments and you wanted to call them `varname`, `n`, `oldval`, and `newval`, you would code

```
program progname
        args varname n oldval newval
        ...
end
```

`varname`, `n`, `oldval`, and `newval` become new local macros, and `args` simply copies `‘1’`, `‘2’`, `‘3’`, and `‘4’` to them. It does not change `‘1’`, `‘2’`, `‘3’`, and `‘4’`—you can still refer to the numbered macros if you wish—and it does not verify that your program receives the right number of arguments. If our example above were invoked with just two arguments, `‘oldval’` and `‘newval’` would contain nothing. If it were invoked with five arguments, the fifth argument would still be out there, stored in local macro `‘5’`.

Let’s make a command to create a dataset containing n observations on `x` ranging from a to b. Such a command would be useful, for instance, if we wanted to graph some complicated mathematical function and experiment with different ranges. It is convenient if we can type the range of `x` over which we wish to make the graph rather than concocting the range by hand. (In fact, Stata already has such a command—`range`—but it will be instructive to write our own.)

Before writing this program, we had better know how to proceed, so here is how you could create a dataset containing n observations with `x` ranging from a to b:

1. `clear`
   to clear whatever data are in memory.
2. `set obs` n
   to make a dataset of n observations on no variables; if n were 100, we would type `set obs 100`.
3. `gen x = (_n-1)/(`n`-1)*(`b`-`a`)+`a
   because the built-in variable `_n` is 1 in the first observation, 2 in the second, and so on; see **[U] 13.4 System variables (_variables)**.

So, the first version of our program might read

```
program rng                                  // arguments are n a b
        clear
        set obs ‘1’
        generate x = (_n-1)/(_N-1)*(‘3’-‘2’)+‘2’
end
```

The above is just a direct translation of what we just said. ‘1’ corresponds to n, ‘2’ corresponds to a, and ‘3’ corresponds to b. This program, however, would be far more understandable if we changed it to read

```
program rng
        args n a b
        clear
        set obs ‘n’
        generate x = (_n-1)/(_N-1)*(‘b’-‘a’)+‘a’
end
```

18.4.2 Incrementing through positional arguments

Some programs contain k arguments, where k varies, but it does not much matter because the same thing is done to each argument. One such program is `summarize`: type `summarize mpg` to obtain summary statistics on `mpg`, and type `summarize mpg weight` to obtain first summary statistics on `mpg` and then summary statistics on `weight`.

```
program ...
        local i = 1
        while "‘‘i’’" != "" {
                logic stated in terms of ‘‘i’’
                local ++i
        }
end
```

Equivalently, if the logic that uses `"i"` contains only one reference to `"i"`,

```
program ...
        local i = 1
        while "‘‘i’’" != "" {
                logic stated in terms of ‘‘i++’’
        }
end
```

Note the tricky construction `"i"`, which then itself is placed in double quotes—`""i""`—for the `while` loop. To understand it, say that `i` contains 1 or, equivalently, ‘i’ is 1. Then `"i"` is ‘1’ is the name of the first variable. `""i""` is the name of the first variable in quotes. The `while` asks if the name of the variable is nothing and, if it is not, executes. Now ‘i’ is 2, and `""i""` is the name of the second variable, in quotes. If that name is not `""`, we continue. If the name is `""`, we are done.

Say that you were writing a subroutine that was to receive k variables, but the code that processes each variable needs to know (while it is processing) how many variables were passed to the subroutine. You need first to count the variables (and so derive k) and then, knowing k, pass through the list again.

```
program progname
        local k = 1                 // count the number of arguments
        while "‘‘k’’" != "" {
                local ++k
        }
        local --k                   // k contains one too many

                                    // now pass through again
        local i = 1
        while ‘i’ <= ‘k’ {
                code in terms of ‘‘i’’ and ‘k’
                local ++i
        }
end
```

In the above example, we have used `while`, Stata's all-purpose looping command. Stata has two other looping commands, `foreach` and `forvalues`, and they sometimes produce code that is more readable and executes more quickly. We direct you to read [P] **foreach** and [P] **forvalues**, but at this point, there is nothing they can do that `while` cannot do. Above we coded

```
local i = 1
while `i' <= `k' {
        code in terms of ``i'' and `k'
        local ++i
}
```

to produce logic that looped over the values `i` = 1 to `k`. We could have instead coded

```
forvalues i = 1(1)`k' {
        code in terms of ``i'' and `k'
}
```

Similarly, at the beginning of this subsection, we said that you could use the following code in terms of `while` to loop over the arguments received:

```
program ...
        local i = 1
        while "``i''" != "" {
                logic stated in terms of ``i''
                local ++i
        }
end
```

Equivalent to the above would be

```
program ...
        foreach x of local 0 {
                logic stated in terms of `x'
        }
end
```

See [P] **foreach** and [P] **forvalues**.

You can combine `args` and incrementing through an unknown number of positional arguments. Say that you were writing a subroutine that was to receive `varname`, the name of some variable; `n`, which is some sort of count; and at least one and maybe 20 variable names. Perhaps you are to sum the variables, divide by `n`, and store the result in the first variable. What the program does is irrelevant; here is how we could receive the arguments:

```
program progname
        args varname n
        local i 3
        while "``i''" != "" {
                logic stated in terms of ``i''
                local ++i
        }
end
```

18.4.3 Using macro shift

Another way to code the repeat-the-same-process problem for each argument is

```
program ...
        while "`1'" != "" {
                logic stated in terms of `1'
                macro shift
        }
end
```

`macro shift` shifts `1`, `2`, `3`, ..., one to the left: what was `1` disappears, what was `2` becomes `1`, what was `3` becomes `2`, and so on.

The outside `while` loop continues the process until macro `1` contains nothing.

`macro shift` is an older construct that we no longer advocate using. Instead, we recommend that you use the techniques described in the previous subsection, that is, references to `"i"` and `foreach` or `forvalues`.

There are two reasons we make this recommendation: `macro shift` destroys the positional macros `1`, `2`, which must then be reset using `tokenize` should you wish to pass through the argument list again, and (more importantly) if the number of arguments is large (which in Stata/MP and Stata/SE is more likely), `macro shift` can be extremely slow.

❑ Technical note

`macro shift` can do one thing that would be difficult to do by other means.

`*`, the result of listing the contents of the numbered macros one after the other with one blank between, changes with `macro shift`. Say that your program received a list of variables and that the first variable was the dependent variable and the rest were independent variables. You want to save the first variable name in `lhsvar` and all the rest in `rhsvars`. You could code

```
program progname
        local lhsvar "`1'"
        macro shift 1
        local rhsvars "`*'"
        ...
end
```

Now suppose that one macro contains a list of variables and you want to split the contents of the macro in two. Perhaps `varlist` is the result of a `syntax` command (see **[U] 18.4.4 Parsing standard Stata syntax**), and you now wish to split `varlist` into `lhsvar` and `rhsvars`. `tokenize` will reset the numbered macros:

```
program progname
        ...
        tokenize `varlist'
        local lhsvar "`1'"
        macro shift 1
        local rhsvars "`*'"
        ...
end
```

❑

18.4.4 Parsing standard Stata syntax

Let's now switch to `‘0’` from the positional arguments `‘1’`, `‘2’`, ...

You can parse `‘0’` (what the user typed) according to standard Stata syntax with one command. Remember that standard Stata syntax is

[by *varlist*:] *command* [*varlist*] [=*exp*] [using *filename*] [*if*] [*in*] [*weight*]
[, *options*]

See **[U] 11 Language syntax**.

The `syntax` command parses standard syntax. You code what amounts to the syntax diagram of your command in your program, and then `syntax` looks at `‘0’` (it knows to look there) and compares what the user typed with what you are willing to accept. Then one of two things happens: either `syntax` stores the pieces in an easily processable way or, if what the user typed does not match what you specified, `syntax` issues the appropriate error message and stops your program.

Consider a program that is to take two or more variable names along with an optional `if` *exp* and `in` *range*. The program would read

```
program ...
        syntax varlist(min=2) [if] [in]
        ...
 end
```

You will have to read [P] **syntax** to learn how to specify the syntactical elements, but the command is certainly readable, and it will not be long until you are guessing correctly about how to fill it in. And yes, the square brackets really do indicate optional elements, and you just use them with `syntax` in the natural way.

The one `syntax` command you code encompasses the parsing process. Here, if what the user typed matches "two or more variables and an optional if and in", `syntax` defines new local macros:

`‘varlist’`	the two or more variable names
`‘if’`	the `if` *exp* specified by the user (or nothing)
`‘in’`	the `in` *range* specified by the user (or nothing)

To see that this works, experiment with the following program:

```
program tryit
        syntax varlist(min=2) [if] [in]
        display "varlist now contains |‘varlist’|"
        display ‘"if now contains |‘if’|"’
        display "in now contains |‘in’|"
 end
```

Below we experiment:

```
. tryit mpg weight
varlist now contains |mpg weight|
if now contains ||
in now contains ||
. tryit mpg weight displ if foreign==1
varlist now contains |mpg weight displ|
if now contains |if foreign==1|
in now contains ||
```

```
. tryit mpg wei in 1/10
varlist now contains |mpg weight|
if now contains ||
in now contains |in 1/10|

. tryit mpg
too few variables specified
r(102);
```

In our third try we abbreviated the weight variable as `wei`, yet, after parsing, `syntax` unabbreviated the variable for us.

If this program were next going to step through the variables in the varlist, the positional macros `‘1’`, `‘2’`, …could be reset by coding

```
tokenize ‘varlist’
```

See [P] **tokenize**. `tokenize ‘varlist’` resets `‘1’` to be the first word of `‘varlist’`, `‘2’` to be the second word, and so on.

18.4.5 Parsing immediate commands

Immediate commands are described in [U] **19 Immediate commands**—they take numbers as arguments. By convention, when you name immediate commands, you should make the last letter of the name *i*. Assume that `mycmdi` takes as arguments two numbers, the first of which must be a positive integer, and allows the options `alpha` and `beta`. The basic structure is

```
program mycmdi
        gettoken n 0 : 0, parse(" ,")          /* get first number */
        gettoken x 0 : 0, parse(" ,")          /* get second number */
        confirm integer number ‘n’             /* verify first is integer */
        confirm number ‘x’                     /* verify second is number */
        if ‘n’<=0 error 2001                   /* check that n is positive */
        place any other checks here
        syntax [, Alpha Beta]                  /* parse remaining syntax */
        make calculation and display output
end
```

See [P] **gettoken**.

18.4.6 Parsing nonstandard syntax

If you wish to interpret nonstandard syntax and positional arguments are not adequate for you, you know that you face a formidable programming task. The key to the solution is the `gettoken` command.

gettoken can pull one token from the front of a macro according to the parsing characters you specify and, optionally, define another macro or redefine the initial macro to contain the remaining (unparsed) characters. That is,

Say that `‘0’` contains	“this is what the user typed”
After gettoken,	
new macro `‘token’` could contain	“this”
and `‘0’` could still contain	“this is what the user typed”
or	
new macro `‘token’` could contain	“this”
and new macro `‘rest’` could contain	“ is what the user typed”
and `‘0’` could still contain	“this is what the user typed”
or	
new macro `‘token’` could contain	“this”
and `‘0’` could contain	“ is what the user typed”

A simplified syntax of gettoken is

gettoken *emname1* [*emname2*] : *emname3* [, parse(*pchars*) quotes
match(*lmacname*) bind]

where *emname1*, *emname2*, *emname3*, and *lmacname* are the names of local macros. (Stata provides a way to work with global macros, but in practice that is seldom necessary; see [P] **gettoken**.)

gettoken pulls the first token from *emname3* and stores it in *emname1*, and if *emname2* is specified, stores the remaining characters from *emname3* in *emname2*. Any of *emname1*, *emname2*, and *emname3* may be the same macro. Typically, gettoken is coded

gettoken *emname1* : 0 [, *options*]
gettoken *emname1* 0 : 0 [, *options*]

because `‘0’` is the macro containing what the user typed. The first coding is used for token lookahead, should that be necessary, and the second is used for committing to taking the token.

gettoken’s options are

parse("*string*")	for specifying parsing characters the default is parse(" "), meaning to parse on white space it is common to specify parse(‘"" "’), meaning to parse on white space and double quote (‘"" "’ is the string double-quote-space in compound double quotes)
quotes	to specify that outer double quotes *not* be stripped
match(*lmacname*)	to bind on parentheses and square brackets *lmacname* will be set to contain “(”, “[”, or nothing, depending on whether *emname1* was bound on parentheses or brackets or if match() turned out to be irrelevant *emname1* will have the outside parentheses or brackets removed

gettoken binds on double quotes whenever a (simple or compound) double quote is encountered at the beginning of *emname3*. Specifying parse(‘"" "’) ensures that double-quoted strings are isolated.

quote specifies that double quotes not be removed from the source in defining the token. For instance, in parsing “"this is" a test”, the next token is “this is” if quote is not specified and is “"this is"” if quote is specified.

`match()` specifies that parentheses and square brackets be matched in defining tokens. The outside level of parentheses or brackets is stripped. In parsing "`(2+3)/2`", the next token is "`2+3`" if `match()` is specified. In practice, `match()` might be used with expressions, but it is more likely to be used to isolate bound varlists and time-series varlists.

18.5 Scalars and matrices

In addition to macros, scalars and matrices are provided for programmers; see **[U] 14 Matrix expressions**, [P] **scalar** and [P] **matrix**.

As far as scalar calculations go, you can use macros or scalars. Remember, macros can hold numbers. Stata's scalars are, however, slightly faster and are a little more accurate than macros. The speed issue is so slight as to be nearly immeasurable. Macros are accurate to a minimum of 12 decimal digits, and scalars are accurate to roughly 16 decimal digits. Which you use makes little difference except in iterative calculations.

Scalars can hold strings, and, in fact, can hold longer strings than macros can. Scalars can also hold binary "strings". See **[U] 12.4.14 Notes for programmers**.

Stata has a serious matrix programming language called Mata, which is the subject of another manual. Mata can be used to write subroutines that are called by Stata programs. See the *Mata Reference Manual*, and in particular, [M-1] **Ado**.

18.6 Temporarily destroying the data in memory

It is sometimes necessary to modify the data in memory to accomplish a particular task. A well-behaved program, however, ensures that the user's data are always restored. The `preserve` command makes this easy:

```
code before the data need changing
preserve
code that changes data freely
```

When you use the `preserve` command, Stata/MP and Stata/SE make a copy of the user's data in memory. Stata/BE makes a copy on disk. There is a setting, `max_preservemem`, to control how much memory Stata/MP will use for such copies before falling back to disk. See [P] **preserve**. When your program terminates—no matter how—Stata restores the data and erases the temporary file.

An alternative to `preserve` is to use frames to make a copy of the data that need changing, manipulate the data in the newly copied frame, and then drop that frame afterward. See *Example of use in programs* in [D] **frame prefix**.

18.7 Temporary objects

If you write a substantial program, it will invariably require the use of temporary variables in the data, or temporary scalars, matrices, or files. Temporary objects are necessary while the program is making its calculations, and once the program completes they are discarded.

Stata provides three commands to create temporary objects: `tempvar` creates names for variables in the dataset, `tempname` creates names for scalars and matrices, and `tempfile` creates names for files. All are described in [P] **macro**, and all have the same syntax:

{ `tempvar` | `tempname` | `tempfile` } *macname* [*macname* ...]

The commands create local macros containing names you may use.

18.7.1 Temporary variables

Say that, in making a calculation, you need to add variables sum_y and sum_z to the data. You might be tempted to code

```
...
generate sum_y = ...
generate sum_z = ...
...
```

but that would be poor because the dataset might already have variables named sum_y and sum_z in it and you will have to remember to drop the variables before your program concludes. Better is

```
...
tempvar sum_y
generate `sum_y' = ...
tempvar sum_z
generate `sum_z' = ...
...
```

or

```
...
tempvar sum_y sum_z
generate `sum_y' = ...
generate `sum_z' = ...
...
```

It is not necessary to explicitly drop `sum_y' and `sum_z' when you are finished, although you may if you wish. Stata will automatically drop any variables with names assigned by tempvar. After issuing the tempvar command, you must refer to the names with the enclosing quotes, which signifies macro expansion. Thus, after typing tempvar sum_y—the one case where you do not put single quotes around the name—refer thereafter to the variable `sum_y', with quotes. tempvar does not create temporary variables. Instead tempvar creates names that may later be used to create new variables that will be temporary, and tempvar stores that name in the local macro whose name you provide.

A full description of tempvar can be found in [P] **macro**.

18.7.2 Temporary scalars and matrices

tempname works just like tempvar. For instance, a piece of your code might read

```
tempname YXX XXinv
matrix accum `YXX' = price weight mpg
matrix `XXinv' = invsym(`YXX'[2..., 2...])
tempname b
matrix `b' = `XXinv'*`YXX'[1..., 1]
```

The above code solves for the coefficients of a regression on price on weight and mpg; see **[U] 14 Matrix expressions** and [P] **matrix** for more information on the matrix commands.

As with temporary variables, temporary scalars and matrices are automatically dropped at the conclusion of your program.

18.7.3 Temporary files

In cases where you ordinarily might think you need temporary files, you may not because of Stata's ability to preserve and automatically restore the data in memory; see **[U] 18.6 Temporarily destroying the data in memory** above.

For more complicated programs, Stata does provide temporary files. A code fragment might read

```
preserve                          /* save original data */
tempfile males females
keep if sex==1
save "‘males’"
restore, preserve                 /* get back original data */
keep if sex==0
save "‘females’"
```

As with temporary variables, scalars, and matrices, it is not necessary to delete the temporary files when you are through with them; Stata automatically erases them when your program ends.

18.7.4 Temporary frames

You might want a program to temporarily create an additional dataset in memory without disturbing the dataset in the current frame. You can obtain a temporary name for a frame, copy or load data into it, and perform manipulations on those data. When your program is done, that frame and the data in it will automatically be removed from memory. For example, some code might read

```
tempname frname
frame copy default ‘frname’
frame ‘frname’ {
    commands which modify the data in frame ‘frname’
}
...
```

When your program exits, successfully or not, any temporary frames it created will automatically be removed from memory.

18.8 Accessing results calculated by other programs

Stata commands that report results also store the results where they can be subsequently used by other commands or programs. This is documented in the *Stored results* section of the particular command in the reference manuals. Commands store results in one of three places:

1. r-class commands, such as `summarize`, store their results in `r()`; most commands are r-class.
2. e-class commands, such as `regress`, store their results in `e()`; e-class commands are Stata's model estimation commands.
3. s-class commands (there are no good examples) store their results in `s()`; this is a rarely used class that programmers sometimes find useful to help parse input.

Commands that do not store results are called n-class commands. More correctly, these commands require that you state where the result is to be stored, as in `generate` *newvar* = ...

▷ Example 1

You wish to write a program to calculate the standard error of the mean, which is given by the formula $\sqrt{s^2/n}$, where s^2 is the calculated variance. (You could obtain this statistic by using the `ci` command, but we will pretend that is not true.) You look at [R] **summarize** and learn that the mean is stored in `r(mean)`, the variance in `r(Var)`, and the number of observations in `r(N)`. With that knowledge, you write the following program:

```
program meanse
        quietly summarize `1'
        display "      mean = " r(mean)
        display "SE of mean = " sqrt(r(Var)/r(N))
end
```

The result of executing this program is

```
. meanse mpg
      mean = 21.297297
SE of mean = .67255109
```

◁

If you run an r-class command and type `return list` or run an e-class command and type `ereturn list`, Stata will summarize what was stored:

```
. use https://www.stata-press.com/data/r19/auto
(1978 automobile data)
. regress mpg weight displ
  (output omitted)
. ereturn list
scalars:
                  e(N) =  74
              e(sum_w) =  74
               e(df_m) =  2
               e(df_r) =  71
                  e(F) =  66.78504752026517
                 e(r2) =  .6529306984682528
               e(rmse) =  3.45606176570828
                e(mss) =  1595.409691543724
                e(rss) =  848.0497679157351
               e(r2_a) =  .643154098425105
                 e(ll) =  -195.2397979466294
               e(ll_0) =  -234.3943376482347
               e(rank) =  3
macros:
            e(cmdline) : "regress mpg weight displ"
              e(title) : "Linear regression"
          e(marginsok) : "XB default"
                e(vce) : "ols"
            e(depvar) : "mpg"
                e(cmd) : "regress"
         e(properties) : "b V"
            e(predict) : "regres_p"
              e(model) : "ols"
          e(estat_cmd) : "regress_estat"
```

```
matrices:
                  e(b) :  1 x 3
                  e(V) :  3 x 3
               e(beta) :  1 x 2
functions:
             e(sample)
. summarize mpg if foreign
    Variable |        Obs        Mean    Std. dev.       Min        Max
-------------+---------------------------------------------------------
         mpg |         22    24.77273    6.611187         14         41
. return list
scalars:
                  r(N) =  22
              r(sum_w) =  22
               r(mean) =  24.77272727272727
                r(Var) =  43.70779220779221
                 r(sd) =  6.611186898567625
                r(min) =  14
                r(max) =  41
                r(sum) =  545
```

In the example above, we ran `regress` followed by `summarize`. As a result, `e(N)` records the number of observations used by `regress` (equal to 74), and `r(N)` records the number of observations used by `summarize` (equal to 22). `r(N)` and `e(N)` are not the same.

If we now ran another r-class command—say, `tabulate`—the contents of `r()` would change, but those in `e()` would remain unchanged. You might, therefore, think that if we then ran another e-class command, say, `probit`, the contents of `e()` would change, but `r()` would remain unchanged. Although it is true that `e()` results remain in place until the next e-class command is executed, do not depend on `r()` remaining unchanged. If an e-class or n-class command were to use an r-class command as a subroutine, that would cause `r()` to change. Anyway, most commands are r-class, so the contents of `r()` change often.

❑ Technical note

It is, therefore, of great importance that you access results stored in `r()` immediately after the command that sets them. If you need the mean and variance of the variable `‘1’` for subsequent calculation, do *not* code

```
summarize ‘1’
...
... r(mean) ... r(Var) ...
```

Instead, code

```
summarize ‘1’
local mean = r(mean)
local var = r(Var)
...
... ‘mean’ ... ‘var’ ...
```

or

```
tempname mean var
summarize `1'
scalar `mean' = r(mean)
scalar `var' = r(Var)
...
... `mean' ... `var' ...
```

❑

Stored results, whether in `r()` or `e()`, come in three types: scalars, macros, and matrices. If you look back at the `ereturn list` and `return list` output, you will see that `regress` stores examples of all three, whereas `summarize` stores just scalars. (`regress` also stores the "function" `e(sample)`, as do all the other e-class commands; see **[U] 20.7 Specifying the estimation subsample**.)

Regardless of the type of `e(`*name*`)` or `r(`*name*`)`, you can just refer to `e(`*name*`)` or `r(`*name*`)`. That was the rule we gave in **[U] 13.6 Accessing results from Stata commands**, and that rule is sufficient for most uses. There is, however, another way to refer to stored results. Rather than referring to `r(`*name*`)` and `e(`*name*`)`, you can embed the reference in macro-substitution characters `` ` ' `` to produce `` `r(`*name*`)' `` and `` `e(`*name*`)' ``. The result is the same as macro substitution; the stored result is evaluated, and then the evaluation is substituted:

```
. display "You can refer to " e(cmd) " or to `e(cmd)'"
You can refer to regress or to regress
```

This means, for instance, that typing `` `e(cmd)' `` is the same as typing `regress` because `e(cmd)` contains "`regress`":

```
. `e(cmd)'
      Source |       SS           df       MS      Number of obs   =        74
-------------+----------------------------------   F(2, 71)        =     66.79
       Model |  1595.40969         2  797.704846   Prob > F        =    0.0000
```
(*remaining output omitted*)

In the `ereturn list`, `e(cmd)` was listed as a macro, and when you place a macro's name in single quotes, the macro's contents are substituted, so this is hardly a surprise.

What is surprising is that you can do this with scalar and even matrix stored results. `e(N)` is a scalar equal to 74 and may be used as such in any expression such as "`display e(mss)/e(N)`" or "`local meanss = e(mss)/e(N)`". `` `e(N)' `` substitutes to the string "74" and may be used in any context whatsoever, such as "`local val`` `e(N)' `` = e(N)`" (which would create a macro named `val74`). The rules for referring to stored results are

1. You may refer to `r(`*name*`)` or `e(`*name*`)` without single quotes in any expression and only in an expression. (Referring to s-class `s(`*name*`)` without single quotes is not allowed.)
   - 1.1 If *name* does not exist, missing value (`.`) is returned; it is not an error to refer to a nonexistent stored result.
   - 1.2 If *name* is a scalar, the full double-precision value of *name* is returned.
   - 1.3 If *name* is a macro, it is examined to determine whether its contents can be interpreted as a number. If so, the number is returned; otherwise, the string contents of *name* are returned.
   - 1.4 If *name* is a matrix, the full *matrix* is returned.

2. You may refer to `‘r(`*name*`)’`, `‘e(`*name*`)’`, or `‘s(`*name*`)’`—note the presence of quotes indicating macro substitution—in any context whatsoever.

   2.1 If *name* does not exist, nothing is substituted; it is not an error to refer to a nonexistent stored result. The resulting line is the same as if you had never typed `‘r(`*name*`)’`, `‘e(`*name*`)’`, or `‘s(`*name*`)’`.

   2.2 If *name* is a scalar, a string representation of the number accurate to no less than 12 digits of precision is substituted.

   2.3 If *name* is a macro, the full contents are substituted.

   2.4 If *name* is a matrix, the word `matrix` is substituted.

In general, you should refer to scalar and matrix stored results without quotes—`r(`*name*`)` and `e(`*name*`)`—and to macro stored results with quotes—`‘r(`*name*`)’`, `‘e(`*name*`)’`, and `‘s(`*name*`)’`—but it is sometimes convenient to switch. Say that stored result `r(example)` contains the number of periods patients are observed, and assume that `r(example)` was stored as a macro and not as a scalar. You could still refer to `r(example)` without the quotes in an expression context and obtain the expected result. It would have made more sense for you to have stored `r(example)` as a scalar, but really it would not matter, and the user would not even have to know how the stored result was stored.

Switching the other way is sometimes useful, too. Say that stored result `r(N)` is a scalar that contains the number of observations used. You now want to use some other command that has an `n(#)` option that specifies the number of observations used. You could not type `n(r(N))` because the syntax diagram says that the `n()` option expects its argument to be a literal number. Instead, you could type `n(‘r(N)’)`.

18.9 Accessing results calculated by estimation commands

Estimation results are stored in `e()`, and you access them in the same way you access any stored result; see **[U] 18.8 Accessing results calculated by other programs** above. In summary,

1. Estimation commands—`regress`, `logistic`, etc.—store results in `e()`.
2. Estimation commands store their name in `e(cmd)`. For instance, `regress` stores “`regress`” and `poisson` stores “`poisson`” in `e(cmd)`.
3. Estimation commands store the command they executed in `e(cmdline)`. For instance, if you typed `reg mpg displ`, stored in `e(cmdline)` would be “`reg mpg displ`”.
4. Estimation commands store the number of observations used in `e(N)`, and they identify the estimation subsample by setting `e(sample)`. You could type, for instance, `summarize if e(sample)` to obtain summary statistics on the observations used by the estimator.
5. Estimation commands store the entire coefficient vector and variance–covariance matrix of the estimators in `e(b)` and `e(V)`. These are matrices, and they may be manipulated like any other matrix:

```
. matrix list e(b)
e(b)[1,3]
        weight       displ       _cons
y1  -.00656711   .00528078   40.084522
. matrix y = e(b)*e(V)*e(b)'
. matrix list y
symmetric y[1,1]
          y1
y1  6556.982
```

6. Estimation commands set _b[*name*] and _se[*name*] as convenient ways to use coefficients and their standard errors in expressions; see [U] **13.5 Accessing coefficients and standard errors**.
7. Estimation commands may set other e() scalars, macros, or matrices containing more information. This is documented in the *Stored results* section of the particular command in the command reference.

Estimation commands also store results in r(). The r(table) matrix stores the results that you see in the coefficient table in the output. This includes the coefficients, standard errors, test statistics, *p*-values, and confidence intervals.

▷ Example 2

If you are writing a command for use after regress, early in your code you should include the following:

```
if "`e(cmd)'" != "regress" {
        error 301
}
```

This is how you verify that the estimation results that are stored have been set by regress and not by some other estimation command. Error 301 is Stata's "last estimates not found" error.

◁

18.10 Storing results

If your program calculates something, it should store the results of the calculation so that other programs can access them. In this way, your program not only can be used interactively but also can be used as a subroutine for other commands.

Storing results is easy:

1. On the program line, specify the rclass, eclass, or sclass option according to whether you intend to return results in r(), e(), or s().
2. Code

return scalar *name* = *exp*	(same syntax as scalar without the return)
return local *name* ...	(same syntax as local without the return)
return matrix *name matname*	(moves *matname* to r(*name*))

   to store results in r().
3. Code

ereturn *name* = *exp*	(same syntax as scalar without the ereturn)
ereturn local *name* ...	(same syntax as local without the ereturn)
ereturn matrix *name matname*	(moves *matname* to e(*name*))

   to store results in e(). You do not store the coefficient vector and variance matrix e(b) and e(V) in this way; instead you use ereturn post.
4. Code

sreturn local *name* ...	(same syntax as local without the sreturn)

   to store results in s(). (The s-class has only macros.)

A program must be exclusively r-class, e-class, or s-class.

18.10.1 Storing results in r()

In [U] 18.8 Accessing results calculated by other programs, we showed an example that reported the mean and standard error of the mean. A better version would store in r() the results of its calculations and would read

```
program meanse, rclass
        quietly summarize `1'
        local mean = r(mean)
        local sem  = sqrt(r(Var)/r(N))
        display "      mean = " `mean'
        display "SE of mean = " `sem'
        return scalar mean = `mean'
        return scalar se = `sem'
end
```

Running meanse now sets r(mean) and r(se):

```
. meanse mpg
      mean = 21.297297
SE of mean = .67255109

. return list

scalars:
       r(se)       =  .6725510870764975
       r(mean)     =  21.2972972972973
```

In this modification, we added the rclass option to the program statement, and we added two return commands to the end of the program.

Although we placed the return statements at the end of the program, they may be placed at the point of calculation if that is more convenient. A more concise version of this program would read

```
program meanse, rclass
        quietly summarize `1'
        return scalar mean = r(mean)
        return scalar se = sqrt(r(Var)/r(N))
        display "      mean = " return(mean)
        display "SE of mean = " return(se)
end
```

The return() function is just like the r() function, except that return() refers to the results that this program *will* return rather than to the stored results that currently *are* returned (which here are due to summarize). That is, when you code the return command, the result is not immediately posted to r(). Rather, Stata holds onto the result in return() until your program concludes, and then it copies the contents of return() to r(). While your program is active, you may use the return() function to access results you have already "returned". (return() works just like r() works after your program returns, meaning that you may code `return()' to perform macro substitution.)

18.10.2 Storing results in e()

Storing in e() is in most ways similar to saving in r(): you add the eclass option to the program statement, and then you use ereturn ... just as you used return ... to store results. There are, however, some significant differences:

1. Unlike r(), estimation results are stored in e() the instant you issue an ereturn scalar, ereturn local, or ereturn matrix command. Estimation results can consume considerable memory, and Stata does not want to have multiple copies of the results floating around. That means you must be more organized and post your results at the end of your program.

2. In your code when you have your estimates and are ready to begin posting, you will first clear the previous estimates, set the coefficient vector `e(b)` and corresponding variance matrix `e(V)`, and set the estimation-sample function `e(sample)`. How you do this depends on how you obtained your estimates:

   2.1 If you obtained your estimates by using Stata's likelihood maximizer `ml`, this is automatically handled for you; skip to step 3.

   2.2 If you obtained estimates by "stealing" an existing estimator, `e(b)`, `e(V)`, and `e(sample)` already exist, and you will not want to clear them; skip to step 3.

   2.3 If you write your own code from start to finish, you use the `ereturn post` command; see [P] **ereturn**. You will code something like "`ereturn post 'b' 'V', esample('touse')`", where `'b'` is the name of the coefficient vector, `'V'` is the name of the corresponding variance matrix, and `'touse'` is the name of a variable containing 1 if the observation was used and 0 if it was ignored. `ereturn post` clears the previous estimates and moves the coefficient vector, variance matrix, and variable into `e(b)`, `e(V)`, and `e(sample)`.

   2.4 A variation on (2.3) is when you use an existing estimator to produce the estimates but do not want all the other `e()` results stored by the estimator. Then you code

```
tempvar touse
tempname b V
matrix 'b' = e(b)
matrix 'V' = e(V)
quietly generate byte 'touse' = e(sample)
ereturn post 'b' 'V', esample('touse')
```

3. You now store anything else in `e()` that you wish by using the `ereturn scalar`, `ereturn local`, or `ereturn matrix` command.

4. Save `e(cmdline)` by coding

```
ereturn local cmdline '"cmdname '0'"'
```

   This is not required, but it is considered good style.

5. You code `ereturn local cmd "`*cmdname*`"`. Stata does not consider estimation results complete until this command is posted, and Stata considers the results to be complete when this is posted, so you must remember to do this and to do this last. If you set `e(cmd)` too early and the user pressed *Break*, Stata would consider your estimates complete when they are not.

Say that you wish to write the estimation command with syntax

`myest` *depvar* var_1 var_2 [*if*] [*in*] *optset1 optset2*

where *optset1* affects how results are displayed and *optset2* affects the estimation results themselves. One important characteristic of estimation commands is that, when typed without arguments, they redisplay the previous estimation results. The outline is

```
program myest, eclass
        local options "optset1"
        if replay() {
                if "`e(cmd)'"!="myest" {
                        error 301             /* last estimates not found       */
                }
                syntax [, `options']
        }
        else {
                syntax varlist [if] [in] [, `options' optset2]
                marksample touse
Code contains either this,
                tempnames b V
                commands for performing estimation
                assume produces `b' and `V'
                ereturn post `b' `V', esample(`touse')
                ereturn local depvar "`depv'"
or this,
                ml model ... if `touse' ...
and regardless, concludes,
                perhaps other ereturn commands appear here
                ereturn local cmdline `"myest `0'"'
                ereturn local cmd "myest"
        }
                                              /* (re)display results ...        */
code typically reads
        code to output header above coefficient table
        ereturn display                      /* displays coefficient table      */
or
        ml display                           /* displays header and coef. table */
end
```

Here is a list of the commonly stored `e()` results. Of course, you may create any `e()` results that you wish.

`e(N)` (scalar)
Number of observations.

`e(df_m)` (scalar)
Model degrees of freedom.

`e(df_r)` (scalar)
"Denominator" degrees of freedom if estimates are nonasymptotic.

`e(r2_p)` (scalar)
Value of the pseudo-R^2 if it is calculated. (If a "real" R^2 is calculated as it would be in linear regression, it is stored in (scalar) `e(r2)`.)

`e(F)` (scalar)
Test of the model against the constant-only model, if relevant, and if results are nonasymptotic.

`e(ll)` (scalar)
Log-likelihood value, if relevant.

`e(ll_0)` (scalar)
Log-likelihood value for constant-only model, if relevant.

`e(N_clust)` (scalar)
Number of clusters, if any.

e(chi2) (scalar)
Test of the model against the constant-only model, if relevant, and if results are asymptotic.

e(rank) (scalar)
Rank of e(V).

e(cmd) (macro)
Name of the estimation command.

e(cmdline) (macro)
Command as typed.

e(depvar) (macro)
Names of the dependent variables.

e(wtype) and e(wexp) (macros)
If weighted estimation was performed, e(wtype) contains the weight type (fweight, pweight, etc.) and e(wexp) contains the weighting expression.

e(title) (macro)
Title in estimation output.

e(clustvar) (macro)
Name of the cluster variable, if any.

e(vcetype) (macro)
Text to appear above standard errors in estimation output; typically Robust, Bootstrap, Jackknife, or "".

e(vce) (macro)
vcetype specified in vce().

e(chi2type) (macro)
LR or Wald or other depending on how e(chi2) was performed.

e(properties) (macro)
Typically contains b V.

e(predict) (macro)
Name of the command that predict is to use; if this is blank, predict uses the default _predict.

e(b) and e(V) (matrices)
The coefficient vector and corresponding variance matrix. Stored when you coded ereturn post.

e(sample) (function)
This function was defined by ereturn post's esample() option if you specified it. You specified a variable containing 1 if you used an observation and 0 otherwise. ereturn post stole the variable and created e(sample) from it.

18.10.3 Storing results in s()

s() is a strange class because, whereas the other classes allow scalars, macros, and matrices, s() allows only macros.

s() is seldom used and is for subroutines that you might write to assist in parsing the user's input prior to evaluating any user-supplied expressions.

Here is the problem that s() solves: say that you create a nonstandard syntax for some command so that you have to parse through it yourself. The syntax is so complicated that you want to create subroutines to take pieces of it and then return information to your main routine. Assume that your syntax contains expressions that the user might type. Now say that one of the expressions the user types is, for example, r(mean)/sqrt(r(Var))—perhaps the user is using results left behind by summarize.

If, in your parsing step, you call subroutines that return results in r(), you will wipe out r(mean) and r(Var) before you ever get around to seeing them, much less evaluating them. So, you must be careful to leave r() intact until your parsing is complete; you must use no r-class commands, and any subroutines you write must not touch r(). You must use s-class subroutines because s-class routines return results in s() rather than r(). S-class provides macros only because that is all you need to solve parsing problems.

To create an s-class routine, specify the sclass option on the program line and then use sreturn local to return results.

S-class results are posted to s() at the instant you issue the sreturn() command, so you must organize your results. Also, s() is never automatically cleared, so occasionally coding sreturn clear at appropriate points in your code is a good idea. Few programs need s-class subroutines.

The collect suite of commands is one of the few examples in which results are posted to s(). This collection system gathers results from r() and e(), so posting its results to s() allows it to leave the r() and e() results intact.

18.11 Ado-files

Ado-files were introduced in **[U] 17 Ado-files**.

When a user types '*gobbledygook*', Stata first asks itself if *gobbledygook* is one of its built-in commands. If so, the command is executed. Otherwise, it asks itself if *gobbledygook* is a defined program. If so, the program is executed. Otherwise, Stata looks in various directories for *gobbledygook*.ado. If there is no such file, the process ends with the "unrecognized command" error.

If Stata finds the file, it quietly issues to itself the command '`run` *gobbledygook*`.ado`' (specifying the path explicitly). If that runs without error, Stata asks itself again if *gobbledygook* is a defined program. If not, Stata issues the "unrecognized command" error. (Here somebody wrote a bad ado-file.) If the program is defined, as it should be, Stata executes it.

Thus you can arrange for programs you write to be loaded automatically. For instance, if you were to create hello.ado containing

begin hello.ado
```
program hello
        display "hi there"
end
```
end hello.ado

and store the file in your current directory or your personal directory (see **[U] 17.5.2 Where is my personal ado-directory?**), you could type hello and be greeted by a reassuring

```
. hello
hi there
```

You could, at that point, think of hello as just another part of Stata.

There are two places to put your personal ado-files. One is the current directory, and that is a good choice when the ado-file is unique to a project. You will want to use it only when you are in that directory. The other place is your *personal ado-directory*, which is probably something like `C:\ado\personal` if you use Windows, `~/ado/personal` if you use Unix, and `~/ado/personal` if you use a Mac. We are guessing.

To find your personal ado-directory, enter Stata and type

```
. personal
```

❑ Technical note

Stata looks in various directories for ado-files, defined by the c-class value `c(adopath)`, which contains

```
BASE;SITE;.;PERSONAL;PLUS;OLDPLACE
```

The words in capital letters are codenames for directories, and the mapping from codenames to directories can be obtained by typing the `sysdir` command. Here is what `sysdir` shows on one particular Windows computer:

```
. sysdir
   STATA:  C:\Program Files\Stata19\
    BASE:  C:\Program Files\Stata19\ado\base\
    SITE:  C:\Program Files\Stata19\ado\site\
    PLUS:  C:\ado\plus\
PERSONAL:  C:\ado\personal\
OLDPLACE:  C:\ado\
```

Even if you use Windows, your mapping might be different because it all depends on where you installed Stata. That is the point of the codenames. They make it possible to refer to directories according to their logical purposes rather than their physical location.

The c-class value `c(adopath)` is the search path, so in looking for an ado-file, Stata first looks in `BASE` then in `SITE`, and so on, until it finds the file. Actually, Stata not only looks in `BASE` but also takes the first letter of the ado-file it is looking for and looks in the lettered subdirectory. For files with the extension `.style`, Stata will look in a subdirectory named `style` rather than a lettered subdirectory. Say that Stata was looking for `gobbledygook.ado`. Stata would look up `BASE` (`C:\Program Files\Stata19\ado\base` in our example) and, if the file were not found there, it would look in the `g` subdirectory of `BASE` (`C:\Program Files\Stata19\ado\base\g`) before looking in `SITE`, whereupon it would follow the same rules. If Stata were looking for `gobbledygook.style`, Stata would look up `BASE` (`C:\Program Files\Stata19\ado\base` in our example) and, if the file were not found there, it would look in the `style` subdirectory of `BASE` (`C:\Program Files\Stata19\ado\base\style`) before looking in `SITE`, whereupon it would follow the same rules.

Why the extra complication? We distribute hundreds of ado-files, help files, and other file types with Stata, and some operating systems have difficulty dealing with so many files in the same directory. All operating systems experience at least a performance degradation. To prevent this, the ado-directory we ship is split 31 ways (letters *a*–*z*, underscore, `jar`, `py`, `resource`, and `style`). Thus the Stata command `ci`, which is implemented as an ado-file, can be found in the subdirectory `c` of `BASE`.

If you write ado-files, you can structure your personal ado-directory this way, too, but there is no reason to do so until you have more than, say, 250 files in one directory.

❑

❑ Technical note

After finding and running *gobbledygook*.ado, Stata calculates the total size of all programs that it has automatically loaded. If this exceeds adosize (see [P] **sysdir**), Stata begins discarding the oldest automatically loaded programs until the total is less than adosize. Oldest here is measured by the time last used, not the time loaded. This discarding saves memory and does not affect you, because any program that was automatically loaded could be automatically loaded again if needed.

It does, however, affect performance. Loading the program takes time, and you will again have to wait if you use one of the previously loaded-and-discarded programs. Increasing adosize reduces this possibility, but at the cost of memory. The set adosize command allows you to change this parameter; see [P] **sysdir**. The default value of adosize is 1,000. A value of 1,000 for adosize means that up to 1,000 K can be allocated to autoloaded programs. Experimentation has shown that this is a good number—increasing it does not improve performance much.

❑

18.11.1 Version

We recommend that the first line following program in your ado-file declare the Stata release under which you wrote the program; hello.ado would read better as

begin hello.ado

```
program hello
version 19.5      // (or version 19 if you do not have StataNow)
        display "hi there"
end
```

end hello.ado

We introduced the concept of version in [U] **16.1.1 Version**. In regular do-files, we recommend that the version line appear as the first line of the do-file. For ado-files, the line appears after the program because loading the ado-file is one step and executing the program is another. It is when Stata executes the program defined in the ado-file that we want to stipulate the interpretation of the commands.

The inclusion of the version line is of more importance in ado-files than in do-files because ado-files have longer lives than do-files, so it is more likely that you will use an ado-file with a later release and ado-files tend to use more of Stata's features, increasing the probability that any change to Stata will affect them.

18.11.2 Comments and long lines in ado-files

Comments in ado-files are handled the same way as in do-files: you enclose the text in /* comment */ brackets, or you begin the line with an asterisk (*), or you interrupt the line with //; see [U] **16.1.2 Comments and blank lines in do-files**.

Logical lines longer than physical lines are also handled as they are in do-files: either you change the delimiter to a semicolon (;) or you comment out the new line by using /// at the end of the previous physical line.

18.11.3 Debugging ado-files

Debugging ado-files is a little tricky because it is Stata and not you that controls when the ado-file is loaded.

Assume that you wanted to change `hello` to say "Hi, Mary". You open `hello.ado` in the Do-file Editor and change it to read

begin `hello.ado`

```
program hello
version 19.5      // (or version 19 if you do not have StataNow)
        display "hi, Mary"
end
```

end `hello.ado`

After saving it, you try it:

```
. hello
hi there
```

Stata ran the old copy of `hello`—the copy it still has in its memory. Stata wants to be fast about executing ado-files, so when it loads one, it keeps it around a while—waiting for memory to get short—before clearing it from its memory. Naturally, Stata can drop `hello` anytime because it can always reload it from disk.

You changed the copy on disk, but Stata still has the old copy loaded into memory. You type `discard` to tell Stata to forget these automatically loaded things and to force itself to get new copies of the ado-files from disk:

```
. discard
. hello
hi, Mary
```

You had to type `discard` only because you changed the ado-file while Stata was running. Had you exited Stata and returned later to use `hello`, the `discard` would not have been necessary because Stata forgets things between sessions anyway.

18.11.4 Local subroutines

An ado-file can contain more than one `program`, and if it does, the other programs defined in the ado-file are assumed to be subroutines of the main program. For example,

begin `decoy.ado`

```
program decoy
        ...
        duck ...
        ...
end
program  duck
        ...
end
```

end `decoy.ado`

`duck` is considered a local subroutine of `decoy`. Even after `decoy.ado` was loaded, if you typed `duck`, you would be told "unrecognized command". To emphasize what *local* means, assume that you have also written an ado-file named `duck.ado`:

begin `duck.ado`

```
program duck
        ...
end
```

end `duck.ado`

Even so, when decoy called duck, it would be the program duck defined in decoy.ado that was called. To further emphasize what *local* means, assume that decoy.ado contains

begin decoy.ado

```
program decoy
        ...
        manic ...
        ...
        duck ...
        ...
end
program duck
        ...
end
```

end decoy.ado

and that manic.ado contained

begin manic.ado

```
program manic
        ...
        duck ...
        ...
end
```

end manic.ado

Here is what would happen when you executed decoy:

1. decoy in decoy.ado would begin execution. decoy calls manic.
2. manic in manic.ado would begin execution. manic calls duck.
3. duck in duck.ado (yes) would begin execution. duck would do whatever and return.
4. manic regains control and eventually returns.
5. decoy is back in control. decoy calls duck.
6. duck in decoy.ado would execute, complete, and return.
7. decoy would regain control and return.

When manic called duck, it was the global ado-file duck.ado that was executed, yet when decoy called duck, it was the local program duck that was executed.

Stata does not find this confusing and neither should you.

18.11.5 Development of a sample ado-command

Below we demonstrate how to create a new Stata command. We will program an influence measure for use with linear regression. It is an interesting statistic in its own right, but even if you are not interested in linear regression and influence measures, the focus here is on programming, not on the particular statistic chosen.

Belsley, Kuh, and Welsch (1980, 24) present a measure of influence in linear regression defined as

$$\frac{\mathrm{Var}\left(\widehat{y}_i^{(i)}\right)}{\mathrm{Var}(\widehat{y}_i)}$$

which is the ratio of the variance of the ith fitted value based on regression estimates obtained by omitting the ith observation to the variance of the ith fitted value estimated from the full dataset. This ratio is estimated using

$$\text{FVARATIO}_i \equiv \frac{n-k}{n-(k+1)}\left\{1-\frac{d_i^2}{1-h_{ii}}\right\}(1-h_{ii})^{-1}$$

where n is the sample size; k is the number of estimated coefficients; $d_i^2 = e_i^2/\mathbf{e}'\mathbf{e}$ and e_i is the ith residual; and h_{ii} is the ith diagonal element of the hat matrix. The ingredients of this formula are all available through Stata, so, after estimating the regression parameters, we can easily calculate FVARATIO_i. For instance, we might type

```
. regress mpg weight displ
. predict hii if e(sample), hat
. predict ei if e(sample), resid
. quietly count if e(sample)
. scalar nreg = r(N)
. generate eTe = sum(ei*ei)
. generate di2 = (ei*ei)/eTe[_N]
. generate FVi = (nreg - 3) / (nreg - 4) * (1 - di2/(1-hii)) / (1-hii)
```

The number 3 in the formula for `FVi` represents k, the number of estimated parameters (which is an intercept plus coefficients on `weight` and `displ`), and the number 4 represents $k+1$.

❑ Technical note

Do you understand why this works? `predict` can create h_{ii} and e_i, but the trick is in getting $\mathbf{e}'\mathbf{e}$—the sum of the squared e_is. Stata's `sum()` function creates a running sum. The first observation of `eTe` thus contains e_1^2; the second, $e_1^2+e_2^2$; the third, $e_1^2+e_2^2+e_3^2$; and so on. The last observation, then, contains $\sum_{i=1}^{N} e_i^2$, which is $\mathbf{e}'\mathbf{e}$. (We specified `if e(sample)` on our `predict` commands to restrict calculations to the estimation subsample, so `hii` and `eii` might have missing values, but that does not matter because `sum()` treats missing values as contributing zero to the sum.) We use Stata's explicit subscripting feature and then refer to `eTe[_N]`, the last observation. (See **[U] 13.3 Functions** and **[U] 13.7 Explicit subscripting**.) After that, we plug into the formula to obtain the result.

❑

Assuming that we often wanted this influence measure, it would be easier and less prone to error if we canned this calculation in a program. Our first draft of the program reflects exactly what we would have typed interactively:

begin `fvaratio.ado`, version 1

```
program fvaratio
version 19.5      // (or version 19 if you do not have StataNow)
        predict hii if e(sample), hat
        predict ei if e(sample), resid
        quietly count if e(sample)
        scalar nreg = r(N)
        generate eTe = sum(ei*ei)
        generate di2 = (ei*ei)/eTe[_N]
        generate FVi = (nreg - 3) / (nreg - 4) * (1 - di2/(1-hii)) / (1-hii)
        drop hii ei eTe di2
end
```

end `fvaratio.ado`, version 1

All we have done is to enter what we would have typed into a file, bracketing it with `program fvaratio` and `end`. Because our command is to be called `fvaratio`, the file must be named `fvaratio.ado` and must be stored in either the current directory or our personal ado-directory (see **[U] 17.5.2 Where is my personal ado-directory?**).

Now when we type `fvaratio`, Stata will be able to find it, load it, and execute it. In addition to copying the interactive lines into a program, we added the line `drop hii ...` to eliminate the working variables we had to create along the way.

So, now we can interactively type

```
. regress mpg weight displ
. fvaratio
```

and add the new variable `FVi` to our data.

Our program is not general. It is suitable for use after fitting a regression model on two, and only two, independent variables because we coded a `3` in the formula for k. Stata statistical commands such as `regress` store information about the problem and answer in `e()`. Looking in *Stored results* in [R] **regress**, we find that `e(df_m)` contains the model degrees of freedom, which is $k-1$, assuming that the model has an intercept. Also, the sample size of the dataset used in the regression is stored in `e(N)`, eliminating our need to count the observations and define a scalar containing this count. Thus the second draft of our program reads

begin `fvaratio.ado`, version 2

```
program fvaratio
version 19.5      // (or version 19 if you do not have StataNow)
        predict hii if e(sample), hat
        predict ei if e(sample), resid
        gen eTe = sum(ei*ei)
        gen di2 = (ei*ei)/eTe[_N]
        gen FVi = (e(N)-(e(df_m)+1)) / (e(N)-(e(df_m)+2)) *     /// changed this
                  (1 - di2/(1-hii)) / (1-hii)                    // version
        drop hii ei eTe di2
end
```

end `fvaratio.ado`, version 2

In the formula for `FVi`, we substituted `(e(df_m)+1)` for the literal number `3`, `(e(df_m)+2)` for the literal number `4`, and `e(N)` for the sample size.

Back to the substance of our problem, `regress` also stores the residual sum of squares in `e(rss)`, so calculating `eTe` is not really necessary:

begin `fvaratio.ado`, version 3

```
program fvaratio
version 19.5      // (or version 19 if you do not have StataNow)
        predict hii if e(sample), hat
        predict ei if e(sample), resid
        gen di2 = (ei*ei)/e(rss)                          // changed this version
        gen FVi = (e(N)-(e(df_m)+1)) / (e(N)-(e(df_m)+2)) *      ///
                  (1 - di2/(1-hii)) / (1-hii)
        drop hii ei di2
end
```

end `fvaratio.ado`, version 3

Our program is now shorter and faster, and it is completely general. This program is probably good enough for most users; if you were implementing this solely for your own occasional use, you could stop right here. The program does, however, have the following deficiencies:

1. When we use it with data with missing values, the answer is correct, but we see messages about the number of missing values generated. (These messages appear when the program is generating the working variables.)

2. We cannot control the name of the variable being produced—it is always called `FVi`. Moreover, when `FVi` already exists (say, from a previous regression), we get an error message that `FVi` already exists. We then have to `drop` the old `FVi` and type `fvaratio` again.

3. If we have created any variables named `hii`, `ei`, or `di2`, we also get an error that the variable already exists, and the program refuses to run.

Fixing these problems is not difficult. The fix for problem 1 is easy; we embed the entire program in a `quietly` block:

begin `fvaratio.ado`, version 4

```
program fvaratio
version 19.5      // (or version 19 if you do not have StataNow)
        quietly {                                       // new this version
                predict hii if e(sample), hat
                predict ei if e(sample), resid
                gen di2 = (ei*ei)/e(rss)
                gen FVi = (e(N)-(e(df_m)+1)) / (e(N)-(e(df_m)+2)) *      ///
                          (1 - di2/(1-hii)) / (1-hii)
                drop hii ei di2
        }                                               // new this version
end
```

end `fvaratio.ado`, version 4

The output for the commands between the `quietly {` and `}` is now suppressed—the result is the same as if we had put `quietly` in front of each command.

Solving problem 2—that the resulting variable is always called `FVi`—requires use of the `syntax` command. Let's put that off and deal with problem 3—that the working variables have nice names like `hii`, `ei`, and `di2`, and so prevent users from using those names in their data.

One solution would be to change the nice names to unlikely names. We could change `hii` to `MyHiiVaR`, which would not guarantee the prevention of a conflict but would certainly make it unlikely. It would also make our program difficult to read, an important consideration should we want to change it in the future. There is a better solution. Stata's `tempvar` command (see **[U] 18.7.1 Temporary variables**) places names into local macros that are guaranteed to be unique:

begin `fvaratio.ado`, version 5

```
program fvaratio
version 19.5      // (or version 19 if you do not have StataNow)
        tempvar hii ei di2                                  // new this version
        quietly {
                predict `hii' if e(sample), hat   // changed, as are other lines
                predict `ei' if e(sample), resid
                gen `di2' = (`ei'*`ei')/e(rss)
                gen FVi = (e(N)-(e(df_m)+1)) / (e(N)-(e(df_m)+2)) *      ///
                          (1 - `di2'/(1-`hii')) / (1-`hii')
        }
end
```

end `fvaratio.ado`, version 5

At the beginning of our program, we declare the temporary variables. (We can do it outside or inside the `quietly`—it makes no difference—and we do not have to do it at the beginning or even all at once; we could declare them as we need them, but at the beginning is prettiest.) When we refer to a temporary variable, we do not refer directly to it (such as by typing `hii`); we refer to it indirectly by typing open and close single quotes around the name (`` `hii' ``). And at the end of our program, we no longer bother to `drop` the temporary variables—temporary variables are dropped automatically by Stata when a program concludes.

❑ Technical note

Why do we type single quotes around the names? `tempvar` creates local macros containing the real temporary variable names. `hii` in our program is now a local macro, and `‘hii’` refers to the contents of the local macro, which is the variable’s actual name.

❑

We now have an excellent program—its only fault is that we cannot specify the name of the new variable to be created. Here is the solution to that problem:

begin `fvaratio.ado`, version 6

```
program fvaratio
version 19.5      // (or version 19 if you do not have StataNow)
        syntax newvarname                                   // new this version
        tempvar hii ei di2
        quietly {
                predict ‘hii’ if e(sample), hat
                predict ‘ei’ if e(sample), resid
                gen ‘di2’ = (‘ei’*‘ei’)/e(rss)
                gen ‘typlist’ ‘varlist’ = ///               changed this version
                        (e(N)-(e(df_m)+1)) / (e(N)-(e(df_m)+2)) *      ///
                        (1 - ‘di2’/(1-‘hii’)) / (1-‘hii’)
        }
end
```

end `fvaratio.ado`, version 6

It took a change to one line and the addition of another to obtain the solution. This magic all happens because of `syntax` (see **[U] 18.4.4 Parsing standard Stata syntax** above).

‘`syntax newvarname`’ specifies that one new variable name must be specified (had we typed ‘`syntax [newvarname]`’, the new varname would have been optional; had we typed ‘`syntax newvarlist`’, the user would have been required to specify at least one new variable and allowed to specify more). In any case, `syntax` compares what the user types to what is allowed. If what the user types does not match what we have declared, `syntax` will issue the appropriate error message and stop our program. If it does match, our program will continue, and what the user typed will be broken out and stored in local macros for us. For a `newvarname`, the new name typed by the user is placed in the local macro `varlist`, and the type of the variable (`float`, `double`, …) is placed in `typlist` (even if the user did not specify a storage type, in which case the type is the current default storage type).

This is now an excellent program. There are, however, two more improvements we could make. First, we have demonstrated that, by the use of ‘`syntax newvarname`’, we can allow the user to define not only the name of the created variable but also the storage type. However, when it comes to the creation of intermediate variables, such as `‘hii’` and `‘di2’`, it is good programming practice to keep as much precision as possible. We want our final answer to be precise as possible, regardless of how we ultimately decide to store it. Any calculation that uses a previously generated variable would benefit if the previously generated variable were stored in double precision. Below we modify our program appropriately:

begin fvaratio.ado, version 7

```
program fvaratio
version 19.5      // (or version 19 if you do not have StataNow)
        syntax newvarname
        tempvar hii ei di2
        quietly {
                predict double `hii' if e(sample), hat        // changed, as are
                predict double `ei' if e(sample), resid       // other lines
                gen double `di2' = (`ei'*`ei')/e(rss)
                gen `typlist' `varlist' =  ///
                        (e(N)-(e(df_m)+1)) / (e(N)-(e(df_m)+2)) *      ///
                        (1 - `di2'/(1-`hii')) / (1-`hii')
        }
end
```

end fvaratio.ado, version 7

As for the second improvement we could make, `fvaratio` is intended to be used sometime after `regress`. How do we know the user is not misusing our program and executing it after, say, `logistic`? `e(cmd)` will tell us the name of the last estimation command; see **[U] 18.9 Accessing results calculated by estimation commands** and **[U] 18.10.2 Storing results in e()**. We should change our program to read

begin fvaratio.ado, version 8

```
program fvaratio
version 19.5      // (or version 19 if you do not have StataNow)
        if "`e(cmd)'"!="regress" {                      // new this version
                error 301
        }
        syntax newvarname
        tempvar hii ei di2
        quietly {
                predict double `hii' if e(sample), hat
                predict double `ei' if e(sample), resid
                gen double `di2' = (`ei'*`ei')/e(rss)
                gen `typlist' `varlist' = ///
                        (e(N)-(e(df_m)+1)) / (e(N)-(e(df_m)+2)) *      ///
                        (1 - `di2'/(1-`hii')) / (1-`hii')
        }
end
```

end fvaratio.ado, version 8

The `error` command issues one of Stata's prerecorded error messages and stops our program. Error 301 is "last estimates not found"; see **[P] error**. (Try typing `error 301` at the command line.)

In any case, this is a perfect program.

❑ Technical note

You do not have to go to all the trouble we did to program the FVARATIO measure of influence or any other statistic that appeals to you. Whereas version 1 was not really an acceptable solution—it was too specialized—version 2 was acceptable. Version 3 was better, and version 4 better yet, but the improvements were of less and less importance.

Putting aside the details of Stata's language, you should understand that final versions of programs do not just happen—they are the results of drafts that have been refined. How much refinement depends on how often and who will be using the program. In this sense, the "official" ado-files that come with Stata are poor examples. They have been subject to substantial refinement because they will be used by strangers with no knowledge of how the code works. When writing programs for yourself, you may want to stop refining at an earlier draft.

❑

18.11.6 Writing help files

When you write an ado-file, you should also write a help file to go with it. This file is a standard text file, named *command*`.sthlp`, that you place in the same directory as your ado-file *command*`.ado`. This way, when users type `help` followed by the name of your new command (or pull down **Help**), they will see something better than "help for … not found".

You can obtain examples of help files by examining the `.sthlp` files in the official ado-directory; type "`sysdir`" and look in the lettered subdirectories of the directory defined as `BASE`:

```
. sysdir
   STATA:  C:\Program Files\Stata19\
    BASE:  C:\Program Files\Stata19\ado\base\
    SITE:  C:\Program Files\Stata19\ado\site\
    PLUS:  C:\ado\plus\
PERSONAL:  C:\ado\personal\
OLDPLACE:  C:\ado\
```

Here you would find examples of `.sthlp` files in the `a`, `b`, … subdirectories of `C:\Program Files\Stata19\ado\base`.

Help files are physically written on the disk in text format, but their contents are Stata Markup and Control Language (SMCL). For the most part, you can ignore that. If the file contains a line that reads

```
Also see help for the finishup command
```

it will display in just that way. However, SMCL contains many special directives, so that if the line in the file were to read

```
Also see {hi:help} for the {helpb finishup} command
```

what would be displayed would be

```
Also see help for the finishup command
```

and moreover, `finishup` would appear as a hypertext link, meaning that if users clicked on it, they would see help on `finishup`.

You can read about the details of SMCL in [P] **smcl**.

If you would like to see an example of SMCL code for a Stata help file, type `viewsource examplehelpfile.sthlp`. You can view the equivalent help file by selecting **Help > Stata command**, typing `examplehelpfile`, and clicking on **OK**, or you can type `help examplehelpfile`.

Users will find it easier to understand your programs if you document them the same way that we document ours. We offer the following guidelines:

1. The first line must be

   ```
   {smcl}
   ```

   This notifies Stata that the help file is in SMCL format.

2. The second line should be

   ```
   {* *! version #.#.#  date}{...}
   ```

   The `*` indicates a comment and the `{...}` will suppress the blank line. Whenever you edit the help file, update the version number and the date found in the comment line.

3. The next several lines denote what will be displayed in the quick access toolbar with the three pulldown menus: Dialog, Also See, and Jump To.

```
{vieweralsosee "[R] help" "help help "}{...}
{viewerjumpto "Syntax" "examplehelpfile##syntax"}{...}
{viewerjumpto "Description" "examplehelpfile##description"}{...}
{viewerjumpto "Options" "examplehelpfile##options"}{...}
{viewerjumpto "Remarks" "examplehelpfile##remarks"}{...}
{viewerjumpto "Examples" "examplehelpfile##examples"}{...}
```

4. Then place the title.

```
{title:Title}

{phang}
{bf:yourcmd} {hline 2} Your title
```

5. Include two blank lines, and place the Syntax title, syntax diagram, and options table:

```
{title:Syntax}

{p 8 17 2}
syntax line

{p 8 17 2}
second syntax line, if necessary

{synoptset 20 tabbed}{...}
{synopthdr}
{synoptline}
{syntab:tab}
{synopt:{option}}brief description of option{p_end}
{synoptline}
{p2colreset}{...}

{p 4 6 2}
clarifying text, if required
```

6. Include two blank lines, and place the Description title and text:

```
{title:Description}

{pstd}
description text
```

   Briefly describe what the command does. Do not burden the user with details yet. Assume that the user is at the point of asking whether this is what is wanted.

7. If your command allows options, include two blank lines, and place the Options title and descriptions:

```
{title:Options}

{phang}
{opt optionname} option description

{pmore}
continued option description, if necessary
```

{phang}
{opt *optionname*} *second option description*

Options should be included in the order in which they appear in the option table. Option paragraphs are reverse indented, with the option name on the far left, where it is easily spotted. If an option requires more than one paragraph, subsequent paragraphs are set using {pmore}. One blank line separates one option from another.

8. Optionally include two blank lines, and place the Remarks title and text:

   {title:Remarks}

   {pstd}
   text

   Include whatever long discussion you feel necessary. Stata's official system help files often omit this because the discussions appear in the manual. Stata's official help files for features added between releases (obtained from the *Stata Journal*, the Stata website, etc.), however, include this section because the appropriate *Stata Journal* may not be as accessible as the manuals.

9. Optionally include two blank lines, and place the Examples title and text:

   {title:Examples}

   {phang}
   {cmd:. *first example*}

   {phang}
   {cmd:. *second example*}

   Nothing communicates better than providing something beyond theoretical discussion. Examples rarely need much explanation.

10. Optionally include two blank lines, and place the Author title and text:

    {title:Author}

    {pstd}
    Name, affiliation, etc.

    Exercise caution. If you include a telephone number, expect your phone to ring. An email address may be more appropriate.

11. Optionally include two blank lines, and place the References title and text:

    {title:References}

    {pstd}
    Author. year.
    Title. Location: Publisher.

We also warn that it is easy to use too much {hi:highlighting}. Use it sparingly. In text, use {cmd:...} to show what would be shown in typewriter typeface it the documentation were printed in this manual.

❑ Technical note

Sometimes it is more convenient to describe two or more related commands in the same .sthlp file. Thus xyz.sthlp might document both the xyz and abc commands. To arrange that typing help abc displays xyz.sthlp, create the file abc.sthlp, containing

```
begin abc.sthlp
.h xyz
end abc.sthlp
```

When a `.sthlp` file contains one line of the form '`.h` *refname*', Stata interprets that as an instruction to display `help` for *refname*.

❑

❑ Technical note

If you write a collection of programs, you need to somehow index the programs so that users (and you) can find the command they want. We do that with our `contents.sthlp` entry. You should create a similar kind of entry. We suggest that you call your private entry `user.sthlp` in your personal ado-directory; see **[U] 17.5.2 Where is my personal ado-directory?**. This way, to review what you have added, you can type `help user`.

We suggest that Unix users at large sites also add `site.sthlp` to the `SITE` directory (typically `/usr/local/ado`, but type `sysdir` to be sure). Then you can type `help site` for a list of the commands available sitewide.

❑

18.11.7 Programming dialog boxes

You not only can write new Stata commands and help files but also can create your own interface, or dialog box, for a command you have written. Stata provides a dialog box programming language to allow you to create your own dialog boxes. In fact, most of the dialog boxes you see in Stata's interface have been created using this language.

This is not for the faint of heart, but if you want to create your own dialog box for a command, see **[P] Dialog programming**. The manual entry contains all the details on creating and programming dialog boxes.

18.12 Tools for interacting with programs outside Stata and with other languages

Advanced programmers may wish to interact Stata with other programs or to call programs or libraries written in other languages from Stata. Stata supports the following:

Shell out synchronously or asynchronously to another program	See [D] **shell**
Call code in libraries written in C, C++, FORTRAN, etc.	See [P] **plugin**
Call code written in Java	See [P] **Java intro**
Interact Stata and Python code	See [P] **PyStata intro**
Interact with an H2O cluster	See [P] **H2O intro**
Control Stata—send commands to it and retrieve results from it—from an external program via OLE Automation	See [P] **Automation**

18.13 A compendium of useful commands for programmers

You can use any Stata command in your programs and ado-files. Also, some commands are intended solely for use by Stata programmers. You should see the section under the *Programming* heading in the subject table of contents at the beginning of the *Stata Index*.

Also see the *Mata Reference Manual* for all the details on the Mata language within Stata.

18.14 References

Baum, C. F. 2016. *An Introduction to Stata Programming*. 2nd ed. College Station, TX: Stata Press.

Belsley, D. A., E. Kuh, and R. E. Welsch. 1980. *Regression Diagnostics: Identifying Influential Data and Sources of Collinearity*. New York: Wiley. https://doi.org/10.1002/0471725153.

Drukker, D. M. 2015. Programming an estimation command in Stata: Global macros versus local macros. *The Stata Blog: Not Elsewhere Classified*. https://blog.stata.com/2015/11/03/programming-an-estimation-command-in-stata-global-macros-versus-local-macros/.

Gould, W. W. 2001. Statistical software certification. *Stata Journal* 1: 29–50.

Haghish, E. F. 2019. Seamless interactive language interfacing between R and Stata. *Stata Journal* 19: 61–82.

Herrin, J. 2009. Stata tip 77: (Re)using macros in multiple do-files. *Stata Journal* 9: 497–498.

19 Immediate commands

Contents

19.1 Overview

An *immediate* command is a command that obtains data not from the data stored in memory but from numbers typed as arguments. Immediate commands, in effect, turn Stata into a glorified hand calculator.

There are many instances when you may not have the data, but you do know something about the data, and what you know is adequate to perform statistical tests. For instance, you do not have to have individual-level data to obtain the standard error of the mean, and thereby a confidence interval, if you know the mean, standard deviation, and number of observations. In other instances, you may actually have the data, and you could enter the data and perform the test, but it would be easier if you could just ask for the statistic based on a summary. For instance, you flip a coin 10 times, and it comes up heads twice. You could enter a 10-observation dataset with two ones (standing for heads) and eight zeros (meaning tails).

Immediate commands are meant to solve those problems. Immediate commands have the following properties:

1. They never disturb the data in memory. You can perform an immediate calculation as an aside without changing your data.
2. The syntax for these commands is the same, the command name followed by numbers, which are the summary statistics from which the statistic is calculated. The numbers are almost always summary statistics, and the order in which they are specified is in some sense "natural".
3. Immediate commands all end in the letter *i*, although the converse is not true. Usually, if there is an immediate command, there is a nonimmediate form also, that is, a form that works on the data in memory. For every statistical command in Stata, we have included an immediate form if it is reasonable to assume that you might know the requisite summary statistics without having the underlying data and if typing those statistics is not absurdly burdensome.
4. Immediate commands are documented along with their nonimmediate counterparts. Thus, if you want to obtain a confidence interval, whether it be from summary data with an immediate command or using the data in memory, use the table of contents or index to discover that [R] **ci** discusses confidence intervals. There, you learn that `ci` calculates confidence intervals by using the data in memory and that `cii` does the same with the data specified immediately following the command.

19.1.1 Examples

▷ Example 1

Let's take the example of confidence intervals. Professional papers often publish the mean, standard deviation, and number of observations for variables used in the analysis. Those statistics are sufficient for calculating a confidence interval. If we know that the mean mileage rating of cars in some sample is 24, that the standard deviation is 6, and that there are 97 cars in the sample, we can calculate

```
. cii means 97 24 6
```

Variable	Obs	Mean	Std. err.	[95% conf.	interval]
	97	24	.6092077	22.79073	25.20927

We learn that the mean's standard error is 0.61 and its 95% confidence interval is $[\,22.8, 25.2\,]$. To obtain this, we typed `cii means` (the immediate form of the `ci means` command) followed by the number of observations, the mean, and the standard deviation. We knew the order in which to specify the numbers because we had read [R] **ci**.

We could use the immediate form of the `ttest` command to test the hypothesis that the true mean is 22:

```
. ttesti 97 24 6 22
One-sample t test
```

	Obs	Mean	Std. err.	Std. dev.	[95% conf.	interval]
x	97	24	.6092077	6	22.79073	25.20927

```
    mean = mean(x)                                     t =   3.2830
H0: mean = 22                     Degrees of freedom =       96

    Ha: mean < 22               Ha: mean != 22                 Ha: mean > 22
 Pr(T < t) = 0.9993         Pr(|T| > |t|) = 0.0014          Pr(T > t) = 0.0007
```

The first three numbers were as we specified in the `cii means` command. `ttesti` requires a fourth number, which is the constant against which the mean is being tested; see [R] **ttest**.

◁

▷ Example 2

We mentioned flipping a coin 10 times and having it come up heads twice. We can use `cii proportions` to compute, for example, the 99% confidence interval:

```
. cii proportions 10 2, level(99)
```

Variable	Obs	Proportion	Std. err.	Binomial exact [99% conf.	interval]
	10	.2	.1264911	.0108505	.6482012

The `cii proportions` command requires that we specify the number of trials and the number of successes from a binomial experiment; see [R] **ci**.

The immediate form of the `bitest` command performs exact hypothesis testing:

```
. bitesti 10 2 .5
Binomial probability test
            N   Observed k   Expected k   Assumed p   Observed p
------------------------------------------------------------------
           10            2            5     0.50000      0.20000
  Pr(k >= 2)            = 0.989258  (one-sided test)
  Pr(k <= 2)            = 0.054688  (one-sided test)
  Pr(k <= 2 or k >= 8) = 0.109375  (two-sided test)
```

For a full explanation of this output, see [R] **bitest**.

◁

▷ Example 3

Stata's `tabulate` command makes tables and calculates various measures of association. The immediate form, `tabi`, does the same, but we specify the contents of the table following the command:

```
. tabi 5 10 \ 2 14
           |        col
       row |         1          2 |     Total
-----------+----------------------+----------
         1 |         5         10 |        15
         2 |         2         14 |        16
-----------+----------------------+----------
     Total |         7         24 |        31
          Fisher's exact =                 0.220
  1-sided Fisher's exact =                 0.170
```

The `tabi` command is slightly different from most immediate commands because it uses '\' to indicate where one row ends and another begins.

◁

19.1.2 A list of the immediate commands

Command	Reference	Description
bitesti	[R] **bitest**	Binomial probability test
cci csi iri mcci	[R] **Epitab**	Tables for epidemiologists
cii	[R] **ci**	Confidence intervals for means, proportions, and variances
esizei	[R] **esize**	Effect size based on mean comparison
prtesti	[R] **prtest**	Tests of proportions
sdtesti	[R] **sdtest**	Variance comparison tests
symmi	[R] **symmetry**	Symmetry and marginal homogeneity tests
tabi	[R] **tabulate twoway**	Two-way tables of frequencies
ttesti	[R] **ttest**	t tests (mean-comparison tests)
twoway pci	[G-2] **graph twoway pci**	Paired-coordinate plot with spikes or lines
twoway pcarrowi	[G-2] **graph twoway pcarrowi**	Paired-coordinate plot with arrows
twoway scatteri	[G-2] **graph twoway scatteri**	Two-way scatterplot
ztesti	[R] **ztest**	z tests (mean-comparison tests, known variance)

19.2 The display command

`display` is not really an immediate command, but it can be used as a hand calculator.

```
. display 2+5
7
. display sqrt(2+sqrt(3^2-4*2*-2))/(2*3)
.44095855
```

See [R] **display**.

19.3 The power, precision, and sample-size commands

`power`, `ciwidth`, `gsbounds`, and `gsdesign` are not technically immediate commands because they do not do something on typed numbers that other commands do on the dataset. They do, however, work strictly on numbers you type on the command line and do not disturb the data in memory.

`power` and `ciwidth` perform power, precision, and sample-size analysis. See the *Stata Power, Precision, and Sample-Size Reference Manual*.

`gsbounds` and `gsdesign` calculate stopping boundaries and sample sizes for group sequential designs. See the *Stata Adaptive Designs: Group Sequential Trials Reference Manual*.

20 Estimation and postestimation commands

Contents

20.1 All estimation commands work the same way

All Stata commands that fit statistical models—commands such as `regress`, `logit`, and `sureg`—work similarly. Most single-equation estimation commands have the syntax

command varlist [*if*] [*in*] [*weight*] [, *options*]

and most multiple-equation estimation commands have the syntax

command (*varlist*) (*varlist*) . . . (*varlist*) [*if*] [*in*] [*weight*] [, *options*]

Adopt a loose definition of single and multiple equation in interpreting this. For instance, `heckman` is a two-equation system, mathematically speaking, yet we categorize it, syntactically, with single-equation commands because most researchers think of it as a linear regression with an adjustment for the censoring. The important thing is that most estimation commands have one or the other of these two syntaxes.

In single-equation commands, the first variable in the *varlist* is the dependent variable, and the remaining variables are the independent variables, with some exceptions. For instance, `mixed` allows special variable prefixes to identify random factors.

Prefix commands may be specified in front of an estimation command to modify or extend what it does. The syntax is

prefix: *command* . . .

See **[U] 11.1.10 Prefix commands** for the full list of prefix commands. To find out which prefix commands are available for an estimation command, see the command's syntax section.

Also, all estimation commands—whether single or multiple equation—share the following features:

1. You can use the standard features of Stata's syntax—`if` *exp* and `in` *range*—to specify the estimation subsample; you do not have to make a special dataset.
2. You can retype the estimation command without arguments to redisplay the most recent estimation results. For instance, after fitting a model with `regress`, you can see the estimates again by typing `regress` by itself. You do not have to do this immediately—any number of commands can occur between the estimation and the replaying, and, in fact, you can even replay the last estimates after the data have changed or you have dropped the data altogether. Stata never forgets (unless you type `discard`; see [P] **discard**).
3. You can specify the `level()` option at the time of estimation, or when you redisplay results if that makes sense, to specify the width of the confidence intervals for the coefficients. The default is `level(95)`, meaning 95% confidence intervals. You can reset the default with `set level`; see [R] **level**.
4. You can use the postestimation command `margins` to display model results in terms of marginal effects (dy/dx or even $df(y)/dx$), which can be displayed as either derivatives or elasticities; see [R] **margins**.
5. You can use the postestimation command `margins` to obtain tables of estimated marginal means, adjusted predictions, and predictive margins; see **[U] 20.17 Obtaining conditional and average marginal effects** and [R] **margins**.

6. You can use the postestimation command `pwcompare` to obtain pairwise comparisons across levels of factor variables. You can compare estimated cell means, marginal means, intercepts, marginal intercepts, slopes, or marginal slopes—collectively called margins. See **[U] 20.18 Obtaining pairwise comparisons**, [R] **margins**, and [R] **margins, pwcompare**.

7. You can use the postestimation command `contrast` to obtain contrasts, which is to say, to compare levels of factor variables and their interactions. This command can also produce ANOVA-style tests of main effects, interactions effects, simple effects, and nested effects; and it can be used after most estimation commands. See **[U] 20.19 Obtaining contrasts, tests of interactions, and main effects**, [R] **contrast**, and [R] **margins, contrast**.

8. You can use the postestimation command `marginsplot` to graph any of the results produced by `margins`. And because `margins` can replicate any result produced by `pwcompare` and `contrast`, you can graph any result produced by them, too. See [R] **marginsplot**.

9. You can use the postestimation command `estat` to obtain common statistics associated with the model. The available statistics are documented in the postestimation section following the documentation of the estimation command, for instance, in [R] **regress postestimation** following [R] **regress**.

   You can always use the postestimation command `estat vce` to obtain the variance–covariance matrix of the estimators (VCE), presented as either a correlation matrix or a covariance matrix. (You can also obtain the estimated coefficients and covariance matrix as vectors and matrices and manipulate them with Stata's matrix capabilities; see **[U] 14.5 Accessing matrices created by Stata commands**.)

10. You can use the postestimation command `predict` to obtain predictions, residuals, influence statistics, and the like, either for the data on which you just estimated or for some other data. You can use postestimation command `predictnl` to obtain point estimates, standard errors, etc., for customized predictions. See [R] **predict** and [R] **predictnl**.

11. You can use the postestimation command `forecast` to perform dynamic and static forecasts, with optional forecast confidence intervals. This includes the ability to produce forecasts from multiple estimation commands, even when estimates imply simultaneous systems. An example of a simultaneous system is when `y2` predicts `y1` in estimation 1 and `y1` predicts `y2` in estimation 2. `forecast` provides many facilities for creating comparative forecast scenarios. See [TS] **forecast**.

12. You can refer to the values of coefficients and standard errors in expressions (such as with `generate`) by using standard notation; see **[U] 13.5 Accessing coefficients and standard errors**. You can refer in expressions to the values of other estimation-related statistics by using `e(`*resultname*`)`. For instance, all commands define `e(N)` recording the number of observations in the estimation subsample. After estimation, type `ereturn list` to see a list of all that is available. See the *Stored results* section in the estimation command's documentation for their definitions.

    An especially useful `e()` result is `e(sample)`: it returns 1 if an observation was used in the estimation and 0 otherwise, so you can add `if e(sample)` to the end of other commands to restrict them to the estimation subsample. You could type, for instance, `summarize if e(sample)`.

13. You can use the postestimation command `test` to perform tests on the estimated parameters (Wald tests of linear hypotheses), `testnl` to perform Wald tests of nonlinear hypotheses, and `lrtest` to perform likelihood-ratio tests. You can use the postestimation command `lincom` to obtain point estimates and confidence intervals for linear combinations of the estimated parameters and the postestimation command `nlcom` to obtain nonlinear combinations.

14. You can specify the `coeflegend` option at the time of estimation or when you redisplay results to see how to type your coefficients in postestimation commands, such as `test` and `lincom` (see [R] **test** and [R] **lincom**), and in expressions.

15. You can use the `statsby` prefix command (see [D] **statsby**) to fit models over each category in a categorical variable and collect the results in a Stata dataset.

16. You can use the `collect` suite of commands to collect estimation results and create customized tables from those results. See [TABLES] **Intro**.

17. You can use the postestimation command `etable` to easily create a table of estimation results from one or multiple estimation commands. See [R] **etable**.

18. You can use the postestimation command `estimates` to store estimation results by name for later retrieval or for displaying/comparing multiple models by using `estimates`, or to save estimation results in a file; see [R] **estimates**.

19. You can use the postestimation command `_estimates` to hold estimates, perform other estimation commands, and then restore the prior estimates. This is of particular interest to programmers. See [P] **_estimates**.

20. You can use the postestimation command `suest` to obtain the joint parameter vector and variance–covariance matrix for coefficients from two different models by using seemingly unrelated estimation. This is especially useful for testing the equality, say, of coefficients across models. See [R] **suest**.

21. You can use the postestimation command `hausman` to perform Hausman model-specification tests by using `hausman`; see [R] **hausman**.

22. With some exceptions, you can specify the `vce(robust)` option at the time of estimation to obtain the Huber/White/robust alternate estimate of variance, or you can specify the `vce(cluster` *clustvar*`)` option to relax the assumption of independence of the observations; see [R] ***vce_option***.

    Most estimation commands also allow a `vce(`*vcetype*`)` option to specify other alternative variance estimators—the allowed alternative variance estimators are documented with the estimator—and usually `vce(opg)`, `vce(bootstrap)`, and `vce(jackknife)` are available.

    Where `vce(bootstrap)` and `vce(jackknife)` are available, we recommend using them instead of the prefix commands `bootstrap` and `jackknife`.

As a rule, the points discussed briefly above and in more detail later in this entry do not apply to the Bayesian analysis or the Bayesian model averaging commands. For more information about Bayesian analysis commands, see the *Stata Bayesian Analysis Reference Manual*. For more information about Bayesian model averaging commands, see the *Stata Bayesian Model Averaging Reference Manual*.

20.2 Standard syntax

You can combine Stata's `if` *exp* and `in` *range* with any estimation command. Estimation commands also allow `by` *varlist*`:`, where it would be sensible.

▷ Example 1

We have data on 74 automobiles that record the mileage rating (`mpg`), weight (`weight`), and whether the car is domestic or foreign produced (`foreign`). We can fit a linear regression model of `mpg` on `weight` and the square of `weight`, using just the foreign-made automobiles, by typing

```
. use https://www.stata-press.com/data/r19/auto2
(1978 automobile data)
. regress mpg weight c.weight#c.weight if foreign
```

Source	SS	df	MS	Number of obs	=	22
				F(2, 19)	=	8.31
Model	428.256889	2	214.128444	Prob > F	=	0.0026
Residual	489.606747	19	25.7687762	R-squared	=	0.4666
				Adj R-squared	=	0.4104
Total	917.863636	21	43.7077922	Root MSE	=	5.0763

mpg	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
weight	-.0132182	.0275711	-0.48	0.637	-.0709252	.0444888
c.weight# c.weight	5.50e-07	5.41e-06	0.10	0.920	-.0000108	.0000119
_cons	52.33775	34.1539	1.53	0.142	-19.14719	123.8227

We use the factor-variable notation `c.weight#c.weight` to add the square of `weight` to our regression; see **[U] 11.4.3 Factor variables**.

We can run separate regressions for the domestic and foreign-produced automobiles with the `by` *varlist*`:` prefix:

```
. by foreign: regress mpg weight c.weight#c.weight
```

```
-> foreign = Domestic
```

Source	SS	df	MS	Number of obs	=	52
				F(2, 49)	=	91.64
Model	905.395466	2	452.697733	Prob > F	=	0.0000
Residual	242.046842	49	4.93973146	R-squared	=	0.7891
				Adj R-squared	=	0.7804
Total	1147.44231	51	22.4988688	Root MSE	=	2.2226

mpg	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
weight	-.0131718	.0032307	-4.08	0.000	-.0196642	-.0066794
c.weight# c.weight	1.11e-06	4.95e-07	2.25	0.029	1.19e-07	2.11e-06
_cons	50.74551	5.162014	9.83	0.000	40.37205	61.11896

```
-> foreign = Foreign
      Source |       SS           df       MS      Number of obs   =        22
-------------+----------------------------------   F(2, 19)        =      8.31
       Model |  428.256889         2  214.128444   Prob > F        =    0.0026
    Residual |  489.606747        19  25.7687762   R-squared       =    0.4666
-------------+----------------------------------   Adj R-squared   =    0.4104
       Total |  917.863636        21  43.7077922   Root MSE        =    5.0763

------------------------------------------------------------------------------
         mpg |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      weight |  -.0132182   .0275711    -0.48   0.637    -.0709252    .0444888
             |
    c.weight#|
    c.weight |   5.50e-07   5.41e-06     0.10   0.920    -.0000108    .0000119
             |
       _cons |   52.33775    34.1539     1.53   0.142    -19.14719    123.8227
------------------------------------------------------------------------------
```

Although all estimation commands allow `if` *exp* and `in` *range*, only some allow the `by` *varlist*`:` prefix. For `by()`, the duration of Stata's memory is limited: it remembers the last set of estimates only. This means that, if we were to use any of the other features described below, they would use the last regression estimated, which right now is `mpg` on `weight` and square of `weight` for the `Foreign` subsample.

We can instead collect the statistics from each of the by-groups by using the `statsby` prefix; see [D] **statsby**.

```
. statsby, by(foreign): regress mpg weight c.weight#c.weight
(running regress on estimation sample)

      Command: regress mpg weight c.weight#c.weight
           By: foreign

Statsby groups:
..
```

`statsby` runs the regression first on domestic cars and then on foreign cars, and it saves the coefficients by overwriting our dataset. Do not worry; if the dataset has not been previously saved, `statsby` will refuse to run unless we also specify the `clear` option.

Here is what we now have in memory.

```
. list
```

	foreign	_b_weight	_stat_2	_b_cons
1.	Domestic	-.0131718	1.11e-06	50.74551
2.	Foreign	-.0132182	5.50e-07	52.33775

These are the coefficients from the two regressions above. `statsby` does not know how to name the coefficient for `c.weight#c.weight`, so it labels the coefficient with the generic name `_stat_2`. We can also save the standard errors and other statistics from the regressions; see [D] **statsby**.

◁

20.3 Replaying prior results

When you type an estimation command without arguments, it redisplays prior results.

▷ Example 2

To perform a regression of `mpg` on the variables `weight` and `displacement`, we could type

```
. use https://www.stata-press.com/data/r19/auto2, clear
(1978 automobile data)
. regress mpg weight displacement
```

Source	SS	df	MS	Number of obs	=	74
				F(2, 71)	=	66.79
Model	1595.40969	2	797.704846	Prob > F	=	0.0000
Residual	848.049768	71	11.9443629	R-squared	=	0.6529
				Adj R-squared	=	0.6432
Total	2443.45946	73	33.4720474	Root MSE	=	3.4561

mpg	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
weight	-.0065671	.0011662	-5.63	0.000	-.0088925	-.0042417
displacement	.0052808	.0098696	0.54	0.594	-.0143986	.0249602
_cons	40.08452	2.02011	19.84	0.000	36.05654	44.11251

We now go on to do other things—summarizing data, listing observations, performing hypothesis tests, or anything else. If we decide that we want to see the last set of estimates again, we type the estimation command without arguments.

```
. regress
```

Source	SS	df	MS	Number of obs	=	74
				F(2, 71)	=	66.79
Model	1595.40969	2	797.704846	Prob > F	=	0.0000
Residual	848.049768	71	11.9443629	R-squared	=	0.6529
				Adj R-squared	=	0.6432
Total	2443.45946	73	33.4720474	Root MSE	=	3.4561

mpg	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
weight	-.0065671	.0011662	-5.63	0.000	-.0088925	-.0042417
displacement	.0052808	.0098696	0.54	0.594	-.0143986	.0249602
_cons	40.08452	2.02011	19.84	0.000	36.05654	44.11251

We can also specify most reporting options on replay. For example, if we want to see a legend of terms with which to refer to the estimated coefficients in subsequent commands, we can type

```
. regress, coeflegend
  (output omitted)
```

See [U] 20.12 Accessing estimated coefficients for an example using legend terms.

These features work with every estimation command, so we could just as well have used, say, `stcox` or `logit`.

◁

20.4 Cataloging estimation results

Stata keeps only the results of the most recently fit model in active memory. You can use Stata's `estimates` command, however, to temporarily store estimation results for displaying, comparing, cross-model testing, etc., during the same session. You can also save estimation results to disk, but that will be the subject of the next section. You may temporarily store up to 300 sets of estimation results.

▷ Example 3

Continuing with our automobile data, we fit four models, give each one a title, and then store them. We fit the models `quietly` to minimize output.

```
. quietly regress mpg weight displ
. estimates title: Linear regression, base model
. estimates store r_base
. quietly regress mpg weight displ foreign
. estimates title: Linear regression, alternate model
. estimates store r_alt
. quietly qreg mpg weight displ
. estimates title: Quantile regression, base model
. estimates store q_base
. quietly qreg mpg weight displ foreign
. estimates title: Quantile regression, alternate model
. estimates store q_alt
```

We saved the four models under the names `r_base`, `r_alt`, `q_base`, and `q_alt`, but if we forget, we can ask to see a directory of what is stored:

```
. estimates dir
```

Name	Command	Dependent variable	Number of param.	Title
r_base	regress	mpg	3	*Linear regression, base model*
r_alt	regress	mpg	4	*Linear regression, alternate model*
q_base	qreg	mpg	3	*Quantile regression, base model*
q_alt	qreg	mpg	4	*Quantile regression, alternate model*

We can ask Stata to replay any of the previous models:

```
. estimates replay r_base
```

Model **r_base** (*Linear regression, base model*)

Source	SS	df	MS	Number of obs	=	74
				F(2, 71)	=	66.79
Model	1595.40969	2	797.704846	Prob > F	=	0.0000
Residual	848.049768	71	11.9443629	R-squared	=	0.6529
				Adj R-squared	=	0.6432
Total	2443.45946	73	33.4720474	Root MSE	=	3.4561

mpg	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
weight	-.0065671	.0011662	-5.63	0.000	-.0088925	-.0042417
displacement	.0052808	.0098696	0.54	0.594	-.0143986	.0249602
_cons	40.08452	2.02011	19.84	0.000	36.05654	44.11251

Or we can ask to see all the models in a combined table:

```
. estimates table _all
```

Variable	r_base	r_alt	q_base	q_alt
weight	-.00656711	-.00677449	-.00581172	-.00595056
displacement	.00528078	.00192865	.0042841	.00018552
foreign		-1.6006312		-2.1326005
_cons	40.084522	41.847949	37.559865	39.213348

`estimates` displayed just the coefficients, but we could ask for other statistics.

We can also select one of the stored estimates to be made active, making it as if we had just fit the model:

```
. estimates restore r_alt
(results r_alt are active now)
. regress
```

Source	SS	df	MS	Number of obs	=	74
				F(3, 70)	=	45.88
Model	1619.71935	3	539.906448	Prob > F	=	0.0000
Residual	823.740114	70	11.7677159	R-squared	=	0.6629
				Adj R-squared	=	0.6484
Total	2443.45946	73	33.4720474	Root MSE	=	3.4304

mpg	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
weight	-.0067745	.0011665	-5.81	0.000	-.0091011	-.0044479
displacement	.0019286	.0100701	0.19	0.849	-.0181556	.0220129
foreign	-1.600631	1.113648	-1.44	0.155	-3.821732	.6204699
_cons	41.84795	2.350704	17.80	0.000	37.15962	46.53628

◁

You can do a lot more with `estimates`; see [R] **estimates**. In particular, `estimates` makes it easy to perform cross-model tests, such as the Hausman specification test.

20.5 Saving estimation results

`estimates` can also save estimation results into a file.

```
. estimates save alt
file alt.ster saved
```

That saved the active estimation results, meaning the ones we just estimated or, in our case, the ones we just restored. Later, even in another Stata session, we could reload our estimates:

```
. estimates use alt
. regress
```

Source	SS	df	MS	Number of obs	=	74
				F(3, 70)	=	45.88
Model	1619.71935	3	539.906448	Prob > F	=	0.0000
Residual	823.740114	70	11.7677159	R-squared	=	0.6629
				Adj R-squared	=	0.6484
Total	2443.45946	73	33.4720474	Root MSE	=	3.4304

mpg	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
weight	-.0067745	.0011665	-5.81	0.000	-.0091011	-.0044479
displacement	.0019286	.0100701	0.19	0.849	-.0181556	.0220129
foreign	-1.600631	1.113648	-1.44	0.155	-3.821732	.6204699
_cons	41.84795	2.350704	17.80	0.000	37.15962	46.53628

There is one important difference between storing results in memory and saving them in a file: `e(sample)` is lost. We have not discussed `e(sample)` yet, but it allows us to identify the observations among those currently in memory that were used in the estimation. For instance, after estimation, we could type

```
. summarize mpg weight displ foreign if e(sample)
```

and see the summary statistics of the relevant data. We could do that after `estimates restore`, too. But we cannot do it after `estimates use`. Part of the reason is that we might not even have the relevant data in memory. Even if we do, however, here is what will happen:

```
. summarize mpg weight displ foreign if e(sample)
```

Variable	Obs	Mean	Std. dev.	Min	Max
mpg	0				
weight	0				
displacement	0				
foreign	0				

Stata will just assume that none of the data in memory played a role in obtaining the estimation results.

There is more worth knowing. You could, for instance, type `estimates describe` to see the command line that produced the estimates. See [R] **estimates**.

20.6 Specification search tools

Stata's lasso commands select covariates and fit models for continuous, binary, and count outcomes. See [LASSO] **Lasso intro** for an overview of lasso features.

The commands `stepwise`, `fp`, and `mfp` are not really estimation commands but are combined with estimation commands to assist in specification searches.

`stepwise`, one of Stata's prefix commands, provides stepwise estimation. You can use the `stepwise` prefix with some, but not all, estimation commands. See [R] **stepwise** for a list of supported estimation commands.

`fp` and `mfp` are commands to assist you in performing fractional-polynomial functional specification searches. See [R] **fp** and [R] **mfp** for additional information.

20.7 Specifying the estimation subsample

You specify the estimation subsample—the sample to be used in estimation—by specifying the `if` *exp* and `in` *range* qualifiers with the estimation command.

Once an estimation command has been run or previous estimates restored, Stata remembers the estimation subsample, and you can use the qualifier `if e(sample)` on the end of other Stata commands. The term estimation subsample refers to the set of observations used to produce the active estimation results. That might turn out to be all the observations (as it was in the above example) or only some of the observations:

```
. regress mpg weight 5.rep78 if foreign
      Source |       SS           df       MS      Number of obs   =        21
-------------+----------------------------------   F(2, 18)        =     10.21
       Model |  423.317154         2  211.658577   Prob > F        =    0.0011
    Residual |   372.96856        18  20.7204756   R-squared       =    0.5316
-------------+----------------------------------   Adj R-squared   =    0.4796
       Total |  796.285714        20  39.8142857   Root MSE        =     4.552

------------------------------------------------------------------------------
         mpg |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      weight |  -.0131402   .0029684    -4.43   0.000    -.0193765   -.0069038
             |
       rep78 |
   Excellent |   5.052676    2.13492     2.37   0.029     .5673764    9.537977
       _cons |   52.86088   6.540147     8.08   0.000     39.12054    66.60122
------------------------------------------------------------------------------

. summarize mpg weight 5.rep78 if e(sample)
    Variable |        Obs        Mean    Std. dev.       Min        Max
-------------+---------------------------------------------------------
         mpg |         21    25.28571    6.309856        17         41
      weight |         21    2263.333    364.7099      1760       3170
             |
       rep78 |
   Excellent |         21    .4285714    .5070926         0          1
```

Twenty-one observations were used in the above regression, and we subsequently obtained the means for those same 21 observations by typing `summarize ... if e(sample)`. Observations were dropped for two reasons: we specified `if foreign` when we ran the regression, and there were observations for which `5.rep78` was missing. The reason does not matter; `e(sample)` is true if the observation was used and is false otherwise.

You can use `if e(sample)` on the end of any Stata command that allows `if` *exp*.

Here, Stata has a shorthand command that produces the same results as `summarize ... if e(sample)`:

```
. estat summarize, label
Estimation sample regress                         Number of obs =         21
```

Variable	Mean	Std. dev.	Min	Max	Label
mpg	25.28571	6.309856	17	41	Mileage (mpg)
weight	2263.333	364.7099	1760	3170	Weight (lbs.)
rep78					Repair record 1978
Excellent	.4285714	.5070926	0	1	

See [R] **estat summarize**.

20.8 Specifying the width of confidence intervals

You can specify the width of the confidence intervals for the coefficients by using the `level()` option at estimation or when you play back the results.

▷ Example 4

To obtain narrower, 90% confidence intervals when we fit the model, we type

```
. regress mpg weight displ, level(90)
      Source |       SS           df       MS      Number of obs   =        74
-------------+----------------------------------   F(2, 71)        =     66.79
       Model |  1595.40969         2  797.704846   Prob > F        =    0.0000
    Residual |  848.049768        71  11.9443629   R-squared       =    0.6529
-------------+----------------------------------   Adj R-squared   =    0.6432
       Total |  2443.45946        73  33.4720474   Root MSE        =    3.4561

------------------------------------------------------------------------------
         mpg | Coefficient  Std. err.      t    P>|t|     [90% conf. interval]
-------------+----------------------------------------------------------------
      weight |  -.0065671   .0011662    -5.63   0.000    -.0085108   -.0046234
displacement |   .0052808   .0098696     0.54   0.594    -.0111679    .0217294
       _cons |   40.08452    2.02011    19.84   0.000     36.71781    43.45124
------------------------------------------------------------------------------
```

If we subsequently typed `regress` without arguments, 95% confidence intervals would be reported because that is the default. If we initially fit the model with 95% confidence intervals, we could later type `regress, level(90)` to redisplay results with 90% confidence intervals.

Also, we could type `set level 90` to make 90% intervals our default; see [R] **level**.

Stata allows noninteger confidence intervals between 10.00 and 99.99, with a maximum of two digits following the decimal point. For instance, we could type

```
. regress mpg weight displ, level(92.5)
      Source |       SS           df       MS      Number of obs   =        74
-------------+----------------------------------   F(2, 71)        =     66.79
       Model |  1595.40969         2  797.704846   Prob > F        =    0.0000
    Residual |  848.049768        71  11.9443629   R-squared       =    0.6529
-------------+----------------------------------   Adj R-squared   =    0.6432
       Total |  2443.45946        73  33.4720474   Root MSE        =    3.4561

------------------------------------------------------------------------------
         mpg | Coefficient  Std. err.      t    P>|t|     [92.5% conf. interval]
-------------+----------------------------------------------------------------
      weight |  -.0065671   .0011662    -5.63   0.000    -.0086745   -.0044597
displacement |   .0052808   .0098696     0.54   0.594    -.0125535    .023115
       _cons |   40.08452   2.02011     19.84   0.000     36.43419    43.73485
------------------------------------------------------------------------------
```

20.9 Formatting the coefficient table

You can change the formatting of the coefficient table with the `sformat()`, `pformat()`, and `cformat()` options. The `sformat()` option changes the output format of test statistics; `pformat()` changes p-values; and `cformat()` changes coefficients, standard errors, and confidence limits. We can reduce the number of decimal places by specifying `%f` fixed-width formats:

```
. regress mpg weight displ, cformat(%6.3f) sformat(%4.1f) pformat(%4.2f)
      Source |       SS           df       MS      Number of obs   =        74
-------------+----------------------------------   F(2, 71)        =     66.79
       Model |  1595.40969         2  797.704846   Prob > F        =    0.0000
    Residual |  848.049768        71  11.9443629   R-squared       =    0.6529
-------------+----------------------------------   Adj R-squared   =    0.6432
       Total |  2443.45946        73  33.4720474   Root MSE        =    3.4561

------------------------------------------------------------------------------
         mpg | Coefficient  Std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
      weight |     -0.007      0.001     -5.6   0.00       -0.009      -0.004
displacement |      0.005      0.010      0.5   0.59       -0.014       0.025
       _cons |     40.085      2.020     19.8   0.00       36.057      44.113
------------------------------------------------------------------------------
```

The `cformat(%6.3f)` option, for example, fixes a width of six characters with three digits to the right of the decimal point. For more information on formats, see **[U] 12.5.1 Numeric formats**.

The formatting options may also be specified when replaying results, so you can try different formats without refitting the model:

```
. regress, cformat(%7.4f)
      Source |       SS           df       MS      Number of obs   =        74
-------------+----------------------------------   F(2, 71)        =     66.79
       Model |  1595.40969         2  797.704846   Prob > F        =    0.0000
    Residual |  848.049768        71  11.9443629   R-squared       =    0.6529
-------------+----------------------------------   Adj R-squared   =    0.6432
       Total |  2443.45946        73  33.4720474   Root MSE        =    3.4561

------------------------------------------------------------------------------
         mpg | Coefficient  Std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
      weight |    -0.0066      0.0012    -5.63   0.000      -0.0089     -0.0042
displacement |     0.0053      0.0099     0.54   0.594      -0.0144      0.0250
       _cons |    40.0845      2.0201    19.84   0.000      36.0565     44.1125
------------------------------------------------------------------------------
```

20.10 Obtaining the variance–covariance matrix

Typing `estat vce` displays the variance–covariance matrix of the estimators in active memory.

▷ Example 5

In example 2, we typed `regress mpg weight displacement`. The full variance–covariance matrix of the estimators can be displayed at any time after estimation:

```
. estat vce
Covariance matrix of coefficients of regress model
        e(V) |      weight  displace~t       _cons
-------------+------------------------------------
      weight |   1.360e-06
displacement |   -.0000103    .00009741
       _cons |  -.00207455    .01188356   4.0808455
```

Typing `estat vce` with the `corr` option presents this matrix as a correlation matrix:

```
. estat vce, corr
Correlation matrix of coefficients of regress model
        e(V) |    weight  displa~t     _cons
-------------+------------------------------
      weight |    1.0000
displacement |   -0.8949    1.0000
       _cons |   -0.8806    0.5960    1.0000
```

See [R] **estat vce**.

Also, Stata's matrix commands understand that `e(V)` refers to the matrix:

```
. matrix list e(V)
symmetric e(V)[3,3]
                  weight  displacement         _cons
      weight     1.360e-06
displacement     -.0000103     .00009741
       _cons    -.00207455     .01188356     4.0808455
. matrix Vinv = invsym(e(V))
. matrix list Vinv
symmetric Vinv[3,3]
                  weight  displacement         _cons
      weight      60175851
displacement     4081161.2     292709.46
       _cons     18706.732     1222.3339     6.1953911
```

See **[U] 14.5 Accessing matrices created by Stata commands**.

◁

20.11 Obtaining predicted values

Our discussion below, although cast in terms of predicted values, applies equally to the other statistics generated by `predict`; see [R] **predict**.

When Stata fits a model, whether it is regression or anything else, it internally stores the results, including the estimated coefficients and the variable names. The `predict` command allows you to use that information.

▷ Example 6

Let's perform a linear regression of `mpg` on `weight` and the square of `weight`:

```
. regress mpg weight c.weight#c.weight
```

Source	SS	df	MS	Number of obs	=	74
				F(2, 71)	=	72.80
Model	1642.52197	2	821.260986	Prob > F	=	0.0000
Residual	800.937487	71	11.2808097	R-squared	=	0.6722
				Adj R-squared	=	0.6630
Total	2443.45946	73	33.4720474	Root MSE	=	3.3587

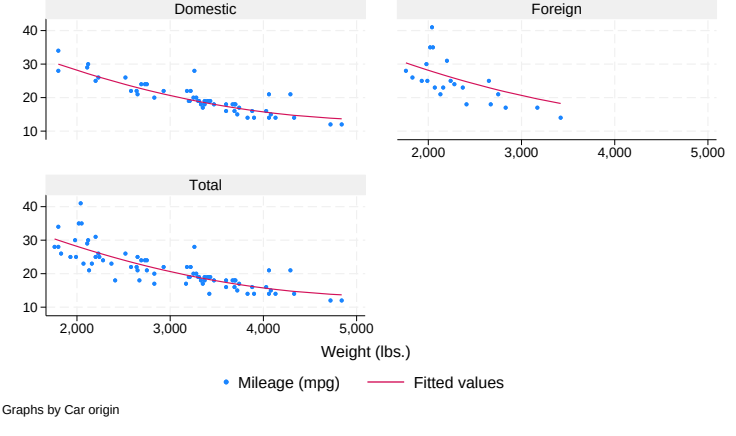
mpg	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
weight	-.0141581	.0038835	-3.65	0.001	-.0219016	-.0064145
c.weight# c.weight	1.32e-06	6.26e-07	2.12	0.038	7.67e-08	2.57e-06
_cons	51.18308	5.767884	8.87	0.000	39.68225	62.68392

After the regression, `predict` is defined to be

$$-0.0141581\texttt{weight} + 1.32 \times 10^{-6}\texttt{weight}^2 + 51.18308$$

(Actually, it is more precise because the coefficients are internally stored at much higher precision than shown in the output.) Thus, we can create a new variable—let's call it `fitted`—equal to the prediction by typing `predict fitted` and then use `scatter` to display the fitted and actual values separately for domestic and foreign automobiles:

```
. predict fitted
(option xb assumed; fitted values)
. scatter mpg fitted weight, by(foreign, total style(altleg)) c(. l) m(o i) sort
```



`predict` can calculate much more than just predicted values. For `predict` after linear regression, `predict` can calculate residuals, standardized residuals, Studentized residuals, influence statistics, and more. In any case, we specify what is to be calculated via an option, so if we wanted the residuals stored in new variable `r`, we would type

```
. predict r, resid
```

The options that may be specified following `predict` vary according to the estimation command previously used; the `predict` options are documented along with the estimation command. For instance, to discover all the things `predict` can do following `regress`, see [R] **regress**.

◁

20.11.1 Using predict

The use of `predict` is not limited to linear regression; it can be used after any estimation command.

▷ Example 7

You fit a logistic regression model of whether a car is manufactured outside the United States on the basis of its weight and mileage rating using either the `logistic` or the `logit` command; see [R] **logistic** and [R] **logit**. We will use `logit`.

```
. use https://www.stata-press.com/data/r19/auto2, clear
(1978 automobile data)
. logit foreign weight mpg
Iteration 0:  Log likelihood =  -45.03321
Iteration 1:  Log likelihood = -29.238536
Iteration 2:  Log likelihood = -27.244139
Iteration 3:  Log likelihood = -27.175277
Iteration 4:  Log likelihood = -27.175156
Iteration 5:  Log likelihood = -27.175156
Logistic regression                                     Number of obs =     74
                                                        LR chi2(2)    =  35.72
                                                        Prob > chi2   = 0.0000
Log likelihood = -27.175156                             Pseudo R2     = 0.3966
```

foreign	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
weight	-.0039067	.0010116	-3.86	0.000	-.0058894	-.001924
mpg	-.1685869	.0919175	-1.83	0.067	-.3487418	.011568
_cons	13.70837	4.518709	3.03	0.002	4.851859	22.56487

After `logit`, `predict` without options calculates the probability of a positive outcome (we learned that by looking at [R] **logit**). To obtain the predicted probabilities that each car is manufactured outside the United States, we type

```
. predict probhat
(option pr assumed; Pr(foreign))
. summarize probhat
```

Variable	Obs	Mean	Std. dev.	Min	Max
probhat	74	.2972973	.3052979	.000729	.8980594

```
. list make mpg weight foreign probhat in 1/5
```

	make	mpg	weight	foreign	probhat
1.	AMC Concord	22	2,930	Domestic	.1904363
2.	AMC Pacer	17	3,350	Domestic	.0957767
3.	AMC Spirit	22	2,640	Domestic	.4220815
4.	Buick Century	20	3,250	Domestic	.0862625
5.	Buick Electra	15	4,080	Domestic	.0084948

◁

20.11.2 Making in-sample predictions

predict does not retrieve a vector of prerecorded values—it calculates the predictions on the basis of the recorded coefficients and the data currently in memory. In the above examples, when we typed things like

```
. predict probhat
```

predict filled in the prediction everywhere that it could be calculated.

We sometimes have more data in memory than were used by the estimation command, either because we explicitly ignored some of the observations by specifying an if *exp* with the estimation command or because there are missing values. In such cases, if we want to restrict the calculation to the estimation subsample, we would do that in the usual way by adding if e(sample) to the end of the command:

```
. predict probhat if e(sample)
```

20.11.3 Making out-of-sample predictions

Because predict makes its calculations on the basis of the recorded coefficients and the data in memory, predict can do more than calculate predicted values for the data on which the estimation took place—it can make out-of-sample predictions, as well.

If you fit your model on a subset of the observations, you could then predict the outcome for all the observations:

```
. logit foreign weight mpg if rep78 > 3
. predict pall
```

If you do not specify if e(sample) at the end of the predict command, predict calculates the predictions for all observations possible.

In fact, because predict works from the active estimation results, you can use predict with *any* dataset that contains the necessary variables.

▷ Example 8

Continuing with our previous logit example, assume that we have a second dataset containing the mpg and weight of a different sample of cars. We have just fit your model and now continue:

```
. use otherdat, clear
(Different cars)
. predict probhat                    Stata remembers the previous model
(option pr assumed; Pr(foreign))
. summarize probhat foreign
    Variable |       Obs        Mean    Std. dev.       Min        Max
-------------+--------------------------------------------------------
     probhat |        12    .2505068    .3187104   .0084948   .8920776
     foreign |        12    .1666667    .3892495          0          1
```

◁

▷ Example 9

We can obtain out-of-sample predictions in many ways. Above, we estimated on one dataset and then used another. If our first dataset had contained both sets of cars, marked, say, by the variable difcars being 0 if from the first sample and 1 if from the second, we could type

```
. logit foreign weight mpg if difcars==0
same output as above appears
. predict probhat
(option pr assumed; Pr(foreign))
. summarize probhat foreign if difcars==1
same output as directly above appears
```

If we just had a few additional cars, we could even input them after estimation. Assume that our data once again contain only the first sample of cars, and assume that we are interested in an additional sample of only two cars; we could type

```
. use https://www.stata-press.com/data/r19/auto2
(1978 automobile data)
. keep make mpg weight foreign
. logit foreign weight mpg
same output as above appears
. input
                make       mpg     weight   foreign
 75. "Merc. Zephyr" 20 2830 0              we type in our new data
 76. "VW Dasher" 23 2160 1
 77. end
. predict probhat                          obtain all the predictions
(option pr assumed; Pr(foreign))
. list in -2/l
```

	make	mpg	weight	foreign	probhat
75.	Merc. Zephyr	20	2,830	Domestic	.3275397
76.	VW Dasher	23	2,160	Foreign	.8009743

◁

20.11.4 Obtaining standard errors, tests, and confidence intervals for predictions

When you use `predict`, you create, for each observation in the prediction sample, a statistic that is a function of the data and the estimated model parameters. You also could have generated your own customized predictions by using `generate`. In either case, to get standard errors, Wald tests, and confidence intervals for your predictions, use `predictnl`. For example, if we want the standard errors for our predicted probabilities, we could type

```
. drop probhat
. predictnl probhat = predict(), se(phat_se)
. list in 1/5
```

	make	mpg	weight	foreign	probhat	phat_se
1.	AMC Concord	22	2,930	Domestic	.1904363	.0658387
2.	AMC Pacer	17	3,350	Domestic	.0957767	.0536297
3.	AMC Spirit	22	2,640	Domestic	.4220815	.0892845
4.	Buick Century	20	3,250	Domestic	.0862625	.0461928
5.	Buick Electra	15	4,080	Domestic	.0084948	.0093079

Comparing this output with our previous listing of the first five predicted probabilities, you will notice that the output is identical except that we now have an additional variable, `phat_se`, which contains the estimated standard error for each predicted probability.

We first had to `drop probhat` because `predictnl` will regenerate it. Note also the use of `predict()` within `predictnl`—it specified that we wanted to generate a point estimate (and standard error) for the default prediction after `logit`; see [R] **predictnl** for more details.

20.12 Accessing estimated coefficients

You can access coefficients and standard errors after estimation by referring to `_b[`*name*`]` and `_se[`*name*`]`; see [U] **13.5 Accessing coefficients and standard errors**.

▷ Example 10

Let's return to linear regression. We are doing a study of earnings of men and women at a particular company. In addition to each person's earnings, we have information on their educational attainment and tenure with the company. We type the following:

```
. regress lnearn ed tenure i.female female#(c.ed c.tenure)
  (output omitted)
```

If you are not familiar with the `#` notation, see [U] **11.4.3 Factor variables**.

We now wish to predict everyone's income as if they were male and then compare these as-if earnings with the actual earnings:

```
. generate asif = _b[_cons] + _b[ed]*ed + _b[tenure]*tenure
```

◁

▷ Example 11

We are analyzing the mileage of automobiles and are using a slightly more sophisticated model than any we have used so far. As we have previously, we will fit a linear regression model of `mpg` on `weight` and the square of `weight`, but we also add the interaction of `foreign` with `weight`, the car's gear ratio (`gear_ratio`), and `foreign` interacted with `gear_ratio`. We will use factor-variable notation to create the squared term and the interactions; see [U] **11.4.3 Factor variables**.

```
. use https://www.stata-press.com/data/r19/auto2, clear
(1978 automobile data)
. regress mpg weight c.weight#c.weight i.foreign#c.weight gear_ratio
> i.foreign#c.gear_ratio
```

Source	SS	df	MS	Number of obs	=	74
				F(5, 68)	=	33.44
Model	1737.05293	5	347.410585	Prob > F	=	0.0000
Residual	706.406534	68	10.3883314	R-squared	=	0.7109
				Adj R-squared	=	0.6896
Total	2443.45946	73	33.4720474	Root MSE	=	3.2231

mpg	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
weight	-.0118517	.0045136	-2.63	0.011	-.0208584	-.002845
c.weight# c.weight	9.81e-07	7.04e-07	1.39	0.168	-4.25e-07	2.39e-06
foreign# c.weight Foreign	-.0032241	.0015577	-2.07	0.042	-.0063326	-.0001157
gear_ratio	1.159741	1.553418	0.75	0.458	-1.940057	4.259539
foreign# c.gear_ratio Foreign	1.597462	1.205313	1.33	0.189	-.8077036	4.002627
_cons	44.61644	8.387943	5.32	0.000	27.87856	61.35432

If you are not experienced in both regression technology and automobile technology, you may find it difficult to interpret this regression. Putting aside issues of statistical significance, we find that mileage decreases with a car's weight but increases with the square of weight; decreases even more rapidly with weight for foreign cars; increases with higher gear ratio; and increases even more rapidly with higher gear ratio in foreign cars.

Thus, do foreign cars yield better or worse gas mileage? Results are mixed. As the foreign cars' weight increases, they do more poorly in relation to domestic cars, but they do better at higher gear ratios. One way to compare the results is to predict what mileage foreign cars would have if they were manufactured domestically. The regression provides all the information necessary for making that calculation. Mileage for domestic cars is estimated to be

$$-0.012\,\texttt{weight} + 9.81 \times 10^{-7}\,\texttt{weight}^2 + 1.160\,\texttt{gear\_ratio} + 44.6$$

We can use that equation to predict the mileage of foreign cars and then compare it with the true outcome. The `_b[]` function simplifies reference to the estimated coefficients. We can type

```
. generate asif=_b[weight]*weight + _b[c.weight#c.weight]*c.weight#c.weight +
>  _b[gear_ratio]*gear_ratio + _b[_cons]
```

`_b[weight]` refers to the estimated coefficient on `weight`, `_b[c.weight#c.weight]` to the estimated coefficient on `c.weight#c.weight`, and so on.

We might now ask how the actual mileage of a Honda compares with the asif prediction:

```
. list make asif mpg if strpos(make,"Honda")
```

	make	asif	mpg
61.	Honda Accord	26.52597	25
62.	Honda Civic	30.62202	28

Notice the way we constructed our if clause to select Hondas. strpos() is the string function that returns the location in the first string where the second string is found or, if the second string does not occur in the first, returns 0. Thus any recorded make that contains the string "Honda" anywhere in it would be listed; see [FN] **String functions**.

We find that both Honda models yield slightly lower gas mileage than the asif domestic car–based prediction. (We do not endorse this model as a complete model of the determinants of mileage, nor do we single out Honda for any special scorn. In fact, please note that the observed values are within the root mean squared error of the average prediction.)

We might wish to compare the overall average mpg and the asif prediction over all foreign cars in the data:

```
. summarize mpg asif if foreign
```

Variable	Obs	Mean	Std. dev.	Min	Max
mpg	22	24.77273	6.611187	14	41
asif	22	26.67124	3.142912	19.70466	30.62202

We find that, on average, foreign cars yield slightly lower mileage than our asif prediction. This might lead us to ask if any foreign cars do better than the asif prediction:

```
. list make asif mpg if foreign & mpg>asif, sep(0)
```

	make	asif	mpg
55.	BMW 320i	24.31697	25
57.	Datsun 210	28.96818	35
63.	Mazda GLC	29.32015	30
66.	Subaru	28.85993	35
68.	Toyota Corolla	27.01144	31
71.	VW Diesel	28.90355	41

We find six such automobiles.

◁

20.13 Performing hypothesis tests on the coefficients

20.13.1 Linear tests

After estimation, `test` is used to perform tests of linear hypotheses on the basis of the variance–covariance matrix of the estimators (Wald tests).

▷ Example 12

Using the automobile data, we perform the following regression:

```
. use https://www.stata-press.com/data/r19/auto2, clear
(1978 automobile data)
. generate weightsq=weight^2
. regress mpg weight weightsq foreign
```

Source	SS	df	MS	Number of obs	=	74
				F(3, 70)	=	52.25
Model	1689.15372	3	563.05124	Prob > F	=	0.0000
Residual	754.30574	70	10.7757963	R-squared	=	0.6913
				Adj R-squared	=	0.6781
Total	2443.45946	73	33.4720474	Root MSE	=	3.2827

mpg	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
weight	-.0165729	.0039692	-4.18	0.000	-.0244892	-.0086567
weightsq	1.59e-06	6.25e-07	2.55	0.013	3.45e-07	2.84e-06
foreign	-2.2035	1.059246	-2.08	0.041	-4.3161	-.0909002
_cons	56.53884	6.197383	9.12	0.000	44.17855	68.89913

(Note: `test` has many syntaxes and features, so do not use this example as an excuse for not reading [R] **test**.) We can use the `test` command to calculate the joint significance of `weight` and `weightsq`:

```
. test weight weightsq
 ( 1)  weight = 0
 ( 2)  weightsq = 0
       F(  2,    70) =   60.83
            Prob > F =    0.0000
```

We are not limited to testing whether the coefficients are 0. We can test whether the coefficient on `foreign` is −2 by typing

```
. test foreign = -2
 ( 1)  foreign = -2
       F(  1,    70) =    0.04
            Prob > F =    0.8482
```

We can even test more complicated hypotheses because `test` can perform basic algebra. Here is an absurd hypothesis:

```
. test 2*(weight+weightsq)=-3*(foreign-(weight-weightsq))
 ( 1)  - weight + 5*weightsq + 3*foreign = 0
       F(  1,    70) =    4.31
            Prob > F =    0.0416
```

test simplified the algebra of our hypothesis and then presented the test results. We can also use test's accumulate option to combine this test with another test:

```
. test foreign+weight=0, accum
 ( 1)  - weight + 5*weightsq + 3*foreign = 0
 ( 2)  weight + foreign = 0
       F(  2,    70) =    9.12
            Prob > F =    0.0003
```

There are limitations. test can test only linear hypotheses. If we attempt to test a nonlinear hypothesis, test will tell us that it is not possible:

```
. test weight/foreign=0
not possible with test
r(131);
```

Testing nonlinear hypotheses is discussed in [U] 20.13.4 Nonlinear Wald tests below.

◁

20.13.2 Using test

test bases its results on the estimated variance–covariance matrix of the estimators (that is, it performs a Wald test), so it can be used after any estimation command. For maximum likelihood estimation, test's results for a single variable are generally equivalent to the asymptotic z statistic presented in the coefficient table for that variable because test bases its results on the information matrix.

▷ Example 13

Let's examine the repair records of the cars in our automobile data as rated by *Consumer Reports*:

```
. tabulate rep78 foreign
```

Repair record 1978	Car origin: Domestic	Foreign	Total
Poor	2	0	2
Fair	8	0	8
Average	27	3	30
Good	9	9	18
Excellent	2	9	11
Total	48	21	69

The values are coded 1–5, corresponding to Poor, Fair, Average, Good, and Excellent. We will fit this variable by using a maximum-likelihood ordered logit model (the nolog option suppresses the iteration log, saving some space):

```
. ologit rep78 price foreign weight weightsq displ, nolog
Ordered logistic regression                       Number of obs =     69
                                                  LR chi2(5)    =  33.12
                                                  Prob > chi2   = 0.0000
Log likelihood = -77.133082                       Pseudo R2     = 0.1767

------------------------------------------------------------------------------
       rep78 |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       price |   -.000034   .0001188    -0.29   0.775    -.0002669     .000199
     foreign |    2.685647   .9320404     2.88   0.004     .8588817    4.512413
      weight |   -.0037447   .0025609    -1.46   0.144    -.0087639    .0012745
    weightsq |    7.87e-07   4.50e-07     1.75   0.080    -9.43e-08    1.67e-06
displacement |   -.0108919   .0076805    -1.42   0.156    -.0259455    .0041617
-------------+----------------------------------------------------------------
       /cut1 |   -9.417196   4.298202                     -17.84152    -.992874
       /cut2 |   -7.581864   4.234091                     -15.88053    .7168028
       /cut3 |    -4.82209    4.14768                     -12.95139    3.307214
       /cut4 |   -2.793441   4.156221                     -10.93948    5.352602
------------------------------------------------------------------------------
```

We now wonder whether all our variables other than `foreign` are jointly significant. We test the hypothesis just as we would after linear regression:

```
. test weight weightsq displ price
 ( 1)  [rep78]weight = 0
 ( 2)  [rep78]weightsq = 0
 ( 3)  [rep78]displacement = 0
 ( 4)  [rep78]price = 0
           chi2(  4) =    3.63
         Prob > chi2 =    0.4590
```

You will have to decide whether you want to perform tests on the basis of the information matrix instead of constraining the equation, reestimating it, and then calculating the likelihood-ratio test. To compare this with the results performed by a likelihood-ratio test, see **[U] 20.13.3 Likelihood-ratio tests** below. Results will differ little.

◁

20.13.3 Likelihood-ratio tests

After maximum likelihood estimation, you can obtain likelihood-ratio tests by fitting both the unconstrained and the constrained models, storing the results using `estimates store`, and then running `lrtest`. See [R] **lrtest** for the full details.

▷ Example 14

In **[U] 20.13.2 Using test** above, we fit an ordered logit on `rep78` and then tested the significance of all the explanatory variables except `foreign`.

To obtain the likelihood-ratio test, sometime after fitting the full model, we type `estimates store` *full_model_name*, where *full_model_name* is just a label that we assign to these results.

```
. ologit rep78 price foreign weight weightsq displ
  (output omitted)
. estimates store myfullmodel
```

This command saves the current model results with the name `myfullmodel`.

Next, we fit the constrained model. After that, typing '`lrtest myfullmodel .`' compares the current model with the model we saved:

```
. ologit rep78 foreign
Iteration 0:  Log likelihood = -93.692061
Iteration 1:  Log likelihood = -79.696089
Iteration 2:  Log likelihood = -79.034005
Iteration 3:  Log likelihood = -79.029244
Iteration 4:  Log likelihood = -79.029243
Ordered logistic regression                       Number of obs =     69
                                                  LR chi2(1)    =  29.33
                                                  Prob > chi2   = 0.0000
Log likelihood = -79.029243                       Pseudo R2     = 0.1565
------------------------------------------------------------------------------
       rep78 | Coefficient  Std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
     foreign |    2.98155   .6203644     4.81   0.000     1.765658    4.197442
-------------+----------------------------------------------------------------
       /cut1 |  -3.158382   .7224269                     -4.574313   -1.742452
       /cut2 |  -1.362642   .3557343                     -2.059868   -.6654154
       /cut3 |   1.232161   .3431227                      .5596532    1.90467
       /cut4 |   3.246209   .5556657                      2.157124    4.335293
------------------------------------------------------------------------------

. lrtest myfullmodel .
Likelihood-ratio test
Assumption: . nested within myfullmodel
 LR chi2(4) =   3.79
Prob > chi2 = 0.4348
```

When we tested the same constraint with `test` (which performed a Wald test), we obtained a χ^2 of 3.63 and a significance level of 0.4590. We used `.` (the dot) to specify the results in active memory, although we could have stored them with `estimates store` and referred to them by name instead. Also, the order in which you specify the two models to `lrtest` doesn't matter; `lrtest` is smart enough to know the full model from the constrained model.

◁

Two other postestimation commands work in the same way as `lrtest`, meaning that they accept names of stored estimation results as their input: `hausman` for performing Hausman specification tests and `suest` for seemingly unrelated estimation. We do not cover these commands here; see [R] **hausman** and [R] **suest** for more details.

20.13.4 Nonlinear Wald tests

`testnl` can be used to test nonlinear hypotheses about the parameters of the active estimation results. `testnl`, like `test`, bases its results on the variance–covariance matrix of the estimators (that is, it performs a Wald test), so it can be used after any estimation command; see [R] **testnl**.

▷ Example 15

We fit the model

```
. regress price mpg weight foreign
  (output omitted)
```

and then type

```
. testnl (38*_b[mpg]^2 = _b[foreign]) (_b[mpg]/_b[weight]=4)
  (1)  38*_b[mpg]^2 = _b[foreign]
  (2)  _b[mpg]/_b[weight] = 4
               chi2(2) =        0.04
           Prob > chi2 =        0.9806
```

We performed this test on linear regression estimates, but tests of this type could be performed after any estimation command.

◁

A concept of a p-value is fundamental to classical hypothesis testing; see Wasserstein and Lazar (2016) for a useful discussion about its interpretation and use in practice. Also see **[U] 27.34 Bayesian analysis** for an alternative to classical hypothesis testing.

20.14 Obtaining linear combinations of parameters

`lincom` computes point estimates, standard errors, t or z statistics, p-values, and confidence intervals for a linear combination of parameters after any estimation command. Results can optionally be displayed as odds ratios, incidence-rate ratios, or relative-risk ratios.

▷ Example 16

We fit a linear regression:

```
. use https://www.stata-press.com/data/r19/regress, clear
. regress y x1 x2 x3
```

Source	SS	df	MS	Number of obs	=	148
				F(3, 144)	=	96.12
Model	3259.3561	3	1086.45203	Prob > F	=	0.0000
Residual	1627.56282	144	11.3025196	R-squared	=	0.6670
				Adj R-squared	=	0.6600
Total	4886.91892	147	33.2443464	Root MSE	=	3.3619

y	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
x1	1.457113	1.07461	1.36	0.177	-.666934	3.581161
x2	2.221682	.8610358	2.58	0.011	.5197797	3.923583
x3	-.006139	.0005543	-11.08	0.000	-.0072345	-.0050435
_cons	36.10135	4.382693	8.24	0.000	27.43863	44.76407

Suppose that we want to see the difference of the coefficients of `x2` and `x1`. We type

```
. lincom x2 - x1
 ( 1)  - x1 + x2 = 0
```

y	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
(1)	.7645682	.9950282	0.77	0.444	-1.20218	2.731316

◁

`lincom` is handy for computing the odds ratio of one covariate group relative to another.

▷ Example 17

We estimate the parameters of a logistic model of low birthweight:

```
. use https://www.stata-press.com/data/r19/lbw3
(Hosmer & Lemeshow data)
. logit low age lwd i.race smoke ptd ht ui
Iteration 0:  Log likelihood =   -117.336
Iteration 1:  Log likelihood =   -99.3982
Iteration 2:  Log likelihood = -98.780418
Iteration 3:  Log likelihood = -98.777998
Iteration 4:  Log likelihood = -98.777998
Logistic regression                                     Number of obs =    189
                                                        LR chi2(8)    =  37.12
                                                        Prob > chi2   = 0.0000
Log likelihood = -98.777998                             Pseudo R2     = 0.1582
```

low	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
age	-.0464796	.0373888	-1.24	0.214	-.1197603	.0268011
lwd	.8420615	.4055338	2.08	0.038	.0472299	1.636893
race						
Black	1.073456	.5150753	2.08	0.037	.0639273	2.082985
Other	.815367	.4452979	1.83	0.067	-.0574008	1.688135
smoke	.8071996	.404446	2.00	0.046	.0145001	1.599899
ptd	1.281678	.4621157	2.77	0.006	.3759478	2.187408
ht	1.435227	.6482699	2.21	0.027	.1646414	2.705813
ui	.6576256	.4666192	1.41	0.159	-.2569313	1.572182
_cons	-1.216781	.9556797	-1.27	0.203	-3.089878	.656317

Level 1 of `race` designates white, level 2 designates black, and level 3 designates other.

If we want to obtain the odds ratio for black smokers relative to white nonsmokers (the reference group), we type

```
. lincom 2.race + smoke, or
 ( 1)  [low]2.race + [low]smoke = 0
```

low	Odds ratio	Std. err.	z	P>|z|	[95% conf.	interval]
(1)	6.557805	4.744692	2.60	0.009	1.588176	27.07811

`lincom` computed $\exp(\beta_{2.\text{race}} + \beta_{\text{smoke}}) = 6.56$.

◁

20.15 Obtaining nonlinear combinations of parameters

`lincom` is limited to estimating linear combinations of coefficients, for example, `2.race + smoke`, or exponentiated linear combinations, as in the above. For general nonlinear combinations, use `nlcom`.

▷ Example 18

Continuing our previous example, suppose that we want the ratio of the coefficients (and standard errors, Wald test, confidence interval, etc.) of blacks and races other than white and black:

```
. nlcom _b[2.race]/_b[3.race]
       _nl_1: _b[2.race]/_b[3.race]
```

low	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
_nl_1	1.316531	.7359262	1.79	0.074	-.1258574	2.75892

The Wald test given is that of the null hypothesis that the nonlinear combination is 0 versus the two-sided alternative—this is probably not informative for a ratio. If we would instead like to test whether this ratio is 1, we can rerun `nlcom`, this time subtracting 1 from our ratio estimate.

```
. nlcom _b[2.race]/_b[3.race] - 1
       _nl_1: _b[2.race]/_b[3.race] - 1
```

low	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
_nl_1	.3165314	.7359262	0.43	0.667	-1.125857	1.75892

We can interpret this as not much evidence that the ratio minus 1 is different from 0, meaning that we cannot reject the null hypothesis that the ratio equals 1.

When using `nlcom`, we needed to refer to the model coefficients by their "proper" names, for example, `_b[2.race]`, and not by the shorthand `2.race`, such as when using `lincom`. If we had typed

```
. nlcom 2.race/3.race
```

Stata would have reported an error.

If you have difficulty determining what to type for a coefficient when using `lincom` or `nlcom`, replay your results by using the `coeflegend` option. Here are the results for our current estimates:

```
. logit, coeflegend
Logistic regression                                     Number of obs =    189
                                                        LR chi2(8)    =  37.12
                                                        Prob > chi2   = 0.0000
Log likelihood = -98.777998                             Pseudo R2     = 0.1582
```

low	Coefficient	Legend
age	-.0464796	_b[age]
lwd	.8420615	_b[lwd]
race		
Black	1.073456	_b[2.race]
Other	.815367	_b[3.race]
smoke	.8071996	_b[smoke]
ptd	1.281678	_b[ptd]
ht	1.435227	_b[ht]
ui	.6576256	_b[ui]
_cons	-1.216781	_b[_cons]

◁

20.16 Obtaining marginal means, adjusted predictions, and predictive margins

`predict` uses the current estimation results (the coefficients and the VCE) to estimate the value of statistics for observations in the data. `lincom` and `nlcom` use the current estimation results to estimate a specific linear or nonlinear expression of the coefficients. The `margins` command combines aspects of both and estimates margins of responses.

`margins` answers the question "What does my model have to say about such-and-such", where such-and-such might be

- my estimation sample or another sample
- a sample with the values of some covariates fixed
- a sample evaluated at each level of a treatment
- a population represented by a complex survey sample
- someone who looks like the fifth person in my sample
- someone who looks like the mean of the covariates in my sample
- someone who looks like the median of the covariates in my sample
- someone who looks like the 25th percentile of the covariates in my sample
- someone who looks like some other function of the covariates in my sample
- a standardized population
- a balanced experimental design
- any combination of the above
- any comparison of the above

`margins` answers these questions either conditionally on fixed values of all covariates or averaged over the observations in a sample. It answers these questions about almost any predictions or any other response that you can calculate as a function of your estimated parameters—linear responses, probabilities, hazards, survival times, odds ratios, risk differences, etc. You can even make multiple predictions at the same time when appropriate. For example, you may want the predicted probabilities and the linear prediction after `logit`.

`margins` answers these questions in terms of the response given covariate levels, or in terms of the change in the response for a change in levels (also known as marginal effects). It answers these questions providing standard errors, test statistics, and confidence intervals; and those statistics can take the covariates as given or adjust for sampling, also known as predictive margins and survey statistics.

A margin is a statistic based on a response for a fitted model calculated over a dataset in which some of or all the covariates are fixed at values different from what they really are.

Margins go by different names in different fields, and they can estimate many interesting statistics related to a fitted model. We discuss some common uses below; see [R] **margins** for more applications.

20.16.1 Obtaining estimated marginal means

A classic application of margins is to estimate the expected marginal means from a linear estimator as though the design for the covariates were balanced—assuming an equal number of observations for each unique combination of levels for the factor-variable covariates. These means have a long history in the study of ANOVA and MANOVA but are of limited use with nonexperimental data. For a discussion, see *Obtaining margins as though the data were balanced* in [R] **margins** and example 4 in [R] **anova**.

Estimated marginal means are also called least-squares means.

Consider an analysis of variance of the change in systolic blood pressure as determined by one of four drug treatments and adjusting for the patient's disease (Afifi and Azen 1979).

```
. use https://www.stata-press.com/data/r19/systolic
(Systolic blood pressure data)
. tabulate drug disease
```

Drug used	Patient's disease 1	2	3	Total
1	6	4	5	15
2	5	4	6	15
3	3	5	4	12
4	5	6	5	16
Total	19	19	20	58

```
. anova systolic drug##disease
```

Number of obs = 58 R-squared = 0.4560
Root MSE = 10.5096 Adj R-squared = 0.3259

Source	Partial SS	df	MS	F	Prob>F
Model	4259.3385	11	387.21259	3.51	0.0013
drug	2997.4719	3	999.15729	9.05	0.0001
disease	415.87305	2	207.93652	1.88	0.1637
drug#disease	707.26626	6	117.87771	1.07	0.3958
Residual	5080.8167	46	110.45254		
Total	9340.1552	57	163.86237		

Despite having randomized on drug, we see in the tabulation that our data are not balanced—for example, 12 patients were administered drug 3, whereas 16 were administered drug 4. The diseases are also not balanced across drugs. To estimate the marginal mean for each level of drug while treating the design as though it were balanced, we type

```
. margins drug, asbalanced
Adjusted predictions                                    Number of obs = 58
Expression: Linear prediction, predict()
At: disease   (asbalanced)
```

	Margin	Delta-method std. err.	t	P>|t|	[95% conf.	interval]
drug						
1	25.99444	2.751008	9.45	0.000	20.45695	31.53194
2	26.55556	2.751008	9.65	0.000	21.01806	32.09305
3	9.744444	3.100558	3.14	0.003	3.503344	15.98554
4	13.54444	2.637123	5.14	0.000	8.236191	18.8527

Assuming everyone in the sample were treated with drug 4 and that the diseases were equally distributed across the drug treatments, the expected mean change in pressure resulting from treatment with drug 4 is 13.54. Because we are treating the data as balanced, we could also say that 13.54 is the expected mean change resulting from drug 4 for any sample where an equal number of patients has each of the three diseases.

If we want an estimate of the mean that uses the distribution of diseases observed in the sample, we would remove the `asbalanced` option:

```
. margins drug
Predictive margins                                      Number of obs = 58
Expression: Linear prediction, predict()
```

	Margin	Delta-method std. err.	t	P>|t|	[95% conf.	interval]
drug						
1	25.89799	2.750533	9.42	0.000	20.36145	31.43452
2	26.41092	2.742762	9.63	0.000	20.89003	31.93181
3	9.722989	3.099185	3.14	0.003	3.484652	15.96132
4	13.55575	2.640602	5.13	0.000	8.24049	18.871

We can now say that a pressure change of 13.56 is expected if everyone in the sample is given drug 4 and the distribution of diseases is as observed in the sample.

The second set of margins are not usually called estimated marginal means because they do not impose a balanced design when estimating the mean. They are adjusted predictions that just happen to be means because the response is linear.

Neither of these values is the average pressure change for those taking drug 4 in our sample because `margins` treats everyone in the sample as having taken drug 4. Treating everyone as though they have taken each drug is what makes the means comparable. We are essentially standardizing on the values of all the other covariates in our model (in this example, just `disease`).

To obtain the observed mean for those taking drug 4, we must tell `margins` to treat drug 4 as its sample, which we do with the `over()` option.

```
. summarize systolic if drug==4
    Variable |        Obs        Mean    Std. dev.       Min        Max
-------------+---------------------------------------------------------
    systolic |         16        13.5    9.323805        -5         27

. margins, over(drug)
Predictive margins                                      Number of obs = 58
Expression: Linear prediction, predict()
Over:       drug
------------------------------------------------------------------------------
             |            Delta-method
             |     Margin   std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
        drug |
          1  |   26.06667   2.713577     9.61   0.000     20.60452    31.52881
          2  |   25.53333   2.713577     9.41   0.000     20.07119    30.99548
          3  |       8.75   3.033872     2.88   0.006     2.643133    14.85687
          4  |       13.5    2.62741     5.14   0.000     8.211298     18.7887
------------------------------------------------------------------------------
```

The margin in the last line of the table matches the mean from `summarize`.

For many questions, we prefer one of the first two estimates of `margins` to the last one. If we compare drugs 3 and 4 from the last results, the 8.75 and 13.5 include both the effect from the drug and the differing distribution of diseases among patients taking drug 3 and drug 4 in our sample. Our first set of margins, those from `margins drug, asbalanced`, assumed that for both drug 3 and drug 4, we had an equal number of patients with each disease. Our second set of margins, those from `margins drug`, assumed that for both drug 3 and drug 4, we wanted the observed distribution of patients from the whole sample. By assuming a common distribution of diseases across the drugs, our first two sets of margins remove the effect of disease when we compare across drugs.

20.16.2 Obtaining adjusted predictions

We will use the term adjusted predictions to refer to margins that are evaluated at fixed values for all covariates. The `margins` command has a great deal of flexibility in letting you choose what those fixed values are. Consider a model of high blood pressure as a function of sex, age group, and body mass index (BMI, a common measure of weight relative to height; variable `bmi`). We will allow the effect of age to differ for males and females by interacting the age group and sex variables. We will also allow the effect of BMI to differ across all combinations of age group and sex by specifying a full factorial model.

```
. use https://www.stata-press.com/data/r19/nhanes2
. logistic highbp sex##agegrp##c.bmi
Logistic regression                                     Number of obs =  10,351
                                                        LR chi2(23)   = 2521.83
                                                        Prob > chi2   =  0.0000
Log likelihood = -5789.851                              Pseudo R2     =  0.1788
```

highbp	Odds ratio	Std. err.	z	P>|z|	[95% conf.	interval]
sex						
Female	.4012124	.2695666	-1.36	0.174	.107515	1.497199
agegrp						
30-39	.8124869	.6162489	-0.27	0.784	.1837399	3.592768
40-49	1.346976	1.101181	0.36	0.716	.2713222	6.687051
50-59	5.415758	4.254136	2.15	0.032	1.161532	25.2515
60-69	16.31623	10.09529	4.51	0.000	4.852423	54.86321
70+	161.2491	130.7332	6.27	0.000	32.9142	789.9717
sex#agegrp						
Female#30-39	1.441256	1.44721	0.36	0.716	.2013834	10.31475
Female#40-49	6.29497	6.575021	1.76	0.078	.8126879	48.75998
Female#50-59	4.377185	4.43183	1.46	0.145	.6016818	31.84366
Female#60-69	1.790026	1.502447	0.69	0.488	.3454684	9.27492
Female#70+	.1958758	.2165763	-1.47	0.140	.0224297	1.710562
bmi	1.18539	.0221872	9.09	0.000	1.142692	1.229684
sex#c.bmi						
Female	.9809543	.0250973	-0.75	0.452	.9329775	1.031398
agegrp#c.bmi						
30-39	1.021812	.0299468	0.74	0.462	.9647712	1.082225
40-49	1.00982	.0315328	0.31	0.754	.9498702	1.073554
50-59	.979291	.0298836	-0.69	0.493	.9224373	1.039649
60-69	.9413883	.0228342	-2.49	0.013	.8976813	.9872234
70+	.8738056	.0278416	-4.23	0.000	.8209061	.930114
sex#agegrp#c.bmi						
Female#30-39	1.000676	.0377954	0.02	0.986	.9292736	1.077564
Female#40-49	.9702656	.0382854	-0.76	0.444	.8980559	1.048281
Female#50-59	.9852929	.0380345	-0.38	0.701	.9134969	1.062732
Female#60-69	1.028896	.0330473	0.89	0.375	.9661212	1.09575
Female#70+	1.12236	.0480541	2.70	0.007	1.032019	1.220609
_cons	.0052191	.0024787	-11.07	0.000	.0020575	.0132388

Note: **_cons** estimates baseline odds.

We can evaluate the probability of having high blood pressure for each age group while holding the proportion of males and females and the value of bmi to its average by specifying the covariate agegrp to margins and including the atmeans option:

```
. margins agegrp, atmeans
Adjusted predictions                                    Number of obs = 10,351
Model VCE: OIM
Expression: Pr(highbp), predict()
At: 1.sex    = .4748333 (mean)
    2.sex    = .5251667 (mean)
    bmi      =  25.5376 (mean)
```

	Margin	Delta-method std. err.	z	P>|z|	[95% conf.	interval]
agegrp						
20-29	.1611491	.0091135	17.68	0.000	.1432869	.1790113
30-39	.2487466	.0121649	20.45	0.000	.2249038	.2725893
40-49	.3679695	.0144456	25.47	0.000	.3396567	.3962823
50-59	.5204507	.0146489	35.53	0.000	.4917394	.549162
60-69	.5714605	.0095866	59.61	0.000	.5526711	.5902499
70+	.6637982	.0154566	42.95	0.000	.6335038	.6940927

The header of the table showed us the mean values of each covariate. These are the values at which the probabilities were evaluated. The mean values for the levels of agegrp appear in the header even though they were not used. agegrp assumed the values 1, 2, 3, 4, 5, and 6, as shown in the table. The means of the levels of agegrp are shown because we might have asked for more margins in the table, for example, margins sex agegrp.

The modeled probability is just below 25% for those under 40 years of age, and it then increases fairly rapidly to 52% in the 50–59 age group. Above age 59, the probability remains under 67%. It is often easier for nonstatisticians to interpret the statistics computed by margins than it is to interpret the coefficients of a fitted model.

20.16.3 Obtaining predictive margins

Rather than evaluate the probability of having high blood pressure at one fixed point (the means), as we did above, we can evaluate the probability at the covariate values for each observation in our data and average those probabilities. Here is the modeled probability averaged over our sample:

```
. margins
Predictive margins                                      Number of obs = 10,351
Model VCE: OIM
Expression: Pr(highbp), predict()
```

	Margin	Delta-method std. err.	z	P>|z|	[95% conf.	interval]
_cons	.4227611	.0042939	98.46	0.000	.4143451	.4311771

If we fix the level of agegrp to 1, compute the probability for each observation, and then average those probabilities, the result is the predictive margin for level 1 of agegrp. margins, by default, computes these margins for each level of each variable specified on the command line. Let's compute the predictive margins for agegrp:

```
. margins agegrp
Predictive margins                                Number of obs = 10,351
Model VCE: OIM
Expression: Pr(highbp), predict()
```

	Margin	Delta-method std. err.	z	P>|z|	[95% conf.	interval]
agegrp						
20–29	.2030932	.0087166	23.30	0.000	.1860089	.2201774
30–39	.2829091	.010318	27.42	0.000	.2626862	.3031319
40–49	.3769536	.0128744	29.28	0.000	.3517202	.4021871
50–59	.5153439	.0136201	37.84	0.000	.4886491	.5420387
60–69	.5641065	.009136	61.75	0.000	.5462003	.5820127
70+	.6535679	.0151371	43.18	0.000	.6238997	.683236

One way of looking at predictive margins is that they answer the question "What would the average response (probability) be in my sample if everyone were in one age group?" Another way of looking at predictive margins is that they standardize the effect of being in an age group with the distribution of other covariate values in our sample. The margins above are comparable because only the level of agegrp is changing across the margins. They represent our sample because all the other covariates take on their values in the sample when the margins are evaluated.

The predictive margins in this table differ from the adjusted predictions we estimated in **[U] 20.16.2 Obtaining adjusted predictions** because the probability is a nonlinear function of the coefficients in a logistic model; see *Example 3: Average response versus response at average* in [R] **margins** for details.

Our analysis so far has been a bit naïve. The dataset we are using is from the Second National Health and Nutrition Examination Survey (NHANES II). It has weights to make it representative of the population from which it was drawn as well as other survey characteristics—strata and primary sampling units. The data have already been svyset; see [SVY] **svyset**. We should take note of these characteristics and use the svy prefix when fitting our model.

```
. svy: logistic highbp sex##agegrp##c.bmi
(output omitted)
```

If we were to repeat the command margins agegrp, we would see that our point estimates differ only a little, but our standard errors are generally larger.

We are not restricted to margining over a single factor variable. Let's see if the pattern of high blood pressure over age groups differs for men and women. We do that by specifying the interaction of sex and agegrp to margins. We add the vce(unconditional) option to accommodate the survey design.

```
. margins sex#agegrp, vce(unconditional)
Predictive margins
Number of strata = 31                          Number of obs    =      10,351
Number of PSUs   = 62                          Population size = 117,157,513
                                               Design df        =          31
Expression: Pr(highbp), predict()
```

	Margin	Linearized std. err.	t	P>|t|	[95% conf.	interval]
sex#agegrp						
Male#20–29	.2931664	.0204899	14.31	0.000	.251377	.3349557
Male#30–39	.3664032	.0241677	15.16	0.000	.3171128	.4156936
Male#40–49	.3945619	.0240343	16.42	0.000	.3455435	.4435802
Male#50–59	.5376423	.0295377	18.20	0.000	.4773997	.5978849
Male#60–69	.5780997	.0224681	25.73	0.000	.5322756	.6239237
Male#70+	.6507023	.0209322	31.09	0.000	.6080109	.6933938
Female#20–29	.1069761	.0135978	7.87	0.000	.0792432	.1347091
Female#30–39	.1898006	.0143975	13.18	0.000	.1604367	.2191646
Female#40–49	.3250246	.0236775	13.73	0.000	.276734	.3733152
Female#50–59	.4855339	.03364	14.43	0.000	.4169247	.5541431
Female#60–69	.5441773	.0186243	29.22	0.000	.5061928	.5821618
Female#70+	.6195342	.0275568	22.48	0.000	.5633317	.6757367

Each line in the table corresponds to holding both `sex` and `agegrp` to fixed values while using the observed level of `bmi` to evaluate the probability and then averaging over the observations in the sample. To calculate the results in the first line of the table, `margins` fixed `sex` $= 1$ and `agegrp` $= 1$, evaluated the probability for each observation, and then averaged the probabilities. All of these margins reflect the observed distribution of `bmi` in the sample.

The first six lines represent males, and the second six lines represent females. Comparing males with females for the same age groups, males are almost three times as likely to have high blood pressure in the first age group $(0.293/0.107 = 2.7)$; they are almost twice as likely in the second age group; and while the relative gap narrows, it is not until above age 70 that the probability for males drops below the probability for females.

Can the pattern of probabilities be affected by controlling one's `bmi`? Let's reevaluate the probabilities while holding `bmi` to two levels—20 (which is well within the normal range) and 30 (which is at the boundary between overweight and obese). We add the option `at(bmi=(20 30))` to set `bmi` first to 20 and then to 30.

```
. margins sex#agegrp, at(bmi=(20 30)) vce(unconditional)

Adjusted predictions
Number of strata = 31                          Number of obs    =      10,351
Number of PSUs   = 62                          Population size = 117,157,513
                                               Design df        =          31

Expression: Pr(highbp), predict()
1._at: bmi = 20
2._at: bmi = 30
```

	Margin	Linearized std. err.	t	P>|t|	[95% conf.	interval]
_at#sex# agegrp						
1#Male#20–29	.1392353	.0217328	6.41	0.000	.094911	.1835596
1#Male#30–39	.1714727	.0241469	7.10	0.000	.1222249	.2207205
1#Male#40–49	.1914061	.0366133	5.23	0.000	.1167329	.2660794
1#Male#50–59	.3380778	.0380474	8.89	0.000	.2604797	.4156759
1#Male#60–69	.4311378	.0371582	11.60	0.000	.3553532	.5069225
1#Male#70+	.6131166	.0521657	11.75	0.000	.506724	.7195092
1 # Female # 20–29	.0439911	.0061833	7.11	0.000	.0313802	.056602
1 # Female # 30–39	.075806	.0134771	5.62	0.000	.0483193	.1032926
1 # Female # 40–49	.1941274	.0231872	8.37	0.000	.1468367	.2414181
1 # Female # 50–59	.3493224	.0405082	8.62	0.000	.2667055	.4319394
1 # Female # 60–69	.3897998	.0226443	17.21	0.000	.3436165	.4359831
1#Female#70+	.4599175	.0338926	13.57	0.000	.3907931	.5290419
2#Male#20–29	.4506376	.0370654	12.16	0.000	.3750422	.526233
2#Male#30–39	.569466	.04663	12.21	0.000	.4743635	.6645686
2#Male#40–49	.6042078	.039777	15.19	0.000	.5230821	.6853334
2#Male#50–59	.7268547	.0339618	21.40	0.000	.657589	.7961203
2#Male#60–69	.7131811	.0271145	26.30	0.000	.6578807	.7684816
2#Male#70+	.6843337	.0357432	19.15	0.000	.611435	.7572323
2 # Female # 20–29	.1638185	.024609	6.66	0.000	.1136282	.2140088
2 # Female # 30–39	.3038899	.0271211	11.20	0.000	.2485761	.3592037
2 # Female # 40–49	.4523337	.0364949	12.39	0.000	.3779019	.5267655
2 # Female # 50–59	.6132219	.0376898	16.27	0.000	.536353	.6900908
2 # Female # 60–69	.68786	.0274712	25.04	0.000	.631832	.7438879
2#Female#70+	.7643662	.0343399	22.26	0.000	.6943296	.8344029

That is a lot of margins, but they are in sets of six age groups. The first six margins are men with a BMI of 20, the second six are women with a BMI of 20, the third six are men with a BMI of 30, and the last six are women with a BMI of 30. These margins tell a more complete story. The probability of high blood pressure is much lower for both men and women who maintain a BMI of 20. More interesting is that the relationship between men and women differs depending on BMI. While young men who maintain a BMI of 20 are still twice as likely as young women to have high blood pressure (0.139/0.044) and youngish men are over 50% more likely (0.171/0.076), the gap narrows substantially for men in the four older groups. The story is worse for those with a BMI of 30. Both men and women with a high BMI have a substantially increased risk of high blood pressure, with men ages 50–69 almost 10 percentage points higher than women. Before you dismiss these differences as caused by the usual attenuation of the logistic curve in the tails, recall that when we fit the model, we allowed the effect of `bmi` to be different for each combination of `sex` and `agegrp`.

You may have noticed that the header of the prior results says "Adjusted predictions" rather than "Predictive margins". That is because our model has only three covariates, and we have fixed the values of each. `margins` is no longer averaging over the data, but is instead evaluating the margins at fixed points that we have requested. It lets us know that by changing the header.

We could post the results of `margins` and form linear combinations or perform tests about any of the assertions above; see *Example 10: Testing margins—contrasts of margins* in [R] **margins**.

There is much more to know about margins and the `margins` command. See *Remarks and examples* in [R] **margins** for more details.

20.17 Obtaining conditional and average marginal effects

Marginal effects measure the change in a response given a change in a covariate, which is to say that marginal effects are derivatives. As used here, marginal effects can also be the discrete change in a response as an indicator goes from 0 to 1. Some authors reserve the term marginal effect for the continuous change and use the term partial effect for the discrete change. We will not make that distinction. Regardless, marginal effects are most often used to make it easier to interpret how changes in covariates affect a nonlinear response from a fitted model—a probability, a censored dependent variable, a survival time, a hazard, etc.

Marginal effects can either be evaluated at a specified point for all the covariates in our model (conditional marginal effects) or be evaluated at the observed values of the covariates in a dataset and then averaged (average marginal effects).

To Stata, marginal effects are just margins whose response happens to be the derivative of another response. Those interested in marginal effects will be interested in all or most of [R] **margins**.

20.17.1 Obtaining conditional marginal effects

We call a marginal effect conditional when we fix the values of all the covariates and then take the derivative of the response with respect to a covariate. The mean of all covariates is often used as the fixed point, and this is sometimes called the marginal effect at the means.

Consider a simple probit model of union membership for women as a function of having graduated from college (`collgrad`), living in the South (`south`), tenure on the job (`tenure`), and the interaction of `south` and `tenure`. We are interested in how being in the South affects union membership. We fit the model by using an extract from 1988 of the US National Longitudinal Survey of Labor Market Experience (see [XT] **xt**).

```
. use https://www.stata-press.com/data/r19/nlsw88b, clear
(NLSW, 1988 extract)
. probit union i.collgrad i.south tenure south#c.tenure
Iteration 0:  Log likelihood = -1042.6816
Iteration 1:  Log likelihood = -997.71809
Iteration 2:  Log likelihood = -997.60984
Iteration 3:  Log likelihood = -997.60983
Probit regression                                     Number of obs =  1,868
                                                      LR chi2(4)    =  90.14
                                                      Prob > chi2   = 0.0000
Log likelihood = -997.60983                           Pseudo R2     = 0.0432
```

union	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
collgrad						
not grad	.2783278	.0726167	3.83	0.000	.1360018	.4206539
1.south	-.2534964	.1050552	-2.41	0.016	-.4594008	-.0475921
tenure	.0362944	.0068205	5.32	0.000	.0229264	.0496624
south#						
c.tenure						
1	-.0239785	.0119533	-2.01	0.045	-.0474065	-.0005504
_cons	-.8497418	.0664524	-12.79	0.000	-.9799862	-.7194974

Clearly, being located in the South decreases union membership. Using the `dydx()` and `atmeans` options of `margins`, we can ask how much it decreases membership by evaluating the marginal effect of being southern at the means of all covariates:

```
. margins, dydx(south) atmeans
Conditional marginal effects                          Number of obs = 1,868
Model VCE: OIM
Expression: Pr(union), predict()
dy/dx wrt:  1.south
At: 0.collgrad = .7521413 (mean)
    1.collgrad = .2478587 (mean)
    0.south    = .5744111 (mean)
    1.south    = .4255889 (mean)
    tenure     = 6.571065 (mean)
```

	Delta-method dy/dx	std. err.	z	P>|z|	[95% conf.	interval]
1.south	-.1236055	.019431	-6.36	0.000	-.1616896	-.0855215

```
Note: dy/dx for factor levels is the discrete change from the base level.
```

At the means of all the covariates, southern women are 12 percentage points less likely to be members of a union. This marginal effect includes both the direct effect of `i.south` and the interaction `south#c.tenure`.

As `margins` reports below the table, this change in the response is for the discrete change of going from not southern (0) to southern (1).

The header of `margins` tells us where the marginal effect was estimated. This margin fixes `tenure` to be 6.6 years. There is nothing special about this point. We could also evaluate the marginal effect at the median of `tenure`:

```
. margins, dydx(south) atmeans at((medians) _continuous)
Conditional marginal effects                              Number of obs = 1,868
Model VCE: OIM

Expression: Pr(union), predict()
dy/dx wrt:  1.south
At: 0.collgrad = .7521413 (mean)
    1.collgrad = .2478587 (mean)
    0.south    = .5744111 (mean)
    1.south    = .4255889 (mean)
    tenure     = 4.666667 (median)
```

	Delta-method dy/dx	std. err.	z	P>|z|	[95% conf.	interval]
1.south	-.1061338	.0201722	-5.26	0.000	-.1456706	-.066597

Note: dy/dx for factor levels is the discrete change from the base level.

With `tenure` at its median of 4.67, the marginal effect is about 2 percentage points less than it was at the mean of 6.6.

When examining conditional marginal effects, it is often useful to evaluate them at a range of values for the covariates. We can do that by asking both for values of the indicator covariate `collgrad` and for a range of values for `tenure`:

```
. margins collgrad, dydx(south) at(tenure=(0(5)25))
Conditional marginal effects                              Number of obs = 1,868
Model VCE: OIM

Expression: Pr(union), predict()
dy/dx wrt:  1.south
1._at: tenure =  0
2._at: tenure =  5
3._at: tenure = 10
4._at: tenure = 15
5._at: tenure = 20
6._at: tenure = 25
```

	Delta-method dy/dx	std. err.	z	P>|z|	[95% conf.	interval]
0.south	(base outcome)					
1.south						
_at#collgrad						
1#grad	-.0627725	.0254161	-2.47	0.014	-.112587	-.0129579
1#not grad	-.0791483	.0321151	-2.46	0.014	-.1420928	-.0162038
2#grad	-.1031957	.0189184	-5.45	0.000	-.140275	-.0661164
2#not grad	-.1256566	.0232385	-5.41	0.000	-.1712031	-.0801101
3#grad	-.1496772	.022226	-6.73	0.000	-.1932392	-.1061151
3#not grad	-.1760137	.0266874	-6.60	0.000	-.2283202	-.1237073
4#grad	-.2008801	.036154	-5.56	0.000	-.2717407	-.1300196
4#not grad	-.2282	.0419237	-5.44	0.000	-.310369	-.146031
5#grad	-.2549707	.0546355	-4.67	0.000	-.3620543	-.1478872
5#not grad	-.2799495	.0613127	-4.57	0.000	-.4001201	-.1597789
6#grad	-.3097656	.0747494	-4.14	0.000	-.4562717	-.1632594
6#not grad	-.3289702	.0816342	-4.03	0.000	-.4889703	-.1689701

Note: dy/dx for factor levels is the discrete change from the base level.

We now have a more complete picture of the effect that being in the South has on union participation. For those with no tenure and without a college degree (the first line in the table), being in the South decreases union participation by only 6 percentage points. For those with 25 years of tenure and with a college degree (the last line in the table), being in the South decreases participation by almost 33 percentage points. We can read the effect for any combination of tenure and college graduation status from the other lines in the table.

20.17.2 Obtaining average marginal effects

To compute average marginal effects, the marginal effect is first computed for each observation in the dataset and then averaged. If the sample over which we compute the average marginal effect represents a population, then we have estimated the marginal effect for the population.

We continue with our example of labor union participation.

```
. use https://www.stata-press.com/data/r19/nlsw88b
(NLSW, 1988 extract)
. probit union i.collgrad i.south tenure south#c.tenure
  (output omitted)
```

To estimate the average marginal effect for each of our regressors, we type

```
. margins, dydx(*)
Average marginal effects                                  Number of obs = 1,868
Model VCE: OIM
Expression: Pr(union), predict()
dy/dx wrt:  1.collgrad 1.south tenure
```

	dy/dx	Delta-method std. err.	z	P>|z|	[95% conf.	interval]
collgrad						
not grad	.0878847	.0238065	3.69	0.000	.0412248	.1345447
1.south	-.126164	.0191504	-6.59	0.000	-.1636981	-.0886299
tenure	.0083571	.0016521	5.06	0.000	.005119	.0115951

```
Note: dy/dx for factor levels is the discrete change from the base level.
```

For this sample, the average marginal effect is very close to the marginal effect at the mean that we computed earlier. That is not always true; it depends on the distribution of the other covariates. The results also tell us that on average, for populations like the one from which our sample was drawn, union participation increases 0.8 percentage points for every year of tenure on the job. College graduates are, on average, 8.8 percentage points more likely to participate.

In the examples above, we treated the covariates in the sample as fixed and known. We could have accounted for the fact that this sample was drawn from a population and the covariates represent just one sample from that population. We do that by adding the `vce(robust)` or `vce(cluster` *clustvar*`)` option when fitting the model and the `vce(unconditional)` option when estimating the margins; see *Obtaining margins with survey data and representative samples* in [R] **margins**. It makes little difference in the examples above.

20.18 Obtaining pairwise comparisons

`pwcompare` performs pairwise comparisons across the levels of factor variables. It can compare estimated cell means, marginal means, intercepts, marginal intercepts, slopes, or marginal slopes—collectively called margins. `pwcompare` also reports comparisons as contrasts (differences) of margins along with significance tests or confidence intervals. The tests and confidence intervals can be adjusted for multiple comparisons. `pwcompare` is for use after an estimation command in which you have used factor variables; thus, you cannot use `pwcompare` after typing `regress yield fertilizer1-fertilizer5` but you could after typing `regress yield i.fertilizer`.

Let's fit a linear regression of wheat yield on type of fertilizer and then compare the mean yields for each pair of fertilizers and obtain *p*-values and confidence intervals adjusted for multiple comparisons by using Tukey's honestly significant difference.

```
. use https://www.stata-press.com/data/r19/yield
(Artificial wheat yield dataset)
. regress yield i.fertilizer
```

Source	SS	df	MS	Number of obs	=	200
				F(4, 195)	=	5.33
Model	1078.84207	4	269.710517	Prob > F	=	0.0004
Residual	9859.55334	195	50.561812	R-squared	=	0.0986
				Adj R-squared	=	0.0801
Total	10938.3954	199	54.9668111	Root MSE	=	7.1107

yield	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
fertilizer						
10-08-22	3.62272	1.589997	2.28	0.024	.4869212	6.758518
16-04-08	.4906299	1.589997	0.31	0.758	-2.645169	3.626428
18-24-06	4.922803	1.589997	3.10	0.002	1.787005	8.058602
29-03-04	-1.238328	1.589997	-0.78	0.437	-4.374127	1.89747
_cons	41.36243	1.124298	36.79	0.000	39.14509	43.57977

```
. pwcompare fertilizer, effects mcompare(tukey)
Pairwise comparisons of marginal linear predictions
Margins: asbalanced
```

	Number of comparisons
fertilizer	10

	Contrast	Std. err.	Tukey t	Tukey P>|t|	Tukey [95% conf.	Tukey interval]
fertilizer						
10-08-22 vs 10-10-10	3.62272	1.589997	2.28	0.156	-.7552913	8.000731
(*output omitted*)						

See [R] **pwcompare** and [R] **margins, pwcompare**.

20.19 Obtaining contrasts, tests of interactions, and main effects

`contrast` estimates and tests contrasts—comparisons of levels of factor variables. It also performs joint tests of these contrasts and can produce ANOVA-style tests of main effects, interaction effects, simple effects, and nested effects. `contrast` can be used after most estimation commands and provides a set of contrast operators, such as `r.`, `ar.`, and `p.`, which are prefixed onto variable names (for example, `r.`*varname*), to specify the contrasts to be performed. The operators can be used with the `contrast` and `margins` commands.

Below, we fit a regression of cholesterol level on age group category. The reported coefficients on `i.agegrp` will themselves be contrasts, namely, contrasts on the reference category. After estimation, we want to compare the cell mean of each age group with that of the previous group, so we perform a reverse-adjacent contrast by typing the following:

```
. use https://www.stata-press.com/data/r19/cholesterol
(Artificial cholesterol data)
. regress chol i.agegrp
```

Source	SS	df	MS	Number of obs	=	75
				F(4, 70)	=	35.02
Model	14943.3997	4	3735.84993	Prob > F	=	0.0000
Residual	7468.21971	70	106.688853	R-squared	=	0.6668
				Adj R-squared	=	0.6477
Total	22411.6194	74	302.859722	Root MSE	=	10.329

chol	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
agegrp						
20-29	8.203575	3.771628	2.18	0.033	.6812991	15.72585
30-39	21.54105	3.771628	5.71	0.000	14.01878	29.06333
40-59	30.15067	3.771628	7.99	0.000	22.6284	37.67295
60-79	38.76221	3.771628	10.28	0.000	31.23993	46.28448
_cons	180.5198	2.666944	67.69	0.000	175.2007	185.8388

```
. contrast ar.agegrp
Contrasts of marginal linear predictions
Margins: asbalanced
```

	df	F	P>F
agegrp			
(20-29 vs 10-19)	1	4.73	0.0330
(30-39 vs 20-29)	1	12.51	0.0007
(40-59 vs 30-39)	1	5.21	0.0255
(60-79 vs 40-59)	1	5.21	0.0255
Joint	4	35.02	0.0000
Denominator	70		

	Contrast	Std. err.	[95% conf.	interval]
agegrp				
(20-29 vs 10-19)	8.203575	3.771628	.6812991	15.72585
(*output omitted*)				

We could use orthogonal polynomial contrasts to test whether there is a linear, quadratic, or even higher-order trend in the estimated cell means.

```
. contrast p.agegrp, noeffects
Contrasts of marginal linear predictions
Margins: asbalanced
```

	df	F	P>F
agegrp			
(linear)	1	139.11	0.0000
(quadratic)	1	0.15	0.6962
(cubic)	1	0.37	0.5448
(quartic)	1	0.43	0.5153
Joint	4	35.02	0.0000
Denominator	70		

You are not limited to using `contrast` in one-way models. Had we fit

```
. regress chol agegrp##race
```

we could `contrast` to obtain tests of the main effects and interaction effects.

```
. contrast agegrp##race
```

These results would be the same as would be reported by `anova`. We mention this because you can use `contrast` after any estimation command that allows factor variables and works with `margins`.

See [R] **contrast** and [R] **margins, contrast**.

20.20 Graphing margins, marginal effects, and contrasts

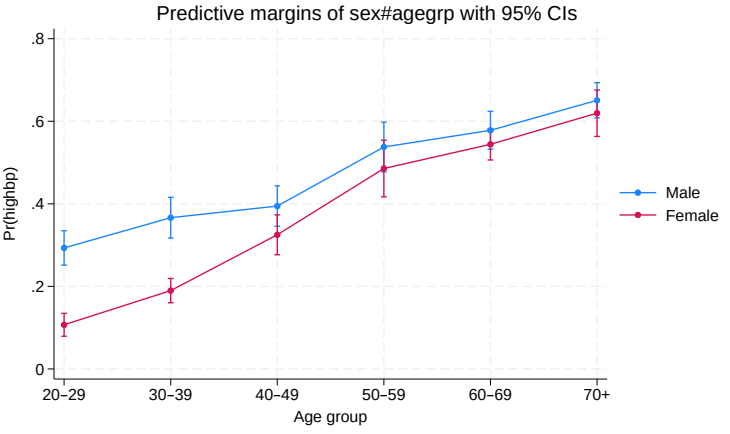
Using `marginsplot`, you can graph any of the results produced by `margins`, and because `margins` can replicate any of the results produced by `pwcompare` and `contrast`, you can graph any of the results produced by them, too.

In **[U] 20.16.3 Obtaining predictive margins**, we did the following:

```
. use https://www.stata-press.com/data/r19/nhanes2
. svy: logistic highbp sex##agegrp##c.bmi
. margins sex#agegrp, vce(unconditional)
```

We can now graph those results by typing

```
. marginsplot, xdimension(agegrp)
Variables that uniquely identify margins: sex agegrp
```



See [R] **marginsplot**. Mitchell (2021) shows how to make similar graphs for a variety of predictions and models.

20.21 Dynamic forecasts and simulations

The `forecast` suite of commands lets you obtain forecasts from forecast models, collections of equations that jointly determine the outcomes of one or more endogenous variables. You fit stochastic equations using estimation commands such as `regress` or `var`, and then you add those results to your forecast model. You can also specify identities that define variables in terms of other variables, and you can also specify exogenous variables whose values are already known or otherwise determined by factors outside your model. `forecast` then solves the resulting system of equations to obtain forecasts.

`forecast` works with time-series and panel datasets, and you can obtain either dynamic or static forecasts. Dynamic forecasts use previous periods' forecast values wherever lags appear in the model's equations and thus allow you to obtain forecasts for multiple periods in the future. Static forecasts use previous periods' actual values wherever lags appear in the model's equations, so if you use lags, you cannot make predictions much beyond the end of the time horizon in your dataset. However, static forecasts are useful during model development.

You can incorporate outside information into your forecasts, and you can specify a future path for some of the model's variables and obtain forecasts for the other variables conditional on that path. These features allow you to produce forecasts under different scenarios, and they allow you to explore how different policy interventions would affect your forecasts.

`forecast` also has the capability to produce confidence intervals around the forecasts. You can have `forecast` account for the sampling variance of the estimated parameters in the stochastic equations. You can request either that `forecast` assume the error terms are normally distributed and take draws from a random-number generator or that `forecast` take random samples from the pool of static-forecast residuals.

See [TS] **forecast**.

20.22 Obtaining robust variance estimates

Many Stata estimation commands provide robust and cluster-robust variance estimates. To obtain these estimates, you simply specify the `vce(robust)` option to obtain robust standard errors or the `vce(cluster` *clustvar*`)` option to obtain cluster-robust standard errors. Below, we provide a general discussion of why you might specify one of these options, how to interpret standard errors with and without `vce(robust)` specified, and an overview of important concepts relating to cluster-robust standard errors.

Estimates of variance refer to estimated standard errors or, more completely, the estimated variance–covariance matrix of the estimators of which the standard errors are a subset, being the square root of the diagonal elements. Call this matrix the variance. All estimation commands produce an estimate of variance and, using that, produce confidence intervals and significance tests.

In addition to the conventional estimator of variance, there is another estimator that has been called by various names because it has been derived independently in different ways by different authors. Two popular names associated with the calculation are Huber and White, but it is also known as the sandwich estimator of variance (because of how the calculation formula physically appears) and the robust estimator of variance (because of claims made about it). Also, this estimator has an independent and long tradition in the survey literature.

The conventional estimator of variance is derived by starting with a model. Let's start with the regression model

$$y_i = \mathbf{x}_i\boldsymbol{\beta} + \epsilon_i, \qquad \epsilon_i \sim N(0, \sigma^2)$$

although it is not important for the discussion that we are using regression. Under the model-based approach, we assume that the model is true and thereby derive an estimator for $\boldsymbol{\beta}$ and its variance.

The estimator of the standard error of $\widehat{\boldsymbol{\beta}}$ we develop is based on the assumption that the model is true in every detail. y_i is not exactly equal to $\mathbf{x}_i\boldsymbol{\beta}$ (so that we would only need to solve an equation to obtain precisely that value of $\boldsymbol{\beta}$) because the observed y_i has noise ϵ_i added to it, the noise is Gaussian, and it has constant variance. That noise leads to the uncertainty about $\boldsymbol{\beta}$, and it is from the characteristics of that noise that we are able to calculate a sampling distribution for $\widehat{\boldsymbol{\beta}}$.

The key thought here is that the standard error of $\widehat{\boldsymbol{\beta}}$ arises because of ϵ and is valid only because the model is absolutely, without question, true; we just do not happen to know the particular values of $\boldsymbol{\beta}$ and σ^2 that make the model true. The implication is that, in an infinite-sized sample, the estimator $\widehat{\boldsymbol{\beta}}$ for $\boldsymbol{\beta}$ would converge to the true value of $\boldsymbol{\beta}$ and that its variance would go to 0.

Now here is another interpretation of the estimation problem: We are going to fit the model

$$y_i = \mathbf{x}_i\mathbf{b} + e_i$$

and, to obtain estimates of $\mathbf{b}$, we are going to use the calculation formula

$$\hat{\mathbf{b}} = (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{y}$$

We have made no claims that the model is true or any claims about e_i or its distribution. We shifted our notation from $\boldsymbol{\beta}$ and ϵ_i to $\mathbf{b}$ and e_i to emphasize this. All we have stated are the physical actions we intend to carry out on the data. Interestingly, it is possible to calculate a standard error for $\hat{\mathbf{b}}$ here. At least, it is possible if you will agree with us on what the standard error measures are.

We are going to define the standard error as measuring the standard error of the calculated $\hat{\mathbf{b}}$ if we were to repeat the data collection followed by estimation over and over again.

This is a different concept of the standard error from the conventional, model-based ideas, but it is related. Both measure uncertainty about **b** (or β). The regression model–based derivation states from where the variation arises and so can make grander statements about the applicability of the measured standard error. The weaker second interpretation makes fewer assumptions and so produces a standard error suitable for one purpose.

There is a subtle difference in interpretation of these identically calculated point estimates. $\widehat{\beta}$ is the estimate of β under the assumption that the model is true. $\hat{\mathbf{b}}$ is the estimate of **b**, which is merely what the estimator would converge to if we collected more and more data.

Is the estimate of **b** unbiased? If we mean, "Does $\mathbf{b} = \beta$?" that depends on whether the model is true. $\hat{\mathbf{b}}$ is, however, an unbiased estimate of **b**, which admittedly is not saying much.

What if **x** and e are correlated? Don't we have a problem then? We may have an interpretation problem—**b** may not measure what we want to measure, namely, β—but we measure $\hat{\mathbf{b}}$ to be such-and-such and expect, if the experiment and estimation were repeated, that we would observe results in the range we have reported.

So, we have two different understandings of what the parameters mean and how the variance in their estimators arises. However, both interpretations must confront the issue of how to make valid statistical inference about the coefficient estimates when the data do not come from a simple random sample or the distribution of $(\mathbf{x}_i, \epsilon_i)$ is not independent and identically distributed (i.i.d.). In essence, we need an estimator of the standard errors that is robust to this deviation from the standard case.

Hence, the name *the robust estimate of variance*; its associated authors are Huber (1967) and White (1980, 1982) (who developed it independently), although many others have extended its development, including Gail, Tan, and Piantadosi (1988); Kent (1982); Royall (1986); and Lin and Wei (1989). In the survey literature, this same estimator has been developed; see Kish and Frankel (1974), Fuller (1975), and Binder (1983). Most of Stata's estimation commands can produce this alternative estimate of variance and do so via the `vce(robust)` option.

20.22.1 Interpreting standard errors

Without `vce(robust)`, we get one measure of variance:

```
. use https://www.stata-press.com/data/r19/auto7
(1978 automobile data)
. regress mpg weight foreign
```

Source	SS	df	MS	Number of obs	=	74
				F(2, 71)	=	69.75
Model	1619.2877	2	809.643849	Prob > F	=	0.0000
Residual	824.171761	71	11.608053	R-squared	=	0.6627
				Adj R-squared	=	0.6532
Total	2443.45946	73	33.4720474	Root MSE	=	3.4071

mpg	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
weight	-.0065879	.0006371	-10.34	0.000	-.0078583	-.0053175
foreign	-1.650029	1.075994	-1.53	0.130	-3.7955	.4954422
_cons	41.6797	2.165547	19.25	0.000	37.36172	45.99768

With `vce(robust)`, we get another:

```
. regress mpg weight foreign, vce(robust)
Linear regression                               Number of obs     =         74
                                                F(2, 71)          =      73.81
                                                Prob > F          =     0.0000
                                                R-squared         =     0.6627
                                                Root MSE          =     3.4071
------------------------------------------------------------------------------
             |               Robust
         mpg |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      weight |  -.0065879   .0005462   -12.06   0.000    -.007677   -.0054988
     foreign |  -1.650029   1.132566    -1.46   0.150    -3.908301    .6082424
       _cons |   41.6797    1.797553    23.19   0.000     38.09548    45.26392
------------------------------------------------------------------------------
```

Either way, the point estimates are the same. (See [R] **regress** for an example where specifying `vce(robust)` produces strikingly different standard errors.)

How do we interpret these results? Let's consider the model-based interpretation. Suppose that

$$y_i = \mathbf{x}_i\boldsymbol{\beta} + \epsilon_i$$

where $(\mathbf{x}_i, \epsilon_i)$ are i.i.d. with variance σ^2. For the model-based interpretation, we also must assume that $\mathbf{x}_i$ and ϵ_i are uncorrelated. With these assumptions and a few technical regularity conditions, our first regression gives us consistent parameter estimates and standard errors that we can use for valid statistical inference about the coefficients. Now suppose that we weaken our assumptions so that $(\mathbf{x}_i, \epsilon_i)$ are independent and—but not necessarily—identically distributed. Our parameter estimates are still consistent, but the standard errors from the first regression can no longer be used to make valid inference. We need estimates of the standard errors that are robust to the fact that the error term is not identically distributed. The standard errors in our second regression are just what we need. We can use them to make valid statistical inference about our coefficients, even though our data are not identically distributed.

Now consider a non–model-based interpretation. If our data come from a survey design that ensures that $(\mathbf{x}_i, e_i)$ are i.i.d., then we can use the nonrobust standard errors for valid statistical inference about the population parameters $\mathbf{b}$. For this interpretation, we do not need to assume that $\mathbf{x}_i$ and e_i are uncorrelated. If they are uncorrelated, the population parameters $\mathbf{b}$ and the model parameters $\boldsymbol{\beta}$ are the same. However, if they are correlated, then the population parameters $\mathbf{b}$ that we are estimating are not the same as the model-based $\boldsymbol{\beta}$. So, what we are estimating is different, but we still need standard errors that allow us to make valid statistical inference. If the process that we used to collect the data caused $(\mathbf{x}_i, e_i)$ to be independent but not identically distributed, then we need to use the robust standard errors to make valid statistical inference about the population parameters $\mathbf{b}$.

20.22.2 Correlated errors: Cluster–robust standard errors

The robust estimator of variance has one feature that the conventional estimator does not have: the ability to relax the assumption of independence of the observations. That is, if you specify the `vce(cluster` *clustvar*`)` option, it can produce "correct" standard errors (in the measurement sense), even if the observations are correlated.

For the automobile data, it is difficult to believe that the models of the various manufacturers are truly independent. Manufacturers, after all, use common technology, engines, and drive trains across their model lines. The VW Dasher in the above regression has a measured residual of −2.80. Having been told

that, do you really believe that the residual for the VW Rabbit is as likely to be above 0 as below? (The residual is −2.32.) Similarly, the measured residual for the Chevrolet Malibu is 1.27. Does that provide information about the expected value of the residual of the Chevrolet Monte Carlo (which turns out to be 1.53)?

We need to be careful about picking examples from data; we have not told you about the Datsun 210 and 510 (residuals +8.28 and −1.01) or the Cadillac Eldorado and Seville (residuals −1.99 and +7.58), but you should at least question the assumption of independence. It may be believable that the measured mpg given the weight of one manufacturer's vehicles is independent of other manufacturers' vehicles, but it is at least questionable whether a manufacturer's vehicles are independent of one another.

In commands with the `vce(robust)` option, another option—`vce(cluster` *clustvar*`)`—relaxes the independence assumption and requires only that the observations be independent across the clusters:

```
. regress mpg weight foreign, vce(cluster manufacturer)
Linear regression                               Number of obs     =         74
                                                F(2, 22)          =      90.93
                                                Prob > F          =     0.0000
                                                R-squared         =     0.6627
                                                Root MSE          =     3.4071

                                  (Std. err. adjusted for 23 clusters in manufacturer)
------------------------------------------------------------------------------
             |               Robust
         mpg |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      weight |  -.0065879   .0005339   -12.34   0.000    -.0076952   -.0054806
     foreign |  -1.650029   1.039033    -1.59   0.127    -3.804852    .5047939
       _cons |    41.6797   1.844559    22.60   0.000     37.85432    45.50508
------------------------------------------------------------------------------
```

It turns out that, in these data, whether or not we specify `vce(cluster` *clustvar*`)` makes little difference. The VW and Chevrolet examples above were not representative; had they been, the confidence intervals would have widened. (In the above, `manuf` is a variable that takes on values such as "Chev." or "VW", recording the manufacturer of the vehicle. This variable was created from variable `make`, which contains values such as "Chev. Malibu" or "VW Rabbit", by extracting the first word.)

As a demonstration of how well clustering can work, in [R] **regress** we fit a random-effects model with `regress, vce(robust)` and then compared the results with ordinary least squares and the generalized least squares (GLS) random-effects estimator. Here we will simply summarize the results.

We start with a dataset on 4,711 women aged 14–46 years. Subjects appear an average of 6.057 times in the data; there are a total of 28,534 observations. The model we use is log wage on age, age-squared, and job tenure. The focus of the example is the estimated coefficient on tenure. We obtain the following results:

Estimator	Point estimate	Confidence interval
(Inappropriate) least squares	0.039	[0.038, 0.041]
Robust clustered	0.039	[0.036, 0.042]
GLS random effects	0.026	[0.025, 0.027]

Notice how well the robust clustered estimate does compared with the GLS random-effects model. We then run a Hausman specification test, obtaining $\chi^2(3) = 336.62$, which casts grave doubt on the assumptions justifying the use of the GLS estimator and hence on the GLS results. At this point, we will simply quote our comments:

> Meanwhile, our robust regression results still stand, as long as we are careful about the interpretation. The correct interpretation is that if the data collection were repeated (on women sampled the same way as in the original sample) and if we were to refit the model, then 95% of the time we would expect the estimated coefficient on tenure to be in the range [0.036, 0.042].
>
> Even with robust regression, we must be careful about going beyond that statement. Here the Hausman test is probably picking up something that differs within- and between-person, which would cast doubt on our robust regression model in terms of interpreting [0.036, 0.042] to contain the rate of return for keeping a job, economywide, for all women, without exception.

The formula for the robust estimator of variance is

$$\widehat{\mathcal{V}} = \widehat{\mathbf{V}}\Big(\sum_{j=1}^{N} \mathbf{u}_j'\mathbf{u}_j\Big)\widehat{\mathbf{V}}$$

where $\widehat{\mathbf{V}} = (-\partial^2 \ln L/\partial\boldsymbol{\beta}^2)^{-1}$ (the conventional estimator of variance) and $\mathbf{u}_j$ (a row vector) is the contribution from the jth observation to $\partial \ln L/\partial\boldsymbol{\beta}$.

In the example above, observations are assumed to be independent. Assume for a moment that the observations denoted by j are not independent but that they can be divided into M groups G_1, G_2, …, G_M that are independent. The robust estimator of variance is

$$\widehat{\mathcal{V}} = \widehat{\mathbf{V}}\Big(\sum_{k=1}^{M} \mathbf{u}_k^{(G)\prime}\mathbf{u}_k^{(G)}\Big)\widehat{\mathbf{V}}$$

where $\mathbf{u}_k^{(G)}$ is the contribution of the kth group to $\partial \ln L/\partial\boldsymbol{\beta}$. That is, application of the robust variance formula merely involves using a different decomposition of $\partial \ln L/\partial\boldsymbol{\beta}$, namely, $\mathbf{u}_k^{(G)}$, $k = 1, \ldots, M$, rather than $\mathbf{u}_j$, $j = 1, \ldots, N$. Moreover, if the log-likelihood function is additive in the observations denoted by j,

$$\ln L = \sum_{j=1}^{N} \ln L_j$$

then $\mathbf{u}_j = \partial \ln L_j/\partial\boldsymbol{\beta}$, so

$$\mathbf{u}_k^{(G)} = \sum_{j \in G_k} \mathbf{u}_j$$

That is what the `vce(cluster` *clustvar*`)` option does. (This point was first made in writing by Rogers [1993], although he considered the point an obvious generalization of Huber [1967] and the calculation—implemented by Rogers—had appeared in Stata a year earlier.)

❑ Technical note

What is written above is asymptotically correct but ignores a finite-sample adjustment to $\widehat{\mathcal{V}}$. For maximum likelihood estimators, when you specify `vce(robust)` but not `vce(cluster` *clustvar*`)`, a better estimate of variance is $\widehat{\mathcal{V}}^* = \{N/(N-1)\}\widehat{\mathcal{V}}$. When you also specify the `vce(cluster` *clustvar*`)` option, this becomes $\widehat{\mathcal{V}}^* = \{M/(M-1)\}\widehat{\mathcal{V}}$.

For linear regression, the finite-sample adjustment is $N/(N-k)$ without `vce(cluster` *clustvar*`)`—where k is the number of regressors—and is $\{M/(M-1)\}\{(N-1)/(N-k)\}$ with `vce(cluster` *clustvar*`)`. Also, two data-dependent modifications to the calculation for $\widehat{\mathcal{V}}^*$, suggested by MacKinnon and White (1985), are provided by `regress`; see [R] **regress**. Angrist and Pischke (2009, chap. 8) is devoted to robust covariance matrix estimation and offers practical guidance on the use of `vce(robust)` and `vce(cluster` *clustvar*`)` in both cross-sectional and panel-data applications.

❑

Halbert Lynn White Jr. (1950–2012) was born in Kansas City. After receiving economics degrees at Princeton and MIT, he taught and researched econometrics at the University of Rochester and, from 1979, at the University of California in San Diego. He also co-founded an economics and legal consulting firm known for its rigorous use of econometrics methods. His 1980 paper on heteroskedasticity introduced the use of robust covariance matrices to economists and passed 16,000 citations in Google Scholar in 2012. His 1982 paper on maximum likelihood estimation of misspecified models helped develop the now-common use of quasimaximum likelihood estimation techniques. Later in his career, he explored the use of neural networks, nonparametric models, and time-series modeling of financial markets.

Among his many awards and distinctions, White was made a fellow of the American Academy of Arts and Sciences and the Econometric Society, and he won a fellowship from the John Simon Guggenheim Memorial Foundation. Had he not died prematurely, many scholars believe he would have eventually been awarded the Sveriges Riksbank Prize in Economic Sciences in Memory of Alfred Nobel.

Aside from his academic work, White was an avid jazz musician who played with well-known jazz trombonist and fellow University of California at San Diego teacher Jimmy Cheatam.

Peter Jost Huber (1934–) was born in Wohlen (Aargau, Switzerland). He gained mathematics degrees from ETH Zürich, including a PhD thesis on homotopy theory, and then studied statistics at Berkeley on postdoctoral fellowships. This visit yielded a celebrated 1964 paper on robust estimation, and Huber's later monographs on robust statistics were crucial in directing that field. Thereafter, his career took him back and forth across the Atlantic, with periods at Cornell, ETH Zürich, Harvard, MIT, and Bayreuth. His work has touched several other major parts of statistics, theoretical and applied, including regression, exploratory multivariate analysis, large datasets, and statistical computing. Huber also has a major long-standing interest in Babylonian astronomy.

20.23 Obtaining scores

Many of the estimation commands that provide the `vce(robust)` option also provide the ability to generate equation-level score variables via the `predict` command. With the `score` option, `predict` returns an important ingredient into the robust variance calculation that is sometimes useful in its own right. As explained above in **[U] 20.22 Obtaining robust variance estimates**, ignoring the finite-sample corrections, the robust estimate of variance is

$$\widehat{\mathcal{V}} = \widehat{\mathbf{V}}\Big(\sum_{j=1}^{N} \mathbf{u}_j'\mathbf{u}_j\Big)\widehat{\mathbf{V}}$$

where $\widehat{\mathbf{V}} = (-\partial^2 \ln L/\partial\boldsymbol{\beta}^2)^{-1}$ is the conventional estimator of variance. If we consider likelihood functions that are additive in the observations

$$\ln L = \sum_{j=1}^{N} \ln L_j$$

then $\mathbf{u}_j = \partial \ln L_j/\partial\boldsymbol{\beta}$. In general, function L_j is a function of $\mathbf{x}_j$ and $\boldsymbol{\beta}$, $L_j(\boldsymbol{\beta};\mathbf{x}_j)$. For many likelihood functions, however, it is only the linear form $\mathbf{x}_j\boldsymbol{\beta}$ that enters the function. In those cases,

$$\frac{\partial \ln L_j(\mathbf{x}_j\boldsymbol{\beta})}{\partial\boldsymbol{\beta}} = \frac{\partial \ln L_j(\mathbf{x}_j\boldsymbol{\beta})}{\partial(\mathbf{x}_j\boldsymbol{\beta})}\frac{\partial(\mathbf{x}_j\boldsymbol{\beta})}{\partial\boldsymbol{\beta}} = \frac{\partial \ln L_j(\mathbf{x}_j\boldsymbol{\beta})}{\partial(\mathbf{x}_j\boldsymbol{\beta})}\mathbf{x}_j$$

By writing $u_j = \partial \ln L_j(\mathbf{x}_j\boldsymbol{\beta})/\partial(\mathbf{x}_j\boldsymbol{\beta})$, this becomes simply $u_j\mathbf{x}_j$. Thus the formula for the robust estimate of variance can be rewritten as

$$\widehat{\mathcal{V}} = \widehat{\mathbf{V}}\Big(\sum_{j=1}^{N} u_j^2\mathbf{x}_j'\mathbf{x}_j\Big)\widehat{\mathbf{V}}$$

We refer to u_j as the equation-level score (in the singular), and it is u_j that is returned when you use `predict` with the `score` option. u_j is like a residual in that

1. $\sum_j u_j = 0$ and
2. correlation of u_j and $\mathbf{x}_j$, calculated over $j = 1, \ldots, N$, is 0.

In fact, for linear regression, u_j is the residual, normalized,

$$\begin{aligned}\frac{\partial \ln L_j}{\partial(\mathbf{x}_j\boldsymbol{\beta})} &= \frac{\partial}{\partial(\mathbf{x}_j\boldsymbol{\beta})} \ln f\Big\{(y_j - \mathbf{x}_j\boldsymbol{\beta})/\sigma\Big\} \\ &= (y_j - \mathbf{x}_j\boldsymbol{\beta})/\sigma\end{aligned}$$

where $f(\cdot)$ is the standard normal density.

▷ Example 19

`probit` provides the `vce(robust)` option and `predict, score`. Equation-level scores play an important role in calculating the robust estimate of variance, but we can use `predict, score` regardless of whether we specify `vce(robust)`:

```
. use https://www.stata-press.com/data/r19/auto2
(1978 automobile data)

. probit foreign mpg weight

Iteration 0:  Log likelihood =  -45.03321
Iteration 1:  Log likelihood = -27.914626
Iteration 2:  Log likelihood = -26.858074
Iteration 3:  Log likelihood = -26.844197
Iteration 4:  Log likelihood = -26.844189
Iteration 5:  Log likelihood = -26.844189

Probit regression                                 Number of obs =     74
                                                  LR chi2(2)    =  36.38
                                                  Prob > chi2   = 0.0000
Log likelihood = -26.844189                       Pseudo R2     = 0.4039

------------------------------------------------------------------------------
     foreign | Coefficient  Std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
         mpg |  -.1039503   .0515689    -2.02   0.044    -.2050235   -.0028772
      weight |  -.0023355   .0005661    -4.13   0.000     -.003445   -.0012261
       _cons |   8.275464   2.554142     3.24   0.001     3.269437    13.28149
------------------------------------------------------------------------------

. predict double u, score

. summarize u

    Variable |        Obs        Mean    Std. dev.       Min        Max
-------------+---------------------------------------------------------
           u |         74   -6.64e-14    .5988325  -1.655439   1.660787

. correlate u mpg weight
(obs=74)

             |        u      mpg   weight
-------------+---------------------------
           u |   1.0000
         mpg |   0.0000   1.0000
      weight |  -0.0000  -0.8072   1.0000

. list make foreign mpg weight u if abs(u)>1.65

     +-------------------------------------------------------+
     | make           foreign   mpg   weight          u      |
     |-------------------------------------------------------|
 24. | Ford Fiesta   Domestic    28    1,800   -1.6554395     |
 64. | Peugeot 604    Foreign    14    3,420    1.6607871     |
     +-------------------------------------------------------+
```

The light, high-mileage Ford Fiesta is surprisingly domestic, whereas the heavy, low-mileage Peugeot 604 is surprisingly foreign.

◁

❑ Technical note

For some estimation commands, one score is not enough. Consider a likelihood that can be written as $L_j(\mathbf{x}_j\boldsymbol{\beta}_1, \mathbf{z}_j\boldsymbol{\beta}_2)$, a function of two linear forms (or linear equations). Then $\partial \ln L_j/\partial\boldsymbol{\beta}$ can be written as $(\partial \ln L_j/\partial\boldsymbol{\beta}_1, \partial \ln L_j/\partial\boldsymbol{\beta}_2)$. Each of the components can in turn be written as $[\partial \ln L_j/\partial(\beta_1\mathbf{x})]\mathbf{x} = u_1\mathbf{x}$ and $[\partial \ln L_j/\partial(\beta_2\mathbf{z})]\mathbf{z} = u_2\mathbf{z}$. There are then two equation-level scores, u_1 and u_2, and, in general, there could be more.

Stata's `streg, distribution(weibull)` command is an example of this: it estimates $\boldsymbol{\beta}$ and a shape parameter, $\ln p$, the latter of which can be thought of as a degenerate linear form $(\ln p)\mathbf{z}$ with $\mathbf{z} = \mathbf{1}$. After this command, `predict, scores` requires that you specify two new variable names, or you can specify *stub*`*`, which will generate new variables *stub*`1` and *stub*`2`; the first will be defined containing u_1—the score associated with $\boldsymbol{\beta}$—and the second will be defined containing u_2—the score associated with $\ln p$.

❑

❑ Technical note

Using Stata's matrix commands—see [P] **matrix**—we can make the robust variance calculation for ourselves and then compare it with that made by Stata.

```
. use https://www.stata-press.com/data/r19/auto2, clear
(1978 automobile data)
. quietly probit foreign mpg weight
. predict double u, score
. matrix accum S = mpg weight [iweight=u^2*74/73]
(obs=26.53642547)
. matrix rV = e(V)*S*e(V)
. matrix list rV
symmetric rV[3,3]
                  foreign:    foreign:    foreign:
                      mpg      weight       _cons
   foreign:mpg   .00352299
foreign:weight   .00002216   2.434e-07
 foreign:_cons  -.14090346  -.00117031   6.4474174
. quietly probit foreign mpg weight, vce(robust)
. matrix list e(V)
symmetric e(V)[3,3]
                  foreign:    foreign:    foreign:
                      mpg      weight       _cons
   foreign:mpg   .00352299
foreign:weight   .00002216   2.434e-07
 foreign:_cons  -.14090346  -.00117031   6.4474174
```

The results are the same.

There is an important lesson here for programmers. Given the scores, conventional variance estimates can be easily transformed to robust estimates. If we were writing a new estimation command, it would not be difficult to include a `vce(robust)` option.

It is, in fact, easy if we ignore clustering. With clustering, it is more work because the calculation involves forming sums within clusters. For programmers interested in implementing robust variance calculations, Stata provides a `_robust` command to ease the task. This is documented in [P] **_robust**.

To use _robust, you first produce conventional results (a vector of coefficients and covariance matrix) along with a variable containing the scores u_j (or variables if the likelihood function has more than one stub). You then call _robust, and it will transform your conventional variance estimate into the robust estimate. _robust will handle the work associated with clustering and the details of the finite-sample adjustment, and it will even label your output so that the word *Robust* appears above the standard error when the results are displayed.

Of course, this is all even easier if you write your commands with Stata's ml maximum likelihood optimization, in which case you merely pass the vce(robust) option on to ml. Then, ml will call _robust itself and do all the work for you.

❑

❑ Technical note

For some estimation commands, predict, score computes parameter-level scores $\partial L_j/\partial\beta$ instead of equation-level scores $\partial L_j/\partial\mathbf{x}_j\beta$. Those estimation commands, such as cmclogit, stcox, and the multilevel mixed-effects commands, share the characteristic that there are multiple observations per independent event.

In making the robust variance calculation, parameter-level scores $\partial L_j/\partial\beta$ are really needed, and so you may be asking yourself why predict, score does not always produce parameter-level scores. In the usual case, we can obtain them from equation-level scores via the chain rule, and fewer variables are required if we adopt this approach. In the cases above, however, the likelihood is calculated at the group level and is not split into contributions from the individual observations. Thus, the chain rule cannot be used, and we must use the parameter level scores directly.

_robust can be tricked into using them if each parameter appears to be in its own equation as a constant. This requires resetting the row and column stripes on the covariance matrix before _robust is called. The equation names for each row and column must be unique, and the variable names must all be _cons.

❑

20.24 Weighted estimation

The syntax for weights was introduced in [U] **11.1.6 weight**. Stata provides four kinds of weights: fweights, or frequency weights; pweights, or sampling weights; aweights, or analytic weights; and iweights, or importance weights. The syntax for using each is the same. Type

```
. regress y x1 x2
```

and you obtain unweighted estimates; type

```
. regress y x1 x2 [pweight=pop]
```

and you obtain (in this example) pweighted estimates.

The sections below explain how each type of weight is used in estimation.

20.24.1 Frequency weights

Frequency weights—fweights—are integers and are nothing more than replication counts. The weight is statistically uninteresting, but from a data-processing perspective it is important. Consider the following data,

```
y        x1        x2
        22         1         0
        22         1         0
        22         1         1
        23         0         1
        23         0         1
        23         0         1
```

and the estimation command

```
. regress y x1 x2
```

Equivalent is the following, more compressed data,

```
y        x1        x2       pop
        22         1         0         2
        22         1         1         1
        23         0         1         3
```

and the corresponding estimation command

```
. regress y x1 x2 [fweight=pop]
```

When you specify frequency weights, you are treating each observation as one or more real observations.

❑ Technical note

You might occasionally run across a command that does not allow weights at all, especially among community-contributed commands. You can use expand (see [D] **expand**) with such commands to obtain frequency-weighted results. The expand command duplicates observations so that the data become self-weighting. Suppose that you want to run the command usercmd, which does something or other, and you would like to type usercmd y x1 x2 [fw=pop]. Unfortunately, usercmd does not allow weights. Instead, you type

```
. expand pop
. usercmd y x1 x2
```

to obtain your result. Moreover, there is an important principle here: the results of running any command with frequency weights should be the same as running the command on the unweighted, expanded data. Unweighted, duplicated data and frequency-weighted data are merely two ways of recording identical information.

❑

20.24.2 Analytic weights

Analytic weights—analytic is a term we made up—statistically arise in one particular problem: linear regression on data that are themselves observed means. That is, think of the model

$$y_i = \mathbf{x}_i\boldsymbol{\beta} + \epsilon_i, \qquad \epsilon_i \sim N(0, \sigma^2)$$

and now think about fitting this model on data $(\overline{y}_j, \overline{\mathbf{x}}_j)$ that are themselves observed averages. For instance, a piece of the underlying data for $(y_i, \mathbf{x}_i)$ might be $(3, 1)$, $(4, 2)$, and $(2, 2)$, but you do not know that. Instead, you have one observation $\{(3+4+2)/3, (1+2+2)/3\} = (3, 1.67)$ and know only that the $(3, 1.67)$ arose as the average of three underlying observations. All your data are like that.

`regress` with `aweights` is the solution to that problem:

```
. regress y x [aweight=pop]
```

There is a history of misusing such weights. A researcher does not have cell-mean data but instead has a probability-weighted random sample. Long before Stata existed, some researchers were using `aweights` to produce estimates from such samples. We will come back to this point in **[U] 20.24.3 Sampling weights** below.

Anyway, the statistical problem that `aweights` resolve can be written as

$$y_i = \mathbf{x}_i\boldsymbol{\beta} + \epsilon_i, \qquad \epsilon_i \sim N(0, \sigma^2/w_i)$$

where the w_i are the analytic weights. The details of the solution are to make linear regression calculations using the weights as if they were `fweights` but to normalize them to sum to N before doing that.

Most commands that allow `aweights` handle them in this manner. That is, if you specify `aweights`, they are

1. normalized to sum to N and then
2. inserted in the calculation formulas in the same way as `fweights`.

While we focus on the use of `aweights` in linear regression above, `aweights` are allowed by commands other than `regress`. These weights can be used more generally to account for observations that have different variances or different precisions. In that sense, we could also refer to analytic weights as precision weights.

20.24.3 Sampling weights

Sampling weights—probability weights or `pweights`—refer to probability-weighted random samples. Actually, what you specify in `[pweight=...]` is a variable recording the number of subjects in the full population that the sampled observation in your data represents. That is, an observation that had probability $1/3$ of being included in your sample has pweight 3.

Some researchers have used `aweights` with these kinds of data. If they do, they are probably making a mistake. Consider the regression model

$$y_i = \mathbf{x}_i\boldsymbol{\beta} + \epsilon_i, \qquad \epsilon_i \sim N(0, \sigma^2)$$

Begin by considering the exact nature of the problem of fitting this model on cell-mean data—for which `aweights` are the solution: heteroskedasticity arising from the grouping. The error term ϵ_i is homoskedastic (meaning that it has constant variance σ^2). Say that the first observation in the data is the mean of three underlying observations. Then,

$$\begin{aligned}
y_1 &= \mathbf{x}_1\boldsymbol{\beta} + \epsilon_1, \qquad \epsilon_1 \sim N(0, \sigma^2) \\
y_2 &= \mathbf{x}_2\boldsymbol{\beta} + \epsilon_2, \qquad \epsilon_2 \sim N(0, \sigma^2) \\
y_3 &= \mathbf{x}_3\boldsymbol{\beta} + \epsilon_3, \qquad \epsilon_3 \sim N(0, \sigma^2)
\end{aligned}$$

and taking the mean,

$$(y_1 + y_2 + y_3)/3 = \{(\mathbf{x}_1 + \mathbf{x}_2 + \mathbf{x}_3)/3\}\boldsymbol{\beta} + (\epsilon_1 + \epsilon_2 + \epsilon_3)/3$$

For another observation in the data—which may be the result of summing a different number of observations—the variance will be different. Hence, the model for the data is

$$\overline{y}_j = \overline{x}_j\boldsymbol{\beta} + \overline{\epsilon}_j, \qquad \overline{\epsilon}_j \sim N(0, \sigma^2/N_j)$$

This makes intuitive sense. Consider two observations, one recording means over 2 subjects and the other recording means over 100,000 subjects. You would expect the variance of the residual to be less in the 100,000-subject observation; that is, there is more information in the 100,000-subject observation than in the 2-subject observation.

Now instead say that you are fitting the same model, $y_i = \mathbf{x}_i\boldsymbol{\beta} + \epsilon_i$, $\epsilon_i \sim N(0, \sigma^2)$, on probability-weighted data. Each observation in your data is one subject, but the different subjects have different chances of being included in your sample. Therefore, for each subject in your data,

$$y_i = \mathbf{x}_i\boldsymbol{\beta} + \epsilon_i, \qquad \epsilon_i \sim N(0, \sigma^2)$$

That is, there is no heteroskedasticity problem. The use of the `aweighted` estimator cannot be justified on these grounds.

As a matter of fact, from the argument just given, you do not need to adjust for the weights at all, although the argument does not justify not making an adjustment. If you do not adjust, you are holding tightly to the assumed truth of your model. Two issues arise when considering adjustment for sampling weights:

1. the efficiency of the point estimate $\widehat{\boldsymbol{\beta}}$ of $\boldsymbol{\beta}$ and
2. the reported standard errors (and, more generally, the variance matrix of $\widehat{\boldsymbol{\beta}}$).

Efficiency argues in favor of adjustment, and that, by the way, is why many researchers have used `aweights` with `pweighted` data. The adjustment implied by `pweights` to the point estimates is the same as the adjustment implied by `aweights`.

With regard to the second issue, the use of `aweights` produces incorrect results because it interprets larger weights as designating more accurately measured points. For `pweights`, however, the point is no more accurately measured—it is still just one observation with one residual ϵ_j and variance σ^2. In **[U] 20.22 Obtaining robust variance estimates** above, we introduced another estimator of variance that measures the variation that would be observed if the data collection followed by the estimation were repeated. Those same formulas provide the solution to `pweights`, and they have the added advantage that they are not conditioned on the model being true. If we have any hopes of measuring the variation that would be observed were the data collection followed by estimation repeated, we must include the probability of the observations being sampled in the calculation.

In Stata, when you type

```
. regress y x1 x2 [pw=pop]
```

the results are the same as if you had typed

```
. regress y x1 x2 [pw=pop], vce(robust)
```

That is, specifying `pweights` implies the `vce(robust)` option and, hence, the robust variance calculation (but weighted). In this example, we use `regress` simply for illustration. The same is true of `probit` and all of Stata's estimation commands. Estimation commands that do not have a `vce(robust)` option (there are a few) do not allow `pweights`.

pweights are adequate for handling random samples where the probability of being sampled varies. pweights may be all you need. If, however, the observations are not sampled independently but are sampled in groups—called clusters in the jargon—you should specify the estimator's vce(cluster *clustvar*) option as well:

```
. regress y x1 x2 [pw=pop], vce(cluster block)
```

There are two ways of thinking about this:

1. The robust estimator answers the question of which variation would be observed were the data collection followed by the estimation repeated; if that question is to be answered, the estimator must account for the clustered nature of how observations are selected. If observations 1 and 2 are in the same cluster, then you cannot select observation 1 without selecting observation 2 (and, by extension, you cannot select observations like 1 without selecting observations like 2).
2. If you prefer, you can think about potential correlations. Observations in the same cluster may not really be independent—that is an empirical question to be answered by the data. For instance, if the clusters are neighborhoods, it would not be surprising that the individual neighbors are similar in their incomes, their tastes, and their attitudes, and even more similar than two randomly drawn persons from the area at large with similar characteristics, such as age and sex.

Either way of thinking leads to the same (robust) estimator of variance.

Sampling weights usually arise from complex sampling designs, which often involve not only unequal probability sampling and cluster sampling but also stratified sampling. There is a family of commands in Stata designed to work with the features of complex survey data, and those are the commands that begin with svy. To fit a linear regression model with stratification, for example, you would use the svy: regress command.

Non-svy commands that allow pweights and clustering give essentially identical results to the svy commands. If the sampling design is simple enough that it can be accommodated by the non-svy command, that is a fine way to perform the analysis. The svy commands differ in that they have more features, and they do all the little details correctly for real survey data. See [SVY] **Survey** for a brief discussion of some of the issues involved in the analysis of survey data and for a list of all the differences between the svy and non-svy commands.

Not all model estimation commands in Stata allow pweights. This is often because they are computationally or statistically difficult to implement.

20.24.4 Importance weights

Stata's iweights—importance weights—are the emergency exit. These weights are for those who want to take control and create special effects. For example, programmers have used regress with iweights to compute iteratively reweighted least-squares solutions for various problems.

iweights are treated much like aweights, except that they are not normalized. Stata's iweight rule is that

1. the weights are not normalized and
2. they are generally inserted into calculation formulas in the same way as fweights. There are exceptions; see the *Methods and formulas* for the particular command.

iweights are used mostly by programmers who are often on the way to implementing one of the other kinds of weights.

20.25 A list of postestimation commands

The following commands can be used after estimation:

contrast	contrasts and ANOVA-style joint tests of parameters
estat ic	Akaike's, consistent Akaike's, corrected Akaike's, and Schwarz's Bayesian information criteria (AIC, CAIC, AICc, and BIC, respectively)
estat summarize	summary statistics for the estimation sample
estat vce	variance–covariance matrix of the estimators (VCE)
estimates	cataloging estimation results
etable	table of estimation results
forecast	dynamic forecasts and simulations
hausman	Hausman's specification test
lincom	point estimates, standard errors, testing, and inference for linear combinations of parameters
linktest	link test for model specification
* lrtest	likelihood-ratio test
margins	marginal means, predictive margins, and marginal effects
marginsplot	graph the results from margins (profile plots, interaction plots, etc.)
nlcom	point estimates, standard errors, testing, and inference for nonlinear combinations of parameters
predict	predictions, residuals, influence statistics, and other diagnostic measures
predictnl	point estimates, standard errors, testing, and inference for generalized predictions
pwcompare	pairwise comparisons of parameters
suest	seemingly unrelated estimation
test	Wald tests of simple and composite linear hypotheses
testnl	Wald tests of nonlinear hypotheses

Also see **[U] 13.5 Accessing coefficients and standard errors** for accessing coefficients and standard errors.

The commands above are general-purpose postestimation commands that can be used after almost all estimation commands. Many estimation commands provide other estimator-specific postestimation commands. You can see the full list of postestimation commands available for an estimator by looking in the entry titled *estimator* **postestimation** that immediately follows each estimator's entry in the reference manuals.

You can also see which postestimation commands are available by launching the Postestimation Selector; select **Statistics** > **Postestimation**. You will see a list of all postestimation features that are available for the active estimation results. This list is automatically updated when a new estimation command is run or estimates are restored from memory or disk. See **[R] postest** for more details.

20.26 References

Afifi, A. A., and S. P. Azen. 1979. *Statistical Analysis: A Computer Oriented Approach*. 2nd ed. New York: Academic Press.

Angrist, J. D., and J.-S. Pischke. 2009. *Mostly Harmless Econometrics: An Empiricist's Companion*. Princeton, NJ: Princeton University Press.

Binder, D. A. 1983. On the variances of asymptotically normal estimators from complex surveys. *International Statistical Review* 51: 279–292. https://doi.org/10.2307/1402588.

Buja, A., and H. R. Künsch. 2008. A conversation with Peter Huber. *Statistical Science* 23: 120–135. https://doi.org/10.1214/07-STS251.

Daniels, L., and N. Minot. 2020. *An Introduction to Statistics and Data Analysis Using Stata*. Thousand Oaks, CA: Sage.

Deaton, A. S. 1997. *The Analysis of Household Surveys: A Microeconometric Approach to Development Policy*. Baltimore, MD: Johns Hopkins University Press.

Fuller, W. A. 1975. Regression analysis for sample survey. *Sankhyā*, C ser., 37: 117–132.

Gail, M. H., W. Y. Tan, and S. Piantadosi. 1988. Tests for no treatment effect in randomized clinical trials. *Biometrika* 75: 57–64. https://doi.org/10.2307/2336434.

Hampel, F. R. 1992. "Introduction to Huber (1964) "Robust estimation of a location parameter"". In *Methodology and Distribution*. Breakthroughs in Statistics, edited by S. Kotz and N. L. Johnson, vol. 2: 479–491. New York: Springer.

Huber, P. J. 1967. "The behavior of maximum likelihood estimates under nonstandard conditions". In *Proceedings of the Fifth Berkeley Symposium on Mathematical Statistics and Probability*, vol. 1: 221–233. Berkeley: University of California Press.

———. 2011. *Data Analysis: What Can Be Learned from the Past 50 Years*. Hoboken, NJ: Wiley.

Kaufman, R. L. 2013. *Heteroskedasticity in Regression: Detection and Correction*. Thousand Oaks, CA: Sage.

Kent, J. T. 1982. Robust properties of likelihood ratio tests. *Biometrika* 69: 19–27. https://doi.org/10.2307/2335849.

Kish, L., and M. R. Frankel. 1974. Inference from complex samples. *Journal of the Royal Statistical Society*, B ser., 36: 1–22. https://doi.org/10.1111/j.2517-6161.1974.tb00981.x.

Lin, D. Y., and L. J. Wei. 1989. The robust inference for the Cox proportional hazards model. *Journal of the American Statistical Association* 84: 1074–1078. https://doi.org/10.2307/2290085.

Lumley, T. S. 2020. Weights in statistics. *Biased and Inefficient*. https://notstatschat.rbind.io/2020/08/04/weights-in-statistics/.

MacKinnon, J. G., and H. L. White, Jr. 1985. Some heteroskedasticity-consistent covariance matrix estimators with improved finite sample properties. *Journal of Econometrics* 29: 305–325. https://doi.org/10.1016/0304-4076(85)90158-7.

McAleer, M., and T. Pérez-Amaral. 2012. Professor Halbert L. White, 1950–2012. *Journal of Economic Surveys* 26: 551–554. https://doi.org/10.1111/j.1467-6419.2012.00735.x.

Mitchell, M. N. 2021. *Interpreting and Visualizing Regression Models Using Stata*. 2nd ed. College Station, TX: Stata Press.

Pedace, R. 2013. *Econometrics for Dummies*. Hoboken, NJ: Wiley.

Rogers, W. H. 1993. sg17: Regression standard errors in clustered samples. *Stata Technical Bulletin* 13: 19–23. Reprinted in *Stata Technical Bulletin Reprints*, vol. 3, pp. 88–94. College Station, TX: Stata Press.

Royall, R. M. 1986. Model robust confidence intervals using maximum likelihood estimators. *International Statistical Review* 54: 221–226. https://doi.org/10.2307/1403146.

Wasserstein, R. L., and N. A. Lazar. 2016. The ASA statement on *p*-values: Context, process, and purpose. *American Statistician* 70: 129–133. https://doi.org/10.1080/00031305.2016.1154108.

White, H. L., Jr. 1980. A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. *Econometrica* 48: 817–838. https://doi.org/10.2307/1912934.

———. 1982. Maximum likelihood estimation of misspecified models. *Econometrica* 50: 1–25. https://doi.org/10.2307/1912526.

Williams, R. 2012. Using the margins command to estimate and interpret adjusted predictions and marginal effects. *Stata Journal* 12: 308–331.

21 Creating reports

Contents

21.1 Overview

Stata's commands for report generation allow you to create complete Word, Excel, PDF, and HTML documents that include formatted text, summary statistics, regression results, and graphs.

There are two varieties of commands for creating reports. The first includes the full output from Stata commands in the document and allows you to format the text using Markdown. The second uses stored results from Stata commands and inserts these results into text and tables in the document.

With either variety, you can create reports that are reproducible. Save the do-file or text file that runs the Stata commands and generates the report. Then rerun your commands at any time in the future to reproduce the Stata results and re-create the report. Make sure you include the `version` command so that your results are reproducible; see **[U] 16.1.1 Version**.

These documents can also be dynamic. If your data change, simply rerun the do-file using the updated dataset. All Stata results in the report will be automatically updated.

You can also create highly customized tables to include in your report; see [R] **table intro** and [TABLES] **Intro**.

21.2 The dynamic document commands

Stata's dynamic document commands allow you to embed Stata output in text files and to create HTML files and Word documents from Markdown text and Stata output. Dynamic tags are used to process Stata commands in a text file; they run the code and export the output to the destination file.

To create text files with Stata output, you simply enclose Stata commands within these dynamic tags throughout your source file and then use `dyntext` to create the output file. For instance, suppose we fit a regression model by typing

```
. sysuse auto
. regress mpg weight length i.foreign
```

and we want to create a simple report that includes the output from the regression in a plain text file. In addition, we want a heading that says "Regression results" and a sentence explaining the model. We can create this text file as follows:

begin dynex1.txt

```
Regression results
------------------

Linear regression of mpg on weight, length, and foreign.

<<dd_do>>
sysuse auto, clear
regress mpg weight length i.foreign
<</dd_do>>
```

end dynex1.txt

The «dd_do» and «/dd_do» dynamic tags tell Stata to execute the commands between them and to put the output in the `output.txt` file that is created when we type

```
. dyntext dynex1.txt, saving(output.txt)
```

We might instead want to create an HTML document with the regression results. We can use Markdown to format the heading and to bold the variable names in our text file as follows:

begin dynex2.txt

```
Regression results
==================

Linear regression of **mpg** on **weight**, **length**, and **foreign**.

~~~~
<<dd_do>>
sysuse auto, clear
regress mpg weight length i.foreign
<</dd_do>>
~~~~
```

end dynex2.txt

Then we create an HTML file, `dynex2.html`, with the Markdown-formatted text and the regression results by typing

```
. dyndoc dynex2.txt
```

Alternatively, we could type

```
. dyndoc dynex2.txt, docx
```

to create a Word document named `dynex2.docx` with the same results.

If you prefer a PDF document, you can first create a Word document and then use `docx2pdf` to convert the Word document to a PDF file.

For further introduction to the dynamic document commands, including examples of the text files, HTML documents, and Word documents created by these commands, see [RPT] **Dynamic documents intro**. See [RPT] **Dynamic tags** for information on including graphs, results of expressions, and more in dynamic documents. Also see [RPT] **dyndoc** for examples that demonstrate how to write a single, flexible text file that `dyndoc` can use to create similar reports but with different variables and even different datasets.

21.3 The putdocx, putpdf, and putexcel commands

The putdocx, putpdf, and putexcel commands create customized Word, PDF, and Excel files, respectively, that include Stata results. Unlike the dynamic document commands discussed in the previous section, these commands do not include Stata output directly in the document. Instead, they place the results of Stata commands into tables and text. With a series of commands when creating a document, you can specify formatting for the entire document or specific elements of the document, what text and graphs to include, and how to incorporate the statistical results from Stata commands.

Let's say we want to create a Word document with the results from the regression

```
. sysuse auto
. regress mpg weight length i.foreign
```

We also want a header and a sentence explaining the results. We could type

```
. sysuse auto
. putdocx begin
. putdocx paragraph, style(Heading1)
. putdocx text ("Regression results")
. putdocx paragraph
. putdocx text ("Linear regression of mpg on weight, length, and foreign.")
. regress mpg weight length i.foreign
. putdocx table regtable = e(table)
. putdocx save myreg
```

This creates a Word document named myreg.docx that includes a header with the text "Regression results" and a standard paragraph with the sentence about the regression. The putdocx table regtable = e(table) command creates a table in Word using the results returned from the regress command. The table includes coefficients, standard errors, tests, and confidence intervals for each of the covariates in the model.

Creating a PDF document works in much the same way. We could type

```
. sysuse auto
. putpdf begin
. putpdf paragraph, font("",20)
. putpdf text ("Regression results")
. putpdf paragraph
. putpdf text ("Linear regression of mpg on weight, length, and foreign.")
. regress mpg weight length i.foreign
. putpdf table regtable = e(table)
. putpdf save myreg
```

to create myreg.pdf. We replaced each putdocx command with putpdf, and we specified a font size of 20 points for the heading instead of using one of Word's heading styles.

We can, similarly, put results in an Excel file.

```
. sysuse auto
. putexcel set myreg
. regress mpg weight length i.foreign
. putexcel A3 = etable
```

This creates myreg.xlsx with the header and table of regression results.

For more information on putdocx, including more extensive examples and suggested workflows, see [RPT] **putdocx intro**. For more information on putpdf, see [RPT] **putpdf intro**. For more information on putexcel, see [RPT] **putexcel**.

Advice

22 Entering and importing data

Contents

22.1 Overview

To enter or import data into Stata, you can use the following:

[D] **edit** and [D] **input**	enters data from the keyboard
[D] **import delimited**	reads delimited text data
[D] **import excel**	reads Excel files
[D] **import sas**	reads SAS files
[D] **import sasxport5**	reads data in SAS XPORT Version 5 format
[D] **import sasxport8**	reads data in SAS XPORT Version 8 format
[D] **import spss**	reads SPSS files
[D] **infile (free format)**	reads unformatted text data
[D] **infile (fixed format)** or [D] **infix (fixed format)**	reads formatted text data
[D] **infile (fixed format)**	reads EBCDIC data
[D] **odbc**	reads from an ODBC source
[D] **jdbc**	reads from a JDBC source
[D] **import fred**	reads Federal Reserve Economic Data
[D] **import haver**	reads data from Haver Analytics databases
[D] **import haverdirect**	reads data from Haver Analytics cloud servers
[D] **import dbase**	reads dBase files
[SP] **spshape2dta**	converts shapefiles into a form Stata can use

Because dataset formats differ, you should familiarize yourself with each method.

[D] **infile (fixed format)** and [D] **infix (fixed format)** are two different commands that do the same thing. Read about both, and then use whichever appeals to you.

Alternatively, `edit` and `input` both allow you to enter data from the keyboard. `edit` opens a Data Editor, and `input` allows you to type at the command line.

After you have read this chapter, also see [D] **import** for more examples of the different commands to input data.

❑ Technical note

Strings in Stata are stored in UTF-8 format, the most common string storage format across software packages. You probably do not need to take any special steps when importing strings from other packages. However, if you are importing data with strings that are stored as extended ASCII, including extended ASCII strings in Stata 13 and earlier datasets, you need to convert those strings to UTF-8. You will know whether you have extended ASCII strings that need conversion, because if you do, you will not see the characters you expect in your strings after you import them. Stata provides the command `unicode translate` to help you. See [D] **unicode translate**, [U] **12.4.2 Handling Unicode strings**, and [D] **unicode** for more information.

❑

22.2 Determining which method to use

Below are several rules that, when applied sequentially, will direct you to the appropriate method for entering your data. After the rules is a description of each command, as well as a reference to the corresponding entry in the *Reference* manuals.

1. If you have a few data and simply wish to type the data directly into Stata at the keyboard, see [D] **edit**—doing so should be easy. Also see [D] **input**.
2. If your dataset is in binary format or the internal format of some software package, you have several options:
    a. If the data are in a spreadsheet, copy and paste the data into Stata's Data Editor; see [D] **edit** for details.
    b. If the data are in an Excel spreadsheet, use `import excel` to read them; see [D] **import excel**.
    c. If the data are in a SAS file, use `import sas` to read the data; see [D] **import sas**.
    d. If the data are in SAS XPORT Version 5 or Version 8 format, use `import sasxport5` or `import sasxport8` to read the data; see [D] **import sasxport5** and [D] **import sasxport8**.
    e. If the data are in an SPSS file, use `import spss` to read the data; see [D] **import spss**.
    f. If you wish to import data from the online Federal Reserve Economic Data (FRED) database, use `import fred`; see [D] **import fred**.
    g. If the data are in a Haver Analytics database on your local network (Haver Analytics provides economics and financial databases), and you are using Stata for Windows, use `import haver` to read the data; see [D] **import haver**.
    h. If the data are in a Haver Analytics cloud database and you are using Stata for Windows, use `import haverdirect` to read the data; see [D] **import haverdirect**.
    i. If the data are in a dBase file, use `import dbase`; see [D] **import dbase**.
    j. Translate the data into text format by using the other software. For instance, in most software, you can save data as tab-delimited or comma-separated text. Then, see [D] **import delimited**.

k. If the data are located in an ODBC source, which typically includes databases and spreadsheets, you can use the `odbc load` command to import the data; see [D] **odbc**.

l. If the data are located in a database and the database vendor has a JDBC driver, you can use the `jdbc load` command to import the data; see [D] **jdbc**.

m. If you wish to use shapefile data with Stata, use `spshape2dta` to convert it to a form Stata can use; see [SP] **spshape2dta**.

n. Other software packages are available that will convert non–Stata format data files into Stata-format files.

3. If the dataset has one observation per line and the data are tab- or comma separated, use `import delimited`; see [D] **import delimited**. This is the easiest way to read text data.
4. If the dataset is formatted and that formatting information is required to interpret the data, you can use `infile` with a dictionary or `infix`; see [D] **infile (fixed format)** or [D] **infix (fixed format)**.
5. If there are no string variables, you can use `infile` without a dictionary: see [D] **infile (free format)**.
6. If all the string variables in the data are enclosed in (single or double) quotes, you can use `infile` without a dictionary; see [D] **infile (free format)**.
7. If the string variables have no blanks and are whitespace-delimited, you can use `infile` without a dictionary; see [D] **infile (free format)**.
8. If the data are in EBCDIC format, see [D] **infile (fixed format)**.
9. If you make it to here, see [D] **infile (fixed format)** or [D] **infix (fixed format)**.

22.2.1 Entering data interactively

If you have a few data, you can type the data directly into Stata; see [D] **edit** or [D] **input**. Otherwise, we assume that your data are stored on disk.

22.2.2 Copying and pasting data

If your data are in another program and you wish to analyze them with Stata, first see if the program you are using allows you to copy the data to the clipboard. If it does, do so, and then open the Data Editor in Stata and select **Edit > Paste** to paste the data into Stata.

22.2.2.1 Video example

Copy/paste data from Excel into Stata

22.2.3 If the dataset is in binary format

Stata can read text datasets, which is technical jargon for datasets composed of characters—datasets that can be typed on your screen or printed on your printer. The alternative, binary datasets, can only sometimes be read by Stata. Binary datasets are popular, and almost every software package has its own binary format. Stata `.dta` datasets are an example of a binary format that Stata can read. The Excel `.xls` and `.xlsx` formats are other binary formats that Stata can read. The OpenOffice `.ods` format is a binary format that Stata cannot read.

If your dataset is in binary format or in the internal format of another software package that Stata cannot import, you must translate it into plain text or use some other program for conversion to Stata format. If this dataset is an Excel `.xls` or `.xlsx` file, you can read it by using Stata's `import excel` command; see [D] **import excel**. If this dataset is located in a database or an ODBC source, see **[U] 22.4 ODBC sources**. If this dataset is located in a database and the database vendor has a JDBC driver, see **[U] 22.5 JDBC sources**. If the dataset is in SAS format, you can read it by using `import sas`. If the data are in SAS XPORT Version 5 format or in SAS XPORT Version 8 format, you can read the data by using Stata's `import sasxport5` or `import sasxport8` command; see [D] **import sasxport5** and [D] **import sasxport8**. You can read data in SPSS `.sav` format by using `import spss`; see [D] **import spss**. If the data are available via the Federal Reserve Economic Data (FRED) online database, you can read the data by using Stata's `import fred` command; see [D] **import fred**. If the dataset is in a Haver Analytics database on your local network, you can read it by using Stata's `import haver` command; see [D] **import haver**. If the dataset is in a Haver Analytics cloud database, you can read it by using Stata's `import haverdirect` command; see [D] **import haverdirect**. If the dataset is in dBase format, you can read it by using Stata's `import dbase` command; see [D] **import dbase**. If you have a shapefile and wish to use it with Stata, use `spshape2dta` to convert it to a form that can be used with Stata; see [SP] **spshape2dta**. If the dataset is in EBCDIC format, you can read it by using Stata's `infile` command; see [D] **infile (fixed format)**.

Detecting whether data are stored in binary format can be tricky. For instance, many Windows users wish to read data that have been entered into a word processor—let's assume Word. Unwittingly, they have stored the dataset as a Word document. The dataset looks like text to them: When they look at it in Word, they see readable characters. The dataset seems to even pass the printing test in that Word can print it. Nevertheless, the dataset is not text; it is stored in an internal Word format, and the data cannot really pass the printing test because only Word can print it. To read the dataset, Windows users must use it in Word and then store it as a plain text (`.txt`) file.

So, how do you know whether your dataset is binary? Here's a simple test: regardless of the operating system you use, start Stata and type `type` followed by the name of the file:

```
. type myfile.raw
output will appear
```

You do not have to list the entire file; press *Break* when you have seen enough.

Do you see things that look like hieroglyphics? If so, the dataset is binary.

If it looks like data, however, the file is (probably) plain text.

Let's assume that you have a text dataset that you wish to read. The data's format will determine the command you need to use. The different formats are discussed in the following sections.

22.2.4 If the data are simple

The easiest way to read text data is with `import delimited`; see [D] **import delimited**.

`import delimited` is smart: it looks at the dataset, determines what it contains, and then reads it. That is, `import delimited` is smart given certain restrictions, such as that the dataset has one observation per line and that the values are tab- or comma separated. `import delimited` can read this

begin `data1.csv`

```
M,Joe Smith,288,14
M,K Marx,238,12
F,Farber,211,7
```

end `data1.csv`

or this (which has variable names on the first line)

begin data2.csv
```
sex, name, dept, division
M,Joe Smith,288,14
M,K Marx,238,12
F,Farber,211,7
```
end data2.csv

or this (which has one tab character separating the values):

begin data3.txt
```
M       Joe Smith       288     14
M       K Marx  238     12
F       Farber  211     7
```
end data3.txt

This looks odd because of how tabs work; `data3.txt` could similarly have a variable header, but `import delimited` cannot read

begin data4.txt
```
M       Joe Smith       288     14
M       K Marx          238     12
F       Farber          211     7
```
end data4.txt

which has spaces rather than tabs.

There is a way to tell `data3.txt` from `data4.txt`: Ask Stata to type the data and show the tabs by typing

```
. type data3.txt, showtabs
M<T>Joe Smith<T>288<T>14
M<T>K Marx<T>238<T>12
F<T>Farber<T>211<T>7
. type data4.txt, showtabs
M       Joe Smith       288     14
M       K Marx          238     12
F       Farber          211     7
```

22.2.5 If the dataset is formatted and the formatting is significant

If the dataset is formatted and formatting information is required to interpret the data, see [D] **infile (fixed format)** or [D] **infix (fixed format)**.

Using `infix` or `infile` with a data dictionary is something new users want to avoid if at all possible.

The purpose of this section is only to take you to the most complicated of all cases if there is no alternative. Otherwise, you should wait and see if it is necessary. Do not misinterpret this section and say, "Ah, my dataset is formatted, so at last I have a solution."

Just because a dataset is formatted does not mean that you have to exploit the formatting information. The following dataset is formatted

begin data5.raw
```
1   27.39    12
2    1.00     4
3  100.10   100
```
end data5.raw

in that the numbers line up in neat columns, but you do not need to know the information to read it. Alternatively, consider the same data run together:

begin data6.raw
```
1 27.39 12
2  1.00  4
3100.10100
```
end data6.raw

This dataset is formatted, too, and you must know the formatting information to make sense of "3100.10100". You must know that variable 2 starts in column 4 and is six characters long to extract the 100.10. It is datasets like `data6.raw` that you should be looking for at this stage—datasets that make sense only if you know the starting and ending columns of data elements. To read data such as `data6.raw`, you must use either `infix` or `infile` with a data dictionary.

Reading unformatted data is easier. If you need the formatting information to interpret the data, then you must communicate that information to Stata, which means that you will have to type it. This is the hardest kind of data to read, but Stata can do it. See [D] **infile (fixed format)** or [D] **infix (fixed format)**.

Looking back at `data4.raw`,

begin data4.raw
```
M       Joe Smith       288     14
M       K Marx          238     12
F       Farber          211     7
```
end data4.raw

you may be uncertain whether you have to read it with a data dictionary. If you are uncertain, do not jump yet.

Finally, here is an obvious example of unformatted data:

begin data7.raw
```
1 27.39          12
2 1 4
3 100.1 100
```
end data7.raw

Here blanks separate one data element from the next and, in one case, many blanks, although there is no special meaning attached to more than one blank.

The following sections discuss datasets that are unformatted or formatted in a way that do not require a data dictionary.

22.2.6 If there are no string variables

If there are no string variables, see [D] **infile (free format)**.

Although the dataset `data7.raw` is unformatted, it can still be read using `infile` without a dictionary. This is not the case with `data4.raw` because this dataset contains undelimited string variables with embedded blanks.

❑ Technical note

Some Stata users prefer to read data with a data dictionary, even when we suggest differently, as above. They like the convenience of the data dictionary—they can sit in front of an editor and carefully compose the list of variables and attach variable labels rather than having to type the variable list (correctly) on

the Stata command line. However, they can create a do-file containing the `infile` statement and thus have all the advantages of a data dictionary without some of the (extremely technical) disadvantages of data dictionaries.

Nevertheless, we do tend to agree with such users—we, too, prefer data dictionaries. Our recommendations, however, are designed to work in all cases. If the dataset is unformatted and contains no string variables, it can always be read without a data dictionary, whereas only sometimes can it be read with a data dictionary.

The distinction is that `infile` without a data dictionary performs stream I/O, whereas with a data dictionary it performs record I/O. The difference is intentional—it guarantees that you will be able to read your data into Stata somehow. Some datasets require stream I/O, others require record I/O, and still others can be read either way. Recommendations 1–5 identify datasets that either require stream I/O or can be read either way.

❑

We are now left with datasets that contain at least one string variable.

22.2.7 If all the string variables are enclosed in quotes

If all the string variables in the data are enclosed in (single or double) quotes, see [D] **infile (free format)**.

See [U] **24 Working with strings** for a formal definition of strings, but as a quick guide, a string variable is a variable that takes on values like "`bob`" or "`joe`", as opposed to numeric variables that take on values like 1, 27.5, and –17.393. Undelimited strings—strings not enclosed in quotes—can be difficult to read.

Here is an example including delimited string variables:

begin `data8.raw`

```
"M" "Joe Smith" 288 14
"M" "K Marx" 238 12
"F" "Farber" 211 7
```

end `data8.raw`

or

begin `data8.raw`, alternative format

```
"M" "Joe Smith" 288  14
"M" "K Marx"    238  12
"F" "Farber"    211   7
```

end `data8.raw`, alternative format

Both of these are merely variations on `data4.raw` except that the strings are enclosed in quotes. Here `infile` without a dictionary can be used to read the data.

Here is another version of `data4.raw` without delimiters or even formatting:

begin `data9.raw`

```
M Joe Smith 288 14
M K Marx 238 12
F Farber 211 7
```

end `data9.raw`

What makes these data difficult? Blanks sometimes separate values and sometimes are nothing more than a blank within a string. For instance, you cannot tell whether Farber has first initial F with missing sex or is instead female with a missing first initial.

Fortunately, such data rarely happen. Either the strings are delimited, as we showed in `data8.raw`, or the data are in columns, as in `data4.raw`.

22.2.8 If the undelimited strings have no blanks

There is a case in which uncolumnized, undelimited strings cause no confusion—when they contain no blanks. For instance, if our data contained only last names,

begin `data10.raw`

```
Smith 288 14
Marx 238 12
Farber 211 7
```

end `data10.raw`

Stata could read it without a data dictionary. Caution: the last names must contain no blanks—no Van Owen's or von Beethoven's.

If the undelimited string variables have no blanks, see [D] **infile (free format)**.

22.2.9 If you have EBCDIC data

You may rarely encounter data from a mainframe that is encoded in extended binary coded decimal interchange code (EBCDIC). EBCDIC is used on some IBM mainframe operating systems.

If you have EBCDIC data, you should have information on that data specifying where each field begins and ends and what type of data is in that field. You can read EBCDIC data in the same way that you read fixed-format text data, using `infile` (see [D] **infile (fixed format)**. You create a data dictionary that tells Stata which columns to read for each field, and you merely specify the `ebcdic` option with the `infile` command to read the data.

Alternatively, you can convert an EBCDIC file to an ASCII text file with the `filefilter` command. See [D] **filefilter**.

22.2.10 If you make it to here

If you make it to here, see [D] **infile (fixed format)** or [D] **infix (fixed format)**.

Remember `data4.raw`?

begin `data4.raw`

```
M       Joe Smith       288     14
M       K Marx          238     12
F       Farber          211     7
```

end `data4.raw`

It can be read using either `infile` with a dictionary or `infix`.

22.3 If you run out of memory

You may need to tweak a setting; see **[U] 6 Managing memory** and [D] **memory**.

You can also try to conserve memory.

When you read the data, did you specify variable types? Stata can store integers more compactly than floats and small integers more compactly than large integers; see **[U] 12 Data**.

If that is not sufficient, you will have to resort to reading the data in pieces. Both `infile` and `infix` allow you to specify an `in` *range* qualifier, and, here the range is interpreted as the observation range to read. Thus, `infile ... in 1/100` would read observations 1–100 of your data and stop.

`infile ... in 101/200` would read observations 101–200. The end of the range may be specified as larger than the actual number of observations in the data. If the dataset contained only 150 observations, `infile ... in 101/200` would read observations 101–150.

Another way of reading the data in pieces is to specify the `if` *exp* qualifier. Say that your data contained an equal number of males and females, coded as the variable `sex` (which you will read) being 0 or 1, respectively. You could type `infile ... if sex==0` to read the males. `infile` will read an observation, determine if `sex` is zero, and if not, throw the observation away. You could read just the females by typing `infile ... if sex==1`.

If the dataset is really big, perhaps you need only a random sample of the data—you never intended to analyze the entire dataset. Because `infile` and `infix` allow `if` *exp*, you could type `infile ... if runiform()<.1`. `runiform()` is the uniformly distributed random-number generator; see [FN] **Random-number functions**. This method would read an approximate 10% sample of the data. If you are serious about using random samples, do not forget to set the seed before using `runiform()`; see [R] **set seed**.

The final approach is to read all the observations but only some of the variables. When reading data without a data dictionary, you can specify `_skip` for variables, indicating that the variable is to be skipped. When reading with a data dictionary or using `infix`, you can specify the actual columns to read, skipping any columns you wish to ignore.

If you are using `import excel`, you can read a subset of an Excel worksheet by using the `cellrange()` option. See [D] **import excel**.

22.4 ODBC sources

If your dataset is located in a network database or shared spreadsheet, you may be able to import your data via ODBC. Open Database Connectivity (ODBC) is a standard for exchanging data between programs. Stata supports the ODBC standard for importing data via the `odbc` command and can read from any ODBC source on your computer.

This process requires a data source, such as a database located on a network. To use the `odbc` command to import data from a database requires that the database first be set up as an ODBC source on the same machine that is running Stata. The database itself does not have to be on the same machine, just the definition of that database as the ODBC source. On a Windows machine, an ODBC source is added via a Control Panel called "Data Sources". Also, typing `odbc list` from Stata displays all the ODBC sources that are provided by the computer.

If the database is functioning and the appropriate data source has been set up on the same machine as Stata, one call using `odbc load` is all that is needed to import data. For a more thorough description of this process, see [D] **odbc**.

22.5 JDBC sources

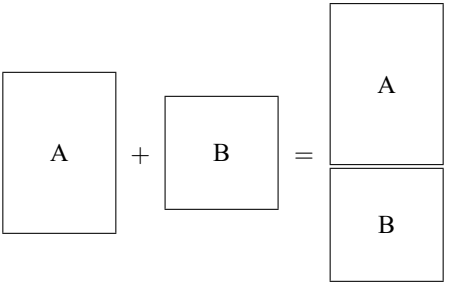
If your dataset is located in a database, you may be able to import your data via JDBC. Java Database Connectivity (JDBC) is a standard for exchanging data between programs. Stata supports the JDBC standard for importing data from relational databases or nonrelational database-management systems that have rectangular data.

Using the `jdbc` command to import data from a database requires that the database vendor supply a JDBC driver for you to download and install. If the database is functioning and the driver can be found by Stata, one call using `jdbc load` is all that is needed to import data. For a more thorough description of this process, see [D] **jdbc**.

23 Combining datasets

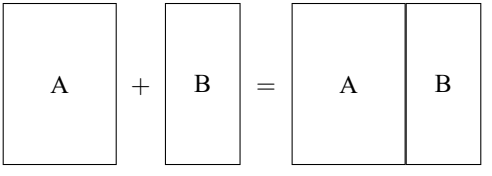
You have two datasets that you wish to combine. Below, we will draw a dataset as a box where, in the box, the variables go across and the observations go down.

See [D] **append** if you want to combine datasets vertically:



`append` adds observations to the existing variables. That is an oversimplification because `append` does not require that the datasets have the same variables. `append` is appropriate, for instance, when you have data on hospital patients and then receive data on more patients.

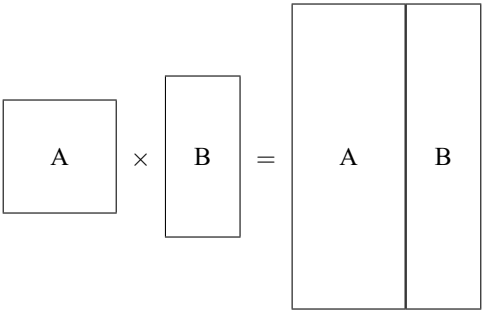
See [D] **merge** if you want to combine datasets horizontally:



`merge` adds variables to the existing observations. That is an oversimplification because `merge` does not require that the datasets have the same observations. `merge` is appropriate, for instance, when you have data on survey respondents and then receive data on part 2 of the questionnaire.

There is another way to combine datasets horizontally, or more precisely, hierarchically, by loading them into separate frames and linking them. See [D] **frlink** for a discussion of when you might want to use `merge` versus `frlink`.

See [D] **joinby** when you want to combine datasets horizontally but form all pairwise combinations within group:



`joinby` is similar to `merge` but forms all combinations of the observations where it makes sense. `joinby` would be appropriate, for instance, where A contained data on parents and B contained data on their children. `joinby` *familyid* would form a dataset of each parent joined with each of his or her children.

Also see [D] **cross** for a less frequently used command that forms every pairwise combination of two datasets.

See Mitchell (2020, chap. 7) for more information on combining datasets in Stata.

23.1 References

Golbe, D. L. 2010. Stata tip 83: Merging multilingual datasets. *Stata Journal* 10: 152–156.

Gould, W. W. 2011a. Merging data, part 1: Merges gone bad. *The Stata Blog: Not Elsewhere Classified*. https://blog.stata.com/2011/04/18/merging-data-part-1-merges-gone-bad/.

———. 2011b. Merging data, part 2: Multiple-key merges. *The Stata Blog: Not Elsewhere Classified*. https://blog.stata.com/2011/05/27/merging-data-part-2-multiple-key-merges/.

Mitchell, M. N. 2020. *Data Management Using Stata: A Practical Handbook*. 2nd ed. College Station, TX: Stata Press.

24 Working with strings

Contents

Please read **[U] 12 Data** before reading this entry.

24.1 Description

The word *string* is shorthand for a string of characters. "Male" and "Female", "yes" and "no", and "R. Smith" and "P. Jones" are examples of strings. The alternative to strings is numbers—0, 1, 2, 5.7, and so on. Variables containing strings—called *string variables*—occur in data for a variety of reasons. Four of these reasons are listed below.

A variable might contain strings because it is an identifying variable. Employee names in a payroll file, patient names in a hospital file, and city names in a city data file are all examples of this. This is a proper use of string variables.

A variable might contain strings because it records categorical information. "Male" and "Female" and "Yes" and "No" are examples of such use, but this is not an appropriate use of string variables. It is not appropriate because the same information could be coded numerically, and, if it were, it would take less memory to store the data and the data would be more useful. We will explain how to convert categorical strings to categorical numbers below.

Also, a variable might contain strings because of a mistake. For example, the variable contains things like 1, 5, 8.2, but because of an error in reading the data, the data were mistakenly put into a string variable. We will explain how to fix such mistakes.

Finally, a variable might contain strings because the data simply could not be coerced into being stored numerically. "15 Jan 1992", "1/15/92", and "1A73" are examples of such use. We will explain how to deal with such complexities.

In addition to the advice presented here, read **[U] 12.4.2 Handling Unicode strings** if your strings contain Unicode characters.

24.2 Categorical string variables

A variable might contain strings because it records categorical information.

Suppose that you have read in a dataset that contains a variable called `sex`, recorded as "male" and "female", yet when you attempt to run a linear regression, the following message is displayed:

```
. use https://www.stata-press.com/data/r19/hbp2
. regress hbp sex
no observations
r(2000);
```

There are no observations because `regress`, along with most of Stata's "analytic" commands, cannot deal with string variables. Commands want to see numbers, and when they do not, they treat the variable as if it contained numeric missing values. Despite this limitation, it is possible to obtain tables:

```
. encode sex, generate(gender)
. regress hbp gender
```

Source	SS	df	MS	Number of obs	=	1,128
				F(1, 1126)	=	14.04
Model	.644485682	1	.644485682	Prob > F	=	0.0002
Residual	51.6737767	1,126	.045891454	R-squared	=	0.0123
				Adj R-squared	=	0.0114
Total	52.3182624	1,127	.046422593	Root MSE	=	.21422

hbp	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
gender	.0491501	.0131155	3.75	0.000	.0234166	.0748837
_cons	-.0306744	.0221353	-1.39	0.166	-.0741054	.0127566

The magic here is to convert the string variable `sex` into a numeric variable called `gender` with an associated value label, a trick accomplished by `encode`; see **[U] 12.6.3 Value labels** and [D] **encode**.

24.3 Mistaken string variables

A variable might contain strings because of a mistake.

Suppose that you have numeric data in a variable called `x`, but because of a mistake, `x` was made a string variable when you read the data. When you `list` the variable, it looks fine:

```
. list x
```

	x
1.	2
2.	2.5
3.	17

(*output omitted*)

Yet, when you attempt to obtain summary statistics on `x`,

```
. summarize x
```

Variable	Obs	Mean	Std. dev.	Min	Max
x	0				

If this happens to you, type `describe` to confirm that `x` is stored as a string:

```
. describe
Contains data
 Observations:             6
    Variables:             3
-------------------------------------------------------------------------------
Variable      Storage   Display    Value
    name         type    format    label      Variable label
-------------------------------------------------------------------------------
x               str4    %9s
y               float   %9.0g
z               float   %9.0g
-------------------------------------------------------------------------------
Sorted by:
     Note: Dataset has changed since last saved.
```

`x` is stored as a `str4`.

The problem is that `summarize` does not know how to calculate the mean of string variables—how to calculate the mean of "Joe" plus "Bill" plus "Roger"—even when the string variable contains what could be numbers. By using the `destring` command, the variable mistakenly stored as a `str4` can be converted to a numeric variable.

```
. destring x, replace
x: all characters numeric; replaced as double
. summarize x
    Variable |        Obs        Mean    Std. dev.       Min        Max
-------------+---------------------------------------------------------
           x |          6    13.08333    8.452317         2         20
```

An alternative to using the `destring` command is to use `generate` with the `real()` function; see [FN] **String functions**.

24.4 Complex strings

A variable might contain strings because the data simply could not be coerced into being stored numerically.

A complex string is a string that contains more than one piece of information. Complex strings may be very long and may contain binary information. Stata can store strings up to 2-billion characters long and can store strings containing binary information, including binary 0 (`\0`). You can read more about this in [U] **12.4 Strings**. The most common example of a complex string, however, is a date: "15 Jan 1992" contains three pieces of information—a day, a month, and a year. If your complex strings are dates or times, see [U] **25 Working with dates and times**.

Although Stata has functions for dealing with dates, you will have to deal with other complex strings yourself. Assume that you have data that include part numbers:

```
. list partno

     +---------+
     | partno  |
     |---------|
  1. | 5A2713  |
  2. | 2B1311  |
  3. | 8D2712  |
     | (output omitted) |
     +---------+
```

The first digit of the part number is a division number, and the character that follows identifies the plant at which the part was manufactured. The next three digits represent the major part number and the last digit is a modifier indicating the color. This complex variable can be decomposed using the `substr()` and `real()` functions described in [FN] **String functions**:

```
. generate byte div = real(substr(partno,1,1))
. generate str1 plant = substr(partno,2,1)
. generate int part = real(substr(partno,3,3))
. generate byte color = real(substr(partno,6,1))
```

We use the `substr()` function to extract pieces of the string and use the `real()` function, when appropriate, to translate the piece into a number. See **[U] 12.4.2.1 Unicode string functions**.

For a gentle tutorial on problems with string variables containing many tips, see Cox and Schechter (2018). For an extended discussion of numeric and string data types and how to convert from one kind to another, see Cox (2002).

24.5 References

Cox, N. J. 2002. Speaking Stata: On numbers and strings. *Stata Journal* 2: 314–329.

Cox, N. J., and C. B. Schechter. 2018. Speaking Stata: Seven steps for vexatious string variables. *Stata Journal* 18: 981–994.

Schwarz, C. 2019. lsemantica: A command for text similarity based on latent semantic analysis. *Stata Journal* 19: 129–142.

25 Working with dates and times

Contents

25.1 Overview

A complete overview of Stata's date and time capabilities can be found in [D] **Datetime**. It discusses functions used to obtain Stata dates, including string-to-numeric conversions and conversions among different types of dates and times.

For an alphabetical listing of all the datetime functions, see [FN] **Date and time functions**.

Stata can work with dates such as 21nov2006, with times such as 13:42:02.213, and with dates and times such as 21nov2006 13:42:02.213. You can write these dates and times however you wish, such as 11/21/2006, November 21, 2006, and 1:42 p.m.

Stata stores dates, times, and dates and times as integers such as −4,102, 0, 82, 4,227, and 1,479,735,745,213. It works like this:

1. You begin with the datetime variables in your data however they are recorded, such as 21nov2006 or 11/21/2006 or November 21, 2006, or 13:42:02.213 or 1:42 p.m. The original values are usually best stored in string variables.
2. Using functions we will describe below, you convert the original strings into integers that Stata understands and store those values.
3. You specify the appropriate display format for datetimes so that, rather than displaying as the integer values that they are, they display in a way you can read them such as 21nov2006 or 11/21/2006 or November 21, 2006, or 13:42:02.213 or 1:42 p.m.

The numeric encoding that Stata uses is centered on the first millisecond of 01jan1960, that is, 01jan1960 00:00:00.000. That datetime is assigned integer value 0.

Integer value 1 is the millisecond after that: 01jan1960 00:00:00.001.

Integer value −1 is the millisecond before that: 31dec1959 23:59:59.999.

By that logic, 21nov2006 13:42:02.213 is integer value 1,479,735,722,213, or at least it is if we ignore the leap seconds that have been inserted to keep clocks in alignment with astronomical observation. If we account for leap seconds, 21nov2006 13:42:02.213 would be 23 seconds later, namely, 1,479,735,745,213. Stata can work either way.

Obtaining the number of milliseconds associated with a datetime is easy because Stata provides functions that convert things like 21nov2006 13:42:02.213 (written however you wish) to 1,479,735,722,213 or 1,479,735,745,213.

Just remember, Stata records datetime values as the number of milliseconds since the first millisecond of 01jan1960.

Stata records pure time values (clock times independent of date) the same way. Rather than thinking of the numeric value as the number of milliseconds since 01jan1960, however, think of it as the number of milliseconds since the beginning of the day. For instance, at 2 p.m. every day, the airplane takes off from Houston for London. The numeric value associated with 2 p.m. is 50,400,000 because there are that many milliseconds between the beginning of the day (00:00:00.000) and 2 p.m.

The advantage of thinking this way is that you can add dates and times. What is the datetime value for when the plane takes off on 21nov2006? Well, 21nov2006 00:00:00.000 is 1,479,686,400,000 (ignoring leap seconds), and 1,479,686,400,000 + 50,400,000 is 1,479,736,800,000.

Subtracting datetime values is useful, too. How many hours are there between 21jan1952 7:23 a.m. and 21nov2006 3:14 p.m.? Answer: {1,479,741,240,000 − (−250,706,220,000)}/3,600,000 = 480,679.85 hours.

Variables that record the number of milliseconds since 01jan1960 and ignore leap seconds are called datetime/c variables.

Variables that record the number of milliseconds since 01jan1960 and account for leap seconds are called datetime/C variables.

Stata has seven other kinds of date and time variables.

In many applications, calendar dates by themselves are sufficient. The applicant was hired on 15jan2006, for instance. You could use a datetime/c variable to record that value, assigning some arbitrary time that you would ignore, but it is better and easier to use simply a date variable. In date variables, 0 still corresponds to 01jan1960, but a unit change now represents an entire day rather than a millisecond. The value 1 represents 02jan1960. The value −1 represents 31dec1959. When you subtract date variables, you obtain the number of days between dates.

In a financial application, you might use quarterly variables. In quarterly variables, 0 represents the first quarter of 1960, 1 represents the second quarter, and −1 represents the last quarter of 1959. When you subtract quarterly variables, you obtain the number of quarters between dates.

Stata understands nine date and time formats:

Format	Base	Units	Comment
`%tc`	01jan1960	milliseconds	ignores leap seconds
`%tC`	01jan1960	milliseconds	accounts for leap seconds
`%td`	01jan1960	days	calendar date format
`%tw`	1960-w1	weeks	52nd week may have more than 7 days
`%tm`	jan1960	months	calendar month format
`%tq`	1960-q1	quarters	financial quarter
`%th`	1960-h1	half-years	1 half-year = 2 quarters
`%ty`	AD 0	year	1960 means year 1960
`%tb`	–	days	user-defined business calendar format

All formats except `%ty` and `%tb` are based on the beginning of January 1960. The value 0 means the first millisecond, day, week, month, quarter, or half-year of 1960, depending on the format. The value 1 is the millisecond, day, week, month, quarter, or half-year after that. The value −1 is the millisecond, day, week, month, quarter, or half-year before that.

Stata's %ty format records years as numeric values, and it codes them the natural way: rather than 0 meaning 1960, 1960 means 1960, and so 2006 also means 2006.

25.2 Inputting dates and times

Date and time variables are best read as strings. You then use one of the string-to-numeric conversion functions to convert the string to an appropriate numeric value:

Format	String-to-numeric conversion function
%tc	clock(*string*, *mask*)
%tC	Clock(*string*, *mask*)
%td	date(*string*, *mask*)
%tw	weekly(*string*, *mask*)
%tm	monthly(*string*, *mask*)
%tq	quarterly(*string*, *mask*)
%th	halfyearly(*string*, *mask*)
%ty	yearly(*string*, *mask*)

The full documentation of these functions can be found in [D] **Datetime conversion**.

In the above table, *string* is the string variable to be translated, and *mask* specifies the order in which the components of the date or time, or both, appear in *string*. For instance, the *mask* in %td function date() is made up of the letters M, D, and Y.

date(*string*, "DMY") specifies *string* contain dates in the order of day, month, year. With that specification, date() can convert 21nov2006, 21 November 2006, 21-11-2006, 21112006, and other strings that contain dates in the order day, month, year.

date(*string*, "MDY") specifies *string* contain dates in the order of month, day, year. With that specification, date() can convert November 21, 2006, 11/21/2006, 11212006, and other strings that contain dates in the order month, day, year.

You can specify a two-digit prefix in front of Y to handle two-digit years. date(*string*, "MD19Y") specifies that *string* contain dates in the order of month, day, and year and that if the year contains only two digits, it is to be prefixed with 19. With that specification, date() could convert not only November 21, 2006, 11/21/2006, and 11212006 but also Feb. 15 '98, 2/15/98, and 21598.

There is another way to deal with two-digit years so that 98 becomes 1998 while 06 becomes 2006. It involves specifying an optional third argument. See *Working with two-digit years* in [D] **Datetime conversion**.

Let's consider some daily data. We have the following raw-data file:

begin bdays.raw

```
Bill  21 Jan 1952  22
May   11 Jul 1948  18
Sam   12 Nov 1960  25
Kay    9 Aug 1975  16
```

end bdays.raw

We could read these data by typing

```
. infix str name 1-5 str bday 7-17 x 20-21 using bdays
(4 observations read)
```

We read the date not as three separate variables but as one variable. Variable bday contains the entire date:

```
. list
```

	name	bday	x
1.	Bill	21 Jan 1952	22
2.	May	11 Jul 1948	18
3.	Sam	12 Nov 1960	25
4.	Kay	9 Aug 1975	16

The data look fine, but if we set about using them, we would quickly discover there is not much we could do with variable bday. Variable bday looks like a date, but it is just a string. We need to turn bday into a numeric value that Stata understands:

```
. generate birthday = date(bday, "DMY")
. list
```

	name	bday	x	birthday
1.	Bill	21 Jan 1952	22	-2902
2.	May	11 Jul 1948	18	-4191
3.	Sam	12 Nov 1960	25	316
4.	Kay	9 Aug 1975	16	5699

New variable birthday is a numeric date variable. The problem now is that, whereas the new variable is perfectly understandable to Stata, it is not understandable to us. So we apply the corresponding format for a calendar date, %td:

```
. format birthday %td
. list
```

	name	bday	x	birthday
1.	Bill	21 Jan 1952	22	21jan1952
2.	May	11 Jul 1948	18	11jul1948
3.	Sam	12 Nov 1960	25	12nov1960
4.	Kay	9 Aug 1975	16	09aug1975

Using our newly formatted variable, we can create a variable recording how old each of these subjects was on 01jan2000 using the age() function:

```
. generate age2000 = age(birthday, td(01jan2000))
. list
```

	name	bday	x	birthday	age2000
1.	Bill	21 Jan 1952	22	21jan1952	47
2.	May	11 Jul 1948	18	11jul1948	51
3.	Sam	12 Nov 1960	25	12nov1960	39
4.	Kay	9 Aug 1975	16	09aug1975	24

The arguments to age() are numeric dates. The first is the date of birth, and the second the date for which age is calculated. See [D] **Datetime durations**.

td() is a function that converts a single date typed out (01jan2000 in this example) into its equivalent numeric date value. There are also functions tc(), tC(), tw(), tm(), tq(), and th() for the other types of dates and times; see [D] **Datetime**.

Let's consider one more example. We have the following data:

```
. use https://www.stata-press.com/data/r19/datexmpl2, clear
. list
```

	id	timestamp	action
1.	1001	Tue Nov 14 08:59:43 CST 2006	15
2.	1002	Wed Nov 15 07:36:49 CST 2006	15
3.	1003	Wed Nov 15 09:21:07 CST 2006	11
4.	1002	Wed Nov 15 14:57:36 CST 2006	16
5.	1005	Thu Nov 16 08:22:53 CST 2006	12
6.	1001	Thu Nov 16 08:36:44 CST 2006	16

Variable timestamp is a string that we want to convert to a datetime/c variable. From the table above, we know we will use function clock(). The *mask* in clock() uses the letters D, M, Y and h, m, s, which specify the order of the day, month, year and hours, minutes, seconds. timestamp, however, contains more than that. It also contains the day of the week and CST. We want to ignore those, so we specify the mask element #, which is a placeholder for something we want ignored.

timestamp can be converted using clock(timestamp, "# MD hms # Y"), which specifies that the order of the components in ts is something-to-be-ignored, month, day, hours, minutes, seconds, something-to-be-ignored, and year. There is no meaning to the spaces; we could just as well have specified clock(timestamp, "#MDhms#Y"). You can specify spaces when they help to make what you type more readable.

Because datetime values can be so large, whenever you use the function clock(), you must store the results in a double, as we do below:

```
. generate double dt = clock(timestamp, "# MD hms # Y")
. list id dt action
```

	id	dt	action
1.	1001	1.479e+12	15
2.	1002	1.479e+12	15
3.	1003	1.479e+12	11
4.	1002	1.479e+12	16
5.	1005	1.479e+12	12
6.	1001	1.479e+12	16

Don't panic. New variable dt contains numeric values, and large ones, which is why it was so important that we stored the values as doubles. That output above just shows us what a datetime variable looks like with default formatting. If we wanted to see the numeric values better, we could change dt to have a %20.0gc format. We would then see that the first value is 1,479,113,983,000, the second 1,479,195,409,000, and so on. We will not do that. Instead, we will put a %tc format on our datetime variable:

```
. format dt %tc
. list id dt action
```

	id	dt	action
1.	1001	14nov2006 08:59:43	15
2.	1002	15nov2006 07:36:49	15
3.	1003	15nov2006 09:21:07	11
4.	1002	15nov2006 14:57:36	16
5.	1005	16nov2006 08:22:53	12
6.	1001	16nov2006 08:36:44	16

Variable `dt` is a variable we can use in calculations. Say we wanted to know how many hours it had been since the previous action:

```
. sort dt
. generate hours = hours(dt - dt[_n-1])
(1 missing value generated)
. format hours %9.2f
. list id dt action hours
```

	id	dt	action	hours
1.	1001	14nov2006 08:59:43	15	.
2.	1002	15nov2006 07:36:49	15	22.62
3.	1003	15nov2006 09:21:07	11	1.74
4.	1002	15nov2006 14:57:36	16	5.61
5.	1005	16nov2006 08:22:53	12	17.42
6.	1001	16nov2006 08:36:44	16	0.23

We subtracted the previous value of `dt` from `dt`, which results in the number of milliseconds. Converting milliseconds to hours is easy enough: we just have to divide by $60 \times 60 \times 1{,}000 = 3{,}600{,}000$. It is easy to forget or mistype that constant, so we used Stata's `hours()` function, which converts milliseconds to hours. `hours()`, and other useful functions, is documented in [D] **Datetime durations**.

25.3 Displaying dates and times

A calendar date variable should have a `%td` format and a datetime variable should have a `%tc` format. Every type of date and time variable has a corresponding display format. You apply that format by typing `format` *varname* `%td`, `format` *varname* `%tc`, etc.

Formats `%tc`, `%tC`, `%td`, `%tw`, `%tm`, `%tq`, `%th`, and `%ty` are called the default `%t` formats. By specifying codes following them, you can control how the variable is to be displayed.

In the previous example, we started with a string variable that contained a time stamp and looked like "`Tue Nov 14 08:59:43 CST 2006`". After we created a datetime variable from it and put the default `%tc` format on it, our datetimes looked like "`14nov2006 08:59:43`". Below, we specify a `%tc` format that makes our new variable look just like the original:

```
. format dt %tcDay_Mon_DD_HH:MM:SS_!C!S!T_CCYY
. list id dt action hours
```

	id	dt	action	hours
1.	1001	Tue Nov 14 08:59:43 CST 2006	15	.
2.	1002	Wed Nov 15 07:36:49 CST 2006	15	22.62
3.	1003	Wed Nov 15 09:21:07 CST 2006	11	1.74
4.	1002	Wed Nov 15 14:57:36 CST 2006	16	5.61
5.	1005	Thu Nov 16 08:22:53 CST 2006	12	17.42
6.	1001	Thu Nov 16 08:36:44 CST 2006	16	0.23

`%t` display formats are documented in [D] **Datetime display formats**.

25.4 Typing dates and times (datetime literals)

You will sometimes need to type dates and times in expressions. When we needed to calculate the age of subjects as of 01jan2000 in a previous example, for instance, we typed

```
. generate age2000 = age(birthday, td(01jan2000))
```

although we could just as well have typed

```
. generate age2000 = age(birthday, 14610)
```

because 14,610 is the numeric value corresponding to the calendar date 01jan2000. Typing `td(1jan2000)` is easier and less error prone.

Similarly, if we needed 10:55 a.m. on 01jan1960 as a datetime value, rather than typing 39,300,000, we could type `tc(01jan1960 10:55)`. See *Typing dates into expressions* in [D] **Datetime** for details.

25.5 Extracting components of dates and times

Once you have a numeric date or datetime variable, you can use the extraction functions to obtain components of the variable. For instance, the following functions are appropriate for use with daily date variables:

`year(`*date*`)`	returns four-digit year; for example, 1980, 2002
`month(`*date*`)`	returns month; 1, 2, …, 12
`day(`*date*`)`	returns day within month; 1, 2, …, 31
`halfyear(`*date*`)`	returns the half of year; 1 or 2
`quarter(`*date*`)`	returns quarter of year; 1, 2, 3, or 4
`week(`*date*`)`	returns week of year; 1, 2, …, 52
`dow(`*date*`)`	returns day of week; 0, 1, …, 6; 0 = Sunday
`doy(`*date*`)`	returns day of year; 1, 2, …, 366

There are other functions useful with datetime variables. See *Extracting time-of-day components from datetimes* and *Extracting date components from daily dates* in [D] **Datetime**.

25.6 Converting between date and time values

You can convert between date and time values. For instance, the `cofd()` function converts a daily date to a datetime/c value. `cofd()` of 17,126 (21nov2006) returns 1,479,686,400,000 (21nov2006 00:00:00). Function `dofc()` of 1,479,736,920,000 (21nov2006 14:02) returns 17,126 (21nov2006).

There are other functions for converting between other date and time values; see *Converting among units* in [D] **Datetime**.

25.7 Business dates and calendars

Besides the built-in date types above, such as datetime/c and calendar dates, Stata provides a type you can define, called business dates. Business dates are dates that appear on a business calendar, and their corresponding business calendar format is denoted `%tb`.

A business calendar is like an ordinary calendar with some dates crossed out. The crossed-out dates correspond to the dates on which the business is closed:

November 2011

Su	Mo	Tu	We	Th	Fr	Sa
		1	2	3	4	X
X	7	8	9	10	11	X
X	14	15	16	17	18	19
X	21	22	23	X	25	X
X	28	29	30			

With respect to a business date, *yesterday* is the last day the business was open, and *tomorrow* is the next day the business will be open.

Consider *date* = 25nov2011. If *date* is a regular date variable,

$$yesterday = date - 1 = 24\text{nov}2011$$

$$tomorrow = date + 1 = 26\text{nov}2011$$

If *date* is a business (`%tb`) date variable,

$$yesterday = date - 1 = 23\text{nov}2011$$

$$tomorrow = date + 1 = 28\text{nov}2011$$

Business dates work just like regular dates; it is just that some dates are crossed out. That is important because variables containing dates are often used with Stata's lag and lead operators; see **[U] 13.10 Time-series operators**. If variable `trading_date` is an ordinary date variable, then `L.trading_date` really is yesterday, and `F.trading_date` really is tomorrow. But if `trading_date` has an appropriately defined `%tb` format, `L.trading_date` is the previous trading date, and `F.trading_date` is the next trading date.

You can use `bcal create` to create a business calendar based on the current dataset. Alternatively, you can create a file named *calname*`.stbcal`, such as `nyse.stbcal`. After that, Stata understands the new format `%tbnyse`. For more information, see [D] **Datetime business calendars**.

25.8 References

Cox, N. J. 2010. Stata tip 68: Week assumptions. *Stata Journal* 10: 682–685.

———. 2012. Stata tip 111: More on working with weeks. *Stata Journal* 12: 565–569.

———. 2018. Stata tip 130: 106610 and all that: Date variables that need to be fixed. *Stata Journal* 18: 755–757.

———. 2022. Stata tip 145: Numbering weeks within months. *Stata Journal* 22: 224–230.

Samuels, S. J., and N. J. Cox. 2012. Stata tip 105: Daily dates with missing days. *Stata Journal* 12: 159–161.

26 Working with categorical data and factor variables

Contents

26.1 Continuous, categorical, and indicator variables

Although to Stata a variable is a variable, it is helpful to distinguish among three conceptual types:

- A *continuous variable* measures something. Such a variable might measure a person's age, height, or weight; a city's population or land area; or a company's revenues or costs.

  The term "continuous" here is deliberately broad and includes variables that are discrete by convention (ages in years) or by definition (counts of people). Even for such variables, reported values are points on continuous scales with natural origins, and not arbitrary codes.

- A *categorical variable* identifies a group to which the thing belongs. You could categorize persons according to their race or ethnicity, cities according to their geographic location, or companies according to their industry. Sometimes, categorical variables are stored as strings.

- An *indicator variable* denotes whether something is true. For example, is a person a veteran, does a city have a mass transit system, or is a company profitable?

Indicator variables are a special case of categorical variables. Consider a variable that records whether or not a person is employed. Examined one way, it is a categorical variable. A categorical variable identifies the group to which a thing belongs, and here the thing is a person and the basis for categorization is employment. Looked at another way, however, it is an indicator variable. It indicates whether the person is employed. In this example, and most others, there is much scope for a finer or otherwise different categorization, but bear with us.

We can use the same logic on any categorical variable that divides the data into two groups. It is a categorical variable because it identifies whether an observation is a member of this or that group; it is an indicator variable because it denotes the truth value of the statement "the observation is in this group".

All indicator variables are categorical variables, but the opposite is not true. A categorical variable might divide the data into more than two groups. For clarity, let's reserve the term *categorical variable* for variables that divide the data into more than two groups, and let's use the term *indicator variable* for categorical variables that divide the data into exactly two groups.

Stata can convert continuous variables to categorical and indicator variables and categorical variables to indicator variables.

26.1.1 Converting continuous variables to indicator variables

Stata treats logical expressions as taking on the values *true* or *false*, which it identifies with the numbers 1 and 0; see **[U] 13 Functions and expressions**. For instance, if you have a continuous variable measuring a person's age and you wish to create an indicator variable denoting persons aged 21 and over, you could type

```
. generate age21p = age>=21
```

The variable `age21p` takes on the value 1 for persons aged 21 and over and 0 for persons under 21.

Because `age21p` can take on only 0 or 1, it would be more economical to store the variable as a `byte`. Thus it would be better to type

```
. generate byte age21p = age>=21
```

This solution has a problem. The value of `age21` is set to 1 for all persons whose `age` is missing because Stata defines missing to be larger than all other numbers. In our data, we might have no such missing ages, but it still would be safer to type

```
. generate byte age21p = age>=21 if age<.
```

That way, persons whose age is missing would also have a missing `age21p`.

❑ Technical note

Put aside missing values and consider the following alternative to `generate age21p = age>=21` that may have occurred to you:

```
. generate age21p = 1 if age>=21
```

That does not produce the desired result. This statement makes `age21p` 1 (*true*) for all persons aged 21 and above but makes `age21p` missing for everyone else.

If you followed this second approach, you would have to combine it with

```
. replace age21p = 0 if age<21
```

❑

26.1.2 Converting continuous variables to categorical variables

Suppose that you wish to categorize persons into four groups on the basis of their age. You want a variable to denote whether a person is 21 or under, between 22 and 38, between 39 and 64, or 65 and above. Although most people would label these categories 1, 2, 3, and 4, there is really no reason to restrict ourselves to such a meaningless numbering scheme. Let's call this new variable `agecat` and make it so that it takes on the topmost value for each group. Thus persons in the first group will be identified with an `agecat` of 21, persons in the second with 38, persons in the third with 64, and persons in the last (drawing a number out of the air) with 75. Here is a way to create the variable that will work, but it is not the best method for doing so:

```
. use https://www.stata-press.com/data/r19/agexmpl
. generate byte agecat=21 if age<=21
(176 missing values generated)
. replace agecat=38 if age>21 & age<=38
(148 real changes made)
. replace agecat=64 if age>38 & age<=64
(24 real changes made)
. replace agecat=75 if age>64 & age<.
(4 real changes made)
```

We created the categorical variable according to the definition by using the `generate` and `replace` commands. The only thing that deserves comment is the opening `generate`. We (wisely) told Stata to `generate` the new variable `agecat` as a `byte`, thus conserving memory.

We can create the same result with one command using the `recode()` function:

```
. use https://www.stata-press.com/data/r19/agexmpl, clear
. generate byte agecat=recode(age,21,38,64,75)
```

`recode()` takes three or more arguments. It examines the first argument (here `age`) against the remaining arguments in the list. It returns the first element in the list that is greater than or equal to the first argument or, failing that, the last argument in the list. Thus, for each observation, `recode()` asked if `age` was less than or equal to 21. If so, the value is 21. If not, is it less than or equal to 38? If so, the value is 38. If not, is it less than or equal to 64? If so, the value is 64. If not, the value is 75.

Most researchers typically make tables of categorical variables, so we will `tabulate` the result:

```
. tabulate agecat
```

agecat	Freq.	Percent	Cum.
21	28	13.73	13.73
38	148	72.55	86.27
64	24	11.76	98.04
75	4	1.96	100.00
Total	204	100.00	

There is another way to convert continuous variables into categorical variables, and it is even more automated: `autocode()` works like `recode()`, except that all you tell the function is the range and the total number of cells that you want that range broken into:

```
. use https://www.stata-press.com/data/r19/agexmpl, clear
. generate agecat=autocode(age,4,18,65)
. tabulate agecat
```

agecat	Freq.	Percent	Cum.
29.75	82	40.20	40.20
41.5	96	47.06	87.25
53.25	16	7.84	95.10
65	10	4.90	100.00
Total	204	100.00	

In one instruction, we told Stata to break `age` into four evenly spaced categories from 18 to 65. When we `tabulate agecat`, we see the result. In particular, we see that the breakpoints of the four categories are 29.75, 41.5, 53.25, and 65. The first category contains everyone aged 29.75 years or less; the second category contains persons over 29.75 who are 41.5 years old or less; the third category contains persons over 41.5 who are 53.25 years old or less; and the last category contains all persons over 53.25.

❑ Technical note

We chose the range 18–65 arbitrarily. Although you cannot tell from the table above, there are persons in this dataset who are under 18, and there are persons over 65. Those persons are counted in the first and last cells, but we have not divided the age range in the data evenly. We could split the full age range into four categories by obtaining the overall minimum and maximum ages (by typing `summarize`) and substituting the overall minimum and maximum for the 18 and 65 in the `autocode()` function:

```
. use https://www.stata-press.com/data/r19/agexmpl, clear
. summarize age
```

Variable	Obs	Mean	Std. dev.	Min	Max
age	204	31.57353	10.28986	2	66

```
. generate agecat2=autocode(age,4,2,66)
```

We could also `sort` the data into ascending order of `age` and tell Stata to construct four categories over the range `age[1]` (the minimum) to `age[_N]` (the maximum):

```
. use https://www.stata-press.com/data/r19/agexmpl, clear
. sort age
. generate agecat2=autocode(age,4,age[1],age[_N])
. tabulate agecat2
```

agecat2	Freq.	Percent	Cum.
18	10	4.90	4.90
34	138	67.65	72.55
50	41	20.10	92.65
66	15	7.35	100.00
Total	204	100.00	

❑

26.2 Estimation with factor variables

Stata handles categorical variables as factor variables; see [U] **11.4.3 Factor variables**. Categorical variables refer to the variables in your data that take on categorical values, variables such as `sex`, `group`, and `region`. Factor variables refer to Stata's treatment of categorical variables. Factor variables create indicator variables for the levels (categories) of categorical variables and, optionally, for their interactions.

In what follows, the word level means the value that a categorical variable takes on. The variable `employed` might take on levels 0 and 1, with 0 representing not employed and 1 representing employed. We could say that `employed` is a two-level factor variable.

The regressors created by factor variables are called indicators or, more explicitly, virtual indicator variables. They are called virtual because the machinery for factor variables seldom creates new variables in your dataset, even though the indicators will appear just as if they were variables in your estimation results.

To be used as a factor variable, a categorical variable must take on nonnegative integer values. If you have variables with negative values, recode them; see [D] **recode**. If you have string variables, you can use `egen`'s `group()` function to recode them,

```
. egen newcatvar= group(mystringcatvar)
```

If you also specify the `label` option, `egen` will create a value label for the numeric code it produces so that your output will be subsequently more readable:

```
. egen newcatvar= group(mystringcatvar), label
```

Alternatively, you can use `encode` to convert string categorical variables to numeric ones:

```
. encode mystringcatvar, generate(newcatvar)
```

`egen group(), label` and `encode` do the same thing. We tend to use `egen group(), label`. See [D] **egen** and [D] **encode**.

In the unlikely event that you have a noninteger categorical variable, use the `egen` solution. More likely, however, is that you need to read [U] **26.1.2 Converting continuous variables to categorical variables**.

❑ Technical note

If you should ever need to create your own indicator variables from a string or numeric variable—and it is difficult to imagine why you would—type

```
. tabulate var, gen(newstub)
```

Typing that will create indicator variables named *newstub*1, *newstub*2, …; see [R] **tabulate oneway**.

❑

We will be using linear regression in the examples that follow just because it is so easy to explain and to interpret. We could, however, just as well have used logistic regression, Heckman selectivity, or even Cox proportional-hazards regression with shared frailties. Stata's factor-variable features work with nearly every estimation command.

26.2.1 Including factor variables

The fundamental building block of factor variables is the treatment of each factor variable as if it represented a collection of indicators, with one indicator for each level of the variable. To treat a variable as a factor variable, you add `i.` in front of the variable's name:

```
. use https://www.stata-press.com/data/r19/fvex, clear
(Artificial factor variables' data)
. regress y  i.group age
```

Source	SS	df	MS	Number of obs	=	3,000
				F(3, 2996)	=	31.67
Model	42767.8126	3	14255.9375	Prob > F	=	0.0000
Residual	1348665.19	2,996	450.155272	R-squared	=	0.0307
				Adj R-squared	=	0.0298
Total	1391433.01	2,999	463.965657	Root MSE	=	21.217

y	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
group						
2	-2.395169	.9497756	-2.52	0.012	-4.257447	-.5328905
3	.2966833	1.200423	0.25	0.805	-2.057054	2.65042
age	-.318005	.039939	-7.96	0.000	-.3963157	-.2396943
_cons	83.2149	1.963939	42.37	0.000	79.3641	87.06571

In these data, variable `group` takes on the values 1, 2, and 3.

Because we typed

```
. regress y  i.group age
```

rather than

```
. regress y    group age
```

instead of fitting the regression as a continuous function of `group`'s values, `regress` fit the regression on indicators for each level of group included as a separate covariate. In the left column of the coefficient table in the output, the numbers 2 and 3 identify the coefficients that correspond to the values of 2 and 3 of the `group` variable. Using the more precise terminology of **[U] 11.4.3 Factor variables**, the coefficients reported for 2 and 3 are the coefficients for virtual variables `2.group` and `3.group`, the indicator variables for group = 2 and group = 3.

If `group` took on the values 2, 10, 11, and 125 rather than 1, 2, and 3, then we would see 2, 10, 11, and 125 below `group` in the table, corresponding to virtual variables `2.group`, `10.group`, `11.group`, and `125.group`.

We can use as many sets of indicators as we need in a varlist. Thus we can type

```
. regress y  i.group i.sex i.arm ...
```

26.2.2 Specifying base levels

In the above results, group = 1 was used as the base level and `regress` omitted reporting that fact in the output. Somehow, you are just supposed to know that, and usually you do. We can see base levels identified explicitly, however, if we specify the `baselevels` option, either at the time we estimate the model or, as we do now, when we replay results:

```
. regress, baselevels
      Source |       SS           df       MS      Number of obs   =     3,000
-------------+----------------------------------   F(3, 2996)      =     31.67
       Model |  42767.8126         3  14255.9375   Prob > F        =    0.0000
    Residual |  1348665.19     2,996  450.155272   R-squared       =    0.0307
-------------+----------------------------------   Adj R-squared   =    0.0298
       Total |  1391433.01     2,999  463.965657   Root MSE        =    21.217

------------------------------------------------------------------------------
           y | Coefficient  Std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
       group |
           1 |          0  (base)
           2 |  -2.395169   .9497756    -2.52   0.012    -4.257447   -.5328905
           3 |   .2966833   1.200423     0.25   0.805    -2.057054    2.65042
             |
         age |  -.318005    .039939    -7.96   0.000    -.3963157   -.2396943
       _cons |   83.2149    1.963939    42.37   0.000      79.3641    87.06571
------------------------------------------------------------------------------
```

The smallest value of the factor variable is used as the base by default. Using the notation explained in [U] **11.4.3.2 Base levels**, we can request another base level, such as `group` = 2, by typing

```
. regress y  ib2.group age
```

or, such as the largest value of `group`,

```
. regress y  ib(last).group age
```

Changing the base does not fundamentally alter the estimates in the sense that predictions from the model would be identical no matter which base levels we use. Changing the base does change the interpretation of coefficients. In the regression output above, the reported coefficients measure the differences from `group` = 1. Group 2 differs from group 1 by −2.4, and that difference is significant at the 5% level. Group 3 is not significantly different from group 1.

If we fit the above using `group` = 3 as the base,

```
. regress y  ib3.group age
  (output omitted)
```

the coefficients on `group` = 1 and `group` = 2 would be −0.297 and −2.692. Note that the difference between group 2 and group 1 would still be −2.692 − (−0.296) = −2.4. Results may look different, but when looked at correctly, they are the same. Similarly, the significance of `group` = 2 would now be 0.805 rather than 0.012, but that is because what is being tested is different. In the output above, the test against 0 is a test of whether group 2 differs from group 1. In the output that we omit, the test is whether group 2 differs from group 3. If, after running the `ib3.group` specification, we were to type

```
. test 2.group = 1.group
```

we would obtain the same 0.012 result. Similarly, after running the shown result, if we typed `test 3.group = 1.group`, we would obtain 0.805.

26.2.3 Setting base levels permanently

As explained directly above, you can temporarily change the base level by using the `ib.` operator; also see [U] **11.4.3.2 Base levels**. You can change the base level permanently by using the `fvset` command; see [U] **11.4.3.3 Setting base levels permanently**.

26.2.4 Testing significance of a main effect

In the example we have been using,

```
. use https://www.stata-press.com/data/r19/fvex
. regress y i.group age
```

many disciplines refer to the coefficients on the set of indicators for `i.group` as a main effect. Because we have no interactions, the main effect of `i.group` refers to the effect of the levels of `group` taken as a whole. We can test the significance of the indicators by using `contrast` (see [R] **contrast**):

```
. contrast group
Contrasts of marginal linear predictions
Margins: asbalanced
```

	df	F	P>F
group	2	4.89	0.0076
Denominator	2996		

When we specify the name of a factor variable used in the previous estimation command in the `contrast` command, it will perform a joint test on the effects of that variable. Here we are testing whether the coefficients for the group indicators are jointly zero. We reject the hypothesis.

26.2.5 Specifying indicator (dummy) variables as factor variables

We are using the model

```
. use https://www.stata-press.com/data/r19/fvex
. regress y  i.group age
```

We are going to add `sex` to our model. Variable `sex` is a 0/1 variable in our data, a type of variable we call an indicator variable and which many people call a dummy variable. We could type

```
. regress y    sex i.group age
```

but we are going to type

```
. regress y  i.sex i.group age
```

It is better to include indicator variables as factor variables, which is to say, to include indicator variables with the `i.` prefix.

You will obtain the same estimation results either way, but by specifying `i.sex` rather than `sex`, you will communicate to postestimation commands that care that `sex` is not a continuous variable, and that will save you typing later should you use one of those postestimation commands. `margins` (see [R] **margins**) is an example of a postestimation command that cares.

Below we type `regress y i.sex i.group age`, and we will specify the `baselevels` option just to make explicit how `regress` is interpreting our request. Ordinarily, we would not specify the `baselevels` option.

```
. regress y  i.sex i.group age, baselevels
```

Source	SS	df	MS		
Model	214569.509	4	53642.3772	Number of obs	= 3,000
				F(4, 2995)	= 136.51
Residual	1176863.5	2,995	392.942737	Prob > F	= 0.0000
				R-squared	= 0.1542
				Adj R-squared	= 0.1531
Total	1391433.01	2,999	463.965657	Root MSE	= 19.823

y	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
sex						
male	0	(base)				
female	18.44069	.8819175	20.91	0.000	16.71146	20.16991
group						
1	0	(base)				
2	5.178636	.9584485	5.40	0.000	3.299352	7.057919
3	13.45907	1.286127	10.46	0.000	10.93729	15.98085
age	-.3298831	.0373191	-8.84	0.000	-.4030567	-.2567094
_cons	68.63586	1.962901	34.97	0.000	64.78709	72.48463

As with all factor variables, by default the first level of `sex` serves as its base, so the coefficient 18.4 measures the increase in `y` for `sex` $= 1$ as compared with `sex` $= 0$. In these data, `sex` $= 1$ represents females and `sex` $= 0$ represents males.

Notice that in the above output male and female were displayed rather than 0 and 1. The variable `sex` has the value label `sexlab` associated with it, so Stata used the value label in its output. Stata has three options, `nofvlabel`, `fvwrap(#)`, and `fvwrapon(word | width)`, that control how factor-variable value labels are displayed; see [R] **Estimation options**.

26.2.6 Including interactions

We are using the model

```
. use https://www.stata-press.com/data/r19/fvex
. regress y  i.sex i.group age
```

If we are not certain that the levels of `group` have the same effect for females as they do for males, we should add to our model interactions for each combination of the levels in `sex` and `group`. We would need to add indicators for

`sex` = Male	and	`group` = 1
`sex` = Male	and	`group` = 2
`sex` = Male	and	`group` = 3
`sex` = Female	and	`group` = 1
`sex` = Female	and	`group` = 2
`sex` = Female	and	`group` = 3

Doing this would allow each combination of `sex` and `group` to have a different effect on `y`.

Interactions like those listed above are produced using the `#` operator. We could type

```
. regress y  i.sex i.group i.sex#i.group age
```

The # operator assumes that the variables on either side of it are factor variables, so we can omit the i. prefixes and obtain the same result by typing

```
. regress y  i.sex i.group sex#group age
```

We must continue to specify the prefix on the main effects i.sex and i.group, however.

In the output below, we add the allbaselevels option to that. The allbaselevels option is much like baselevels, except allbaselevels lists base levels in interactions as well as in main effects. Specifying allbaselevels will make the output easier to understand the first time, and after that, you will probably never specify it again.

```
. regress y  i.sex i.group sex#group age, allbaselevels
```

Source	SS	df	MS		
Model	217691.706	6	36281.9511	Number of obs	= 3,000
Residual	1173741.3	2,993	392.162145	F(6, 2993)	= 92.52
				Prob > F	= 0.0000
				R-squared	= 0.1565
				Adj R-squared	= 0.1548
Total	1391433.01	2,999	463.965657	Root MSE	= 19.803

y	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
sex						
male	0	(base)				
female	21.71794	1.490858	14.57	0.000	18.79473	24.64115
group						
1	0	(base)				
2	8.420661	1.588696	5.30	0.000	5.305615	11.53571
3	16.47226	1.6724	9.85	0.000	13.19309	19.75143
sex#group						
male#1	0	(base)				
male#2	0	(base)				
male#3	0	(base)				
female#1	0	(base)				
female#2	-4.658322	1.918195	-2.43	0.015	-8.419436	-.8972081
female#3	-6.736936	2.967391	-2.27	0.023	-12.55527	-.9186038
age	-.3305546	.0373032	-8.86	0.000	-.4036972	-.2574121
_cons	65.97765	2.198032	30.02	0.000	61.66784	70.28745

Look at the sex#group term in the output. There are six combinations of sex and group, just as we expected. That four of the cells are labeled base and that only two extra coefficients were estimated should not surprise us, at least after we think about it. There are 3×2 sex#age groups, and thus $3 \times 2 = 6$ means to be estimated, and we indeed estimated six coefficients, including a constant, plus a seventh for continuous variable age. Now look at which combinations were treated as base. Treated as base were all combinations that were the base of sex, plus all combinations that were the base of group. The combination of sex $= 0$ (male) and group $= 1$ was omitted for both reasons, and the other combinations were omitted for one or the other reason.

We entered a two-way interaction between sex and group. If we believed that the effects of sex#group were themselves dependent on the treatment arm of an experiment, we would want the three-way interaction, which we could obtain by typing sex#group#arm. Stata allows up to eight-way interactions among factor variables and another eight-ways of interaction among continuous covariates.

❑ Technical note

The virtual variables associated with the interaction terms have the names `1.sex#2.group` and `1.sex#3.group`.

❑

26.2.7 Testing significance of interactions

We are using the model

```
. use https://www.stata-press.com/data/r19/fvex
. regress y  i.sex i.group sex#group age
```

We can test the overall significance of the `sex#group` interaction by typing

```
. contrast sex#group
Contrasts of marginal linear predictions
Margins: asbalanced
```

	df	F	P>F
sex#group	2	3.98	0.0188
Denominator	2993		

We can type the interaction term to be tested—`sex#group`—in the same way as we typed it to include it in the regression. The interaction is significant beyond the 5% level. That is not surprising because both interaction indicators were significant in the regression.

26.2.8 Including factorial specifications

We have the model

```
. use https://www.stata-press.com/data/r19/fvex
. regress y  i.sex i.group sex#group age
```

The above model is called a factorial specification with respect to `sex` and `group` because `sex` and `group` appear by themselves and an interaction. Were it not for `age` being included in the model, we could call this model a full-factorial specification. In any case, Stata provides a shorthand for factorial specifications. We could fit the model above by typing

```
. regress y  sex##group age
```

When you type *A*`##`*B*, Stata takes that to mean *A B A*`#`*B*.

When you type *A*`##`*B*`##`*C*, Stata takes that to mean *A B C A*`#`*B A*`#`*C B*`#`*C A*`#`*B*`#`*C*.

And so on. Up to eight-way interactions are allowed.

The `##` notation is just a shorthand. Estimation results are unchanged. This time we will not specify the `allbaselevels` option:

```
. regress y  sex##group age
```

Source	SS	df	MS		
Model	217691.706	6	36281.9511	Number of obs	= 3,000
				F(6, 2993)	= 92.52
Residual	1173741.3	2,993	392.162145	Prob > F	= 0.0000
				R-squared	= 0.1565
				Adj R-squared	= 0.1548
Total	1391433.01	2,999	463.965657	Root MSE	= 19.803

y	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
sex						
female	21.71794	1.490858	14.57	0.000	18.79473	24.64115
group						
2	8.420661	1.588696	5.30	0.000	5.305615	11.53571
3	16.47226	1.6724	9.85	0.000	13.19309	19.75143
sex#group						
female#2	-4.658322	1.918195	-2.43	0.015	-8.419436	-.8972081
female#3	-6.736936	2.967391	-2.27	0.023	-12.55527	-.9186038
age	-.3305546	.0373032	-8.86	0.000	-.4036972	-.2574121
_cons	65.97765	2.198032	30.02	0.000	61.66784	70.28745

26.2.9 Including squared terms and polynomials

`#` may be used to interact continuous variables if you specify the `c.` indicator in front of them. The command

```
. regress y  age c.age#c.age
```

fits y as a quadratic function of age. Similarly,

```
. regress y  age c.age#c.age c.age#c.age#c.age
```

fits a third-order polynomial.

Using the `#` operator is preferable to generating squared and cubed variables of `age` because when `#` is used, Stata understands the relationship between `age` and `c.age#c.age` and `c.age#c.age#c.age`. Postestimation commands can take advantage of this to produce smarter answers; see, for example, *Requirements for model specification* in [R] **margins**.

26.2.10 Including interactions with continuous variables

`#` and `##` may be used to create interactions of categorical variables with continuous variables if the continuous variables are prefixed with `c.`, such as `sex#c.age` in

```
. regress y  i.sex age sex#c.age
. regress y  sex##c.age
. regress y  i.sex sex#c.age
```

The result of fitting the first of these models (equivalent to the second) is shown below. We include `allbaselevels` to make results more understandable the first time you see them.

```
. regress y  i.sex age sex#c.age, allbaselevels
      Source |       SS           df       MS      Number of obs   =     3,000
-------------+----------------------------------   F(3, 2996)      =    139.91
       Model |  170983.675         3  56994.5583   Prob > F        =    0.0000
    Residual |  1220449.33     2,996   407.35959   R-squared       =    0.1229
-------------+----------------------------------   Adj R-squared   =    0.1220
       Total |  1391433.01     2,999  463.965657   Root MSE        =    20.183

------------------------------------------------------------------------------
           y | Coefficient  Std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
         sex |
        male |          0  (base)
      female |   14.92308   2.789012     5.35   0.000     9.454508    20.39165
             |
         age |  -.4929608   .0480944   -10.25   0.000    -.5872622   -.3986595
             |
     sex#c.age |
        male |          0  (base)
      female |  -.0224116   .0674167    -0.33   0.740    -.1545994    .1097762
             |
       _cons |   82.36936   1.812958    45.43   0.000      78.8146    85.92413
------------------------------------------------------------------------------
```

The coefficient on the interaction (-0.022) is the difference in the slope of age for females (`sex` $= 1$) as compared with the slope for males. It is far from significant at any reasonable level, so we cannot distinguish the two slopes.

A different but equivalent parameterization of this model would be to omit the main effect of age, the result of which would be that we would estimate the separate slope coefficients of age for males and females:

```
. regress y  i.sex sex#c.age
      Source |       SS           df       MS      Number of obs   =     3,000
-------------+----------------------------------   F(3, 2996)      =    139.91
       Model |  170983.675         3  56994.5583   Prob > F        =    0.0000
    Residual |  1220449.33     2,996   407.35959   R-squared       =    0.1229
-------------+----------------------------------   Adj R-squared   =    0.1220
       Total |  1391433.01     2,999  463.965657   Root MSE        =    20.183

------------------------------------------------------------------------------
           y | Coefficient  Std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
         sex |
      female |   14.92308   2.789012     5.35   0.000     9.454508    20.39165
             |
     sex#c.age |
        male |  -.4929608   .0480944   -10.25   0.000    -.5872622   -.3986595
      female |  -.5153724   .0472435   -10.91   0.000    -.6080054   -.4227395
             |
       _cons |   82.36936   1.812958    45.43   0.000      78.8146    85.92413
------------------------------------------------------------------------------
```

It is now easier to see the slopes themselves, although the test of the equality of the slopes no longer appears in the output. We can obtain the comparison of slopes by using the `lincom` postestimation command:

```
. lincom 1.sex#c.age - 0.sex#c.age
 ( 1)  - 0b.sex#c.age + 1.sex#c.age = 0
```

y	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
(1)	-.0224116	.0674167	-0.33	0.740	-.1545994	.1097762

As noted earlier, it can be difficult at first to know how to refer to individual parameters when you need to type them on postestimation commands. The solution is to replay your estimation results specifying the `coeflegend` option:

```
. regress, coeflegend
```

Source	SS	df	MS	Number of obs	=	3,000
				F(3, 2996)	=	139.91
Model	170983.675	3	56994.5583	Prob > F	=	0.0000
Residual	1220449.33	2,996	407.35959	R-squared	=	0.1229
				Adj R-squared	=	0.1220
Total	1391433.01	2,999	463.965657	Root MSE	=	20.183

y	Coefficient	Legend
sex		
female	14.92308	_b[1.sex]
sex#c.age		
male	-.4929608	_b[0b.sex#c.age]
female	-.5153724	_b[1.sex#c.age]
_cons	82.36936	_b[_cons]

The legend suggests that we type

```
. lincom _b[1.sex#c.age] - _b[0b.sex#c.age]
```

instead of `lincom 1.sex#c.age - 0.sex#c.age`. That is, the legend suggests that we bracket terms in `_b[]` and explicitly recognize base levels. The latter does not matter. Concerning bracketing, some commands allow you to omit brackets, and others do not. All commands will allow bracketing, which is why the legend suggests it.

26.2.11 Parentheses binding

Factor-variable operators can be applied to groups of variables if those variables are bound in parentheses. For instance, you can type

```
. regress y  sex##(group c.age c.age#c.age)
```

rather than

```
. regress y  i.sex i.group sex#group age sex#c.age c.age#c.age sex#c.age#c.age
```

Parentheses may be nested. The parenthetically bound notation does not let you specify anything you could not specify without it, but it can save typing and, as importantly, make what you type more understandable. Consider

```
. regress y  i.sex i.group sex#group age sex#c.age c.age#c.age sex#c.age#c.age
. regress y  sex##(group c.age c.age#c.age)
```

The second specification is shorter and easier to read. We can see that all the covariates have different parameters for males and females.

26.2.12 Including indicators for single levels

Consider the following regression of statewide marriage rates (marriages per 100,000) on the median age in the state of the United States:

```
. use https://www.stata-press.com/data/r19/censusfv
(1980 Census data by state)
. regress marriagert  medage
```

Source	SS	df	MS	Number of obs	=	50
				F(1, 48)	=	0.00
Model	148.944706	1	148.944706	Prob > F	=	0.9949
Residual	173402855	48	3612559.48	R-squared	=	0.0000
				Adj R-squared	=	-0.0208
Total	173403004	49	3538836.82	Root MSE	=	1900.7

marriagert	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
medage	1.029541	160.3387	0.01	0.995	-321.3531	323.4122
_cons	1301.307	4744.027	0.27	0.785	-8237.199	10839.81

There appears to be no effect of median age. We know, however, that couples from around the United States flock to Nevada to be married in Las Vegas, which biases our results. We would like to add a single indicator for the state of Nevada. We `describe` our data, see the value label for state is `st`, and then type `label list st` to discover the label for Nevada. We find it is 30; thus we can now type

```
. regress marriagert  medage i30.state
```

Source	SS	df	MS	Number of obs	=	50
				F(2, 47)	=	2311.15
Model	171657575	2	85828787.6	Prob > F	=	0.0000
Residual	1745428.85	47	37136.784	R-squared	=	0.9899
				Adj R-squared	=	0.9895
Total	173403004	49	3538836.82	Root MSE	=	192.71

marriagert	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
medage	-61.23095	16.2825	-3.76	0.000	-93.98711	-28.47479
state						
Nevada	13255.81	194.9742	67.99	0.000	12863.57	13648.05
_cons	2875.366	481.5533	5.97	0.000	1906.606	3844.126

These results are more reasonable.

There is a subtlety to specifying individual levels. Let's add another indicator, this time for California. The following will not produce the desired results, and we specify the `baselevels` option to help you understand the issue. First, however, here is the result:

```
. regress marriagert  medage i5.state i30.state, baselevels
      Source |       SS           df       MS      Number of obs   =        50
-------------+----------------------------------   F(2, 47)        =   2311.15
       Model |  171657575          2  85828787.6   Prob > F        =    0.0000
    Residual |  1745428.85         47   37136.784   R-squared       =    0.9899
-------------+----------------------------------   Adj R-squared   =    0.9895
       Total |  173403004         49  3538836.82   Root MSE        =    192.71

------------------------------------------------------------------------------
  marriagert | Coefficient  Std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
      medage |  -61.23095   16.2825    -3.76   0.000    -93.98711   -28.47479
             |
       state |
  California |          0  (base)
      Nevada |   13255.81   194.9742    67.99   0.000     12863.57    13648.05
             |
       _cons |   2875.366   481.5533     5.97   0.000     1906.606    3844.126
------------------------------------------------------------------------------
```

Look at the result for `state`. Rather than obtaining a coefficient for `5.state` as we expected, Stata instead chose to omit it as the base category.

Stata considers all the individual specifiers for a factor variable together as being related. In our command, we specified that we wanted `i5.state` and `i30.state` by typing

```
. regress marriagert  medage i5.state i30.state
```

and Stata put that together as "include `state`, levels 5 and 30". Then Stata applied its standard logic for dealing with factor variables: treat the smallest level as the base category.

To achieve the desired result, we need to tell Stata that we want no base, which we do by typing the "base none" (`bn`) modifier:

```
. regress marriagert  medage i5bn.state i30.state
```

We need to specify `bn` only once, and it does not matter where we specify it. We could type

```
. regress marriagert  medage i5.state i30bn.state
```

and we would obtain the same result. We can also specify `bn` more than once.

The result of typing any one of these commands is

```
. regress marriagert  medage i5bn.state i30.state, baselevels
      Source |       SS           df       MS      Number of obs   =        50
-------------+----------------------------------   F(3, 46)        =   1529.59
       Model |  171681987          3  57227328.9   Prob > F        =    0.0000
    Residual |  1721017.33         46  37413.4203   R-squared       =    0.9901
-------------+----------------------------------   Adj R-squared   =    0.9894
       Total |  173403004         49  3538836.82   Root MSE        =    193.43

------------------------------------------------------------------------------
  marriagert | Coefficient  Std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
      medage |  -60.80985   16.35134    -3.72   0.001    -93.7234    -27.8963
             |
       state |
  California |  -157.9413   195.5294    -0.81   0.423    -551.5214    235.6389
      Nevada |    13252.3   195.7472    67.70   0.000     12858.28    13646.32
             |
       _cons |   2866.156    483.478     5.93   0.000     1892.965    3839.346
------------------------------------------------------------------------------
```

26.2.13 Including subgroups of levels

We just typed

```
. regress marriagert medage i5bn.state i30.state
```

You can specify specific levels by using numlists. We could have typed

```
. regress marriagert medage i(5 30)bn.state
```

By including `i(5 30)bn.state`, we have added indicators for levels 5 and 30 to the regression.

We can also specify levels within an interaction term. Consider the regression

```
. regress y  i.arm i.agegroup arm#i(3/4)bn.agegroup
```

Although unusual, it is possible to include different levels of `agegroup` in the main effect and the interaction. In this case, all levels of `agegroup` are used in the main effect but only levels 3 and 4 of `agegroup` are included in the interaction term.

26.2.14 Combining factor variables and time-series operators

You can combine factor-variable operators with the time-series operators `L.` and `F.` to lag and lead factor variables. Terms like `iL.group` (or `Li.group`), `cL.age#cL.age` (or `Lc.age#Lc.age`), and `F.arm#L.group` are all legal as long as the data are `tsset` or `xtset`. See **[U] 11.4.3.6 Using factor variables with time-series operators**.

26.2.15 Treatment of empty cells

Consider the following data:

```
. use https://www.stata-press.com/data/r19/estimability, clear
(margins estimability)
. table sex group, nototals
```

	Group				
	1	2	3	4	5
Sex					
Male	2	9	27	8	2
Female	9	9	3		

In these data, there are no observations for `sex` = Female and `group` = 4, and for `sex` = Female and `group` = 5. Here is what happens when you use these data to fit an interacted model:

```
. regress y  sex##group
note: 1.sex#4.group identifies no observations in the sample.
note: 1.sex#5.group identifies no observations in the sample.
```

Source	SS	df	MS		
Model	839.550121	7	119.935732	Number of obs	= 69
Residual	1500.65278	61	24.6008652	F(7, 61)	= 4.88
				Prob > F	= 0.0002
Total	2340.2029	68	34.4147485	R-squared	= 0.3588
				Adj R-squared	= 0.2852
				Root MSE	= 4.9599

y	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
sex						
Female	-5.666667	3.877352	-1.46	0.149	-13.41991	2.086579
group						
2	-13.55556	3.877352	-3.50	0.001	-21.3088	-5.80231
3	-13	3.634773	-3.58	0.001	-20.26818	-5.731822
4	-12.875	3.921166	-3.28	0.002	-20.71586	-5.034145
5	-11	4.959926	-2.22	0.030	-20.91798	-1.082015
sex#group						
Female#2	12.11111	4.527772	2.67	0.010	3.057271	21.16495
Female#3	10	4.913786	2.04	0.046	.1742775	19.82572
Female#4	0	(empty)				
Female#5	0	(empty)				
_cons	32	3.507197	9.12	0.000	24.98693	39.01307

Stata reports that the results for `sex` = Female and `group` = 4 and for `sex` = Female and `group` = 5 are empty; no coefficients can be estimated. The notes refer to `1.sex#4.group` and `1.sex#5.group` because level 1 corresponds to female.

Empty cells are of no concern when fitting models and interpreting results. If, however, you subsequently perform tests or form linear or nonlinear combinations involving any of the coefficients in the interaction, you should be aware that those tests or combinations may depend on how you parameterized your model. See *Estimability of margins* in [R] **margins**.

26.3 References

Cox, N. J. 2018. Speaking Stata: From rounding to binning. *Stata Journal* 18: 741–754.

Cox, N. J., and C. B. Schechter. 2019. Speaking Stata: How best to generate indicator or dummy variables. *Stata Journal* 19: 246–259.

27 Overview of Stata estimation commands

Contents

27.1 Introduction

Stata has many estimation commands that compute summary statistics and fit statistical models, so it is easy to overlook a few. Some of these commands differ greatly from each other, others are gentle variations on a theme, and still others are equivalent to each other.

There are also estimation prefixes that modify the calculation performed by the command, such as `svy:`, `mi:`, `bayes:`, and `fmm:`.

The majority of Stata's estimation commands share features that this chapter will not discuss; see **[U] 20 Estimation and postestimation commands**. Especially see **[U] 20.22 Obtaining robust variance estimates**, which discusses an alternative calculation for the estimated variance matrix (and hence standard errors) that many of Stata's estimation commands provide. Also see **[U] 20.13 Performing hypothesis tests on the coefficients**. This overview chapter, however, will put all that aside and deal solely with matching commands to their statistical concepts.

This chapter discusses all the official estimation commands included in Stata 19. Users may have written their own estimation commands that they are willing to share. Type `search estimation`, `ssc new`, or `ssc hot` to discover more estimation commands; see **[R] ssc**. And, of course, you can always write your own commands.

27.2 Means, proportions, and related statistics

This group of estimation commands computes summary statistics rather than fitting regression models. However, being estimation commands, they share the features discussed in **[U] 20 Estimation and postestimation commands**, such as allowing the use of postestimation commands.

`mean`, `proportion`, `ratio`, and `total` provide estimates of population means, proportions, ratios, and totals, respectively. Each of these commands allows for obtaining separate estimates within subpopulations, groups defined by a separate categorical variable. In addition, `mean`, `proportion`, and `ratio` can report statistics adjusted by direct standardization.

pwmean provides another option for computing means of one variable for each level of one or more categorical variables. In addition, pwmean computes all pairwise differences in these means along with the corresponding tests and confidence intervals (CIs), which can optionally be adjusted to account for multiple comparisons.

27.3 Continuous outcomes

27.3.1 ANOVA and ANCOVA

ANOVA and ANCOVA fit general linear models and are related to the linear regression models discussed in **[U] 27.3.2 Linear regression**, but we classify them separately. The related Stata commands are anova, oneway, and loneway.

anova fits ANOVA and ANCOVA models, one-way and up—including two-way factorial, three-way factorial, etc.—and fits nested and mixed-design models as well as repeated-measures models.

oneway fits one-way ANOVA models. It reports Bartlett's test for equal variance and can also report multiple-comparison tests. After anova, use pwcompare to perform multiple-comparison tests.

loneway is an alternative to oneway. The results are numerically the same, but loneway can deal with more levels, limited only by dataset size (oneway is limited to 376 levels). loneway also reports some additional statistics, such as the intraclass correlation.

For MANOVA and MANCOVA, see **[U] 27.22 Multivariate analysis**.

27.3.2 Linear regression

Consider models of the form

$$y_j = \mathbf{x}_j\boldsymbol{\beta} + \epsilon_j$$

for a continuous y variable and where σ^2_ϵ is constant across observations j. The model is called the linear regression model, and the estimator is often called the (ordinary) least-squares (OLS) estimator.

regress is Stata's linear regression command. regress produces the robust estimate of variance as well as the conventional estimate, and regress has a collection of commands that can be run after it to explore the nature of the fit.

The following commands will also do linear regressions, but they offer special features:

1. areg fits models $y_j = \mathbf{x}_j\boldsymbol{\beta} + \mathbf{d}_j\boldsymbol{\gamma} + \epsilon_j$, where $\mathbf{d}_j$ is a mutually exclusive and exhaustive dummy variable set. areg obtains estimates of $\boldsymbol{\beta}$ (and associated statistics) without ever forming $\mathbf{d}_j$, meaning that it also does not report the estimated $\boldsymbol{\gamma}$. If your interest is in fitting fixed-effects models, Stata has a better command—xtreg—discussed in **[U] 27.15.1 Continuous outcomes with panel data**. Most users who find areg appealing will probably want to use xtreg because it provides more useful summary and test statistics. areg duplicates the output that regress would produce if you were to generate all the dummy variables. This means, for instance, that the reported R^2 includes the effect of $\boldsymbol{\gamma}$.
2. wildbootstrap regress and wildbootstrap areg fit the same models as regress and areg but provides wild cluster bootstrap p-values and CIs for robust inference. See **[R] wildbootstrap** for details.
3. cnsreg allows you to place linear constraints on the coefficients.

4. eivreg adjusts estimates for errors in variables.
5. rreg fits robust regression models, which are not to be confused with regression with robust standard errors. Robust standard errors are discussed in [U] 20.22 Obtaining robust variance estimates. Robust regression concerns point estimates more than it does standard errors, and it implements a data-dependent method for downweighting outliers.

27.3.3 Regression with heteroskedastic errors

We now consider the model $y_j = \mathbf{x}_j\boldsymbol{\beta} + \epsilon_j$, where the variance of ϵ_j is nonconstant.

hetregress fits models with multiplicative heteroskedasticity, that is, models in which the variance of ϵ_j is an exponential function of one or more covariates. The heteroskedasticity can be modeled using either maximum likelihood or Harvey's two-step generalized least-squares method.

When not much is known about the functional form of the variance of ϵ_j, regress with the vce(robust) option is preferred because it provides unbiased estimates. What Stata calls robust is also known as the White correction for heteroskedasticity.

vwls (variance-weighted least squares) produces estimates of $y_j = \mathbf{x}_j\boldsymbol{\beta}+\epsilon_j$, where the variance of ϵ_j is calculated from group data or is known a priori. vwls is therefore of most interest to categorical-data analysts and physical scientists.

qreg performs quantile regression, which in the presence of heteroskedasticity is most of interest. Median regression (one of qreg's capabilities) is an estimator of $y_j = \mathbf{x}_j\boldsymbol{\beta}+\epsilon_j$ when ϵ_j is heteroskedastic. Even more useful, you can fit models of other quantiles and so model the heteroskedasticity. bsqreg is identical to qreg but reports bootstrap standard errors. Also see the sqreg and iqreg commands; sqreg estimates multiple quantiles simultaneously, and iqreg estimates differences in quantiles.

27.3.4 Estimation with correlated errors

By correlated errors, we mean that observations are grouped; within a group, the observations might be correlated, but across groups, they are uncorrelated. regress with the vce(cluster *clustvar*) option can produce "correct" estimates, that is, inefficient estimates with correct standard errors and a lot of robustness; see [U] 20.22 Obtaining robust variance estimates. Alternatively, you can model the within-group correlation using xtreg, xtgls, or mixed; we discuss these commands in [U] 27.15.1 Continuous outcomes with panel data and [U] 27.16 Multilevel mixed-effects models.

Estimation in the presence of autocorrelated errors is discussed in [U] 27.14 Time-series models.

27.3.5 Regression with censored or truncated outcomes

1. tobit allows estimation of linear regression models when y_i has been subject to left-censoring, right-censoring, or both. Say that y_i is not observed if $y_i < 1000$, but for those observations, it is known that $y_i < 1000$. tobit fits such models.
2. intreg (interval regression) is a generalization of tobit. In addition to allowing open-ended intervals, intreg allows closed intervals. Rather than observing y_j, intreg assumes that y_{0j} and y_{1j} are observed, where $y_{0j} \leq y_j \leq y_{1j}$. Survey data might report that a subject's monthly income was in the range \$1,500–\$2,500. intreg allows such data to be used to fit a regression model. intreg allows $y_{0j} = y_{1j}$ and so can reproduce results reported by regress. intreg allows y_{0j} to be $-\infty$ and y_{1j} to be $+\infty$ and so can reproduce results reported by tobit.

3. `truncreg` fits the regression model when the sample is drawn from a restricted part of the population and so is similar to `tobit`, except that here the independent variables are not observed. Under the normality assumption for the whole population, the error terms in the truncated regression model have a truncated-normal distribution.

4. `churdle` allows estimation of linear or exponential hurdle models when y_i is subject to a lower boundary $\ell\ell$, an upper boundary $u\ell$, or both. The dependent variable is a mixture of discrete observations at the boundary points and continuous observations over the interior. Both boundary and interior observations on y_i are actual realizations. In contrast, censored-data models such as `tobit` and `intreg` treat interior observations as actual realizations and treat boundary observations as indicating only that the actual realizations lie beyond the boundary. Hurdle models use one model to determine whether an observation is on the boundary or in the interior and another model for the values in the interior.

27.3.6 Multiple-equation models

When we have errors that are correlated across equations but not correlated with any of the right-hand-side variables, we can write the system of equations as

$$\begin{aligned} y_{1j} &= \mathbf{x}_{1j}\boldsymbol{\beta} + \epsilon_{1j} \\ y_{2j} &= \mathbf{x}_{2j}\boldsymbol{\beta} + \epsilon_{2j} \\ &\vdots \\ y_{mj} &= \mathbf{x}_{mj}\boldsymbol{\beta} + \epsilon_{mj} \end{aligned}$$

where $\epsilon_{k\cdot}$ and $\epsilon_{l\cdot}$ are correlated with correlation ρ_{kl}, a quantity to be estimated from the data. This is called Zellner's seemingly unrelated regression, and `sureg` fits such models. When $\mathbf{x}_{1j} = \mathbf{x}_{2j} = \cdots = \mathbf{x}_{mj}$, the model is known as multivariate regression, and the corresponding command is `mvreg`.

The equations need not be linear. If they are not linear, use `nlsur`; see **[U] 27.3.8 Nonlinear regression**. Also, see `demandsys` for fitting a set of equations that describe consumers' purchases of goods or services.

27.3.7 Stochastic frontier models

`frontier` fits stochastic production or cost frontier models on cross-sectional data. The model can be expressed as

$$y_i = \mathbf{x}_i\boldsymbol{\beta} + v_i - su_i$$

where

$$s = \begin{cases} 1 & \text{for production functions} \\ -1 & \text{for cost functions} \end{cases}$$

u_i is a nonnegative disturbance standing for technical inefficiency in the production function or cost inefficiency in the cost function. Although the idiosyncratic error term v_i is assumed to have a normal distribution, the inefficiency term is assumed to be one of the three distributions: half-normal, exponential, or truncated-normal. Also, when the nonnegative component of the disturbance is assumed to be either half-normal or exponential, `frontier` can fit models in which the error components are heteroskedastic conditional on a set of covariates. When the nonnegative component of the disturbance is assumed to be from a truncated-normal distribution, `frontier` can also fit a conditional mean model, where the mean of the truncated-normal distribution is modeled as a linear function of a set of covariates.

For panel-data stochastic frontier models, see **[U] 27.15.1 Continuous outcomes with panel data**.

27.3.8 Nonlinear regression

`nl` provides the nonlinear least-squares estimator of $y_j = f(\mathbf{x}_j, \boldsymbol{\beta}) + \epsilon_j$, where $f(\mathbf{x}_j, \boldsymbol{\beta})$ is an arbitrary nonlinear regression function such as the exponential or the lognormal. `nlsur` fits a system of nonlinear equations by feasible generalized nonlinear least squares. It can be viewed as a nonlinear variant of Zellner's seemingly unrelated regression model.

A special case of a nonlinear model is the Box–Cox transform. `boxcox` obtains maximum likelihood estimates of the coefficients and the Box–Cox transform parameters in a model of the form

$$y_i^{(\theta)} = \beta_0 + \beta_1 x_{i1}^{(\lambda)} + \beta_2 x_{i2}^{(\lambda)} + \cdots + \beta_k x_{ik}^{(\lambda)} + \gamma_1 z_{i1} + \gamma_2 z_{i2} + \cdots + \gamma_l z_{il} + \epsilon_i$$

where $\epsilon \sim N(0, \sigma^2)$. Here the y is subject to a Box–Cox transform with parameter θ. Each of the $x_1, x_2, \ldots, x_k$ is transformed by a Box–Cox transform with parameter λ. The $z_1, z_2, \ldots, z_l$ are independent variables that are not transformed. In addition to the general form specified above, `boxcox` can fit three other versions of this model defined by the restrictions $\lambda = \theta$, $\lambda = 1$, and $\theta = 1$.

For nonlinear mixed-effects models, see **[U] 27.16 Multilevel mixed-effects models**.

27.3.9 Nonparametric regression

All the models discussed so far have specified a particular functional form for the relationship between the outcome and the covariates in the model. Nonparametric regression allows you to model the mean of an outcome given the covariates when you are uncertain about its functional form. Stata's commands for nonparametric estimation are `npregress kernel` and `npregress series`. In general, for any outcome that you would be comfortable modeling using `regress`, you can use `npregress kernel` or `npregress series`. The difference is that you no longer have to assume a linear relationship. However, you need more observations for nonparametric estimators than you need for the parametric estimators.

`npregress kernel` implements two nonparametric kernel-based estimators—a local-linear estimator and a local-constant estimator. These kernel-based estimators rely on finding an optimal bandwidth parameter that balances the tradeoff between bias and variance. Both of these kernel-based estimators provide equivalent estimators of the mean, but there are some important differences to consider. The local-linear estimator lets you obtain marginal effects for continuous covariates. Also, if the model is linear, the local-linear estimator will recover a linear mean, whereas the local constant may not. For cases in which your outcome is nonnegative, the local-constant estimator will yield nonnegative predictions. The local-linear estimator may result in negative predictions in such cases.

`npregress series` implements nonparametric series estimators using a B-spline, spline, or polynomial basis. In series estimation, the unknown mean function is approximated by a linear combination of elements in the basis function. For instance, we can consider a polynomial basis. We can approximate the unknown mean function using a polynomial. The more complex the mean function, the more polynomial terms (`x`, $\texttt{x}^2$, $\texttt{x}^3$, ...) we need to include to approximate the mean consistently. Likewise, as the complexity of the the mean function increases, we need more terms in a B-spline or spline basis function. `npregress series` selects the number of terms that optimally balances the tradeoff between bias and variance. Once the terms are selected, we fit a least-squares regression. Having a linear representation of the approximating function and using it to construct inferences makes series estimation appealing.

See [R] **npregress intro** for more information about nonparametric regression.

27.4 Binary outcomes

27.4.1 Logistic, probit, and complementary log–log regression

There are many ways to write these models, one of which is

$$\Pr(y_j \neq 0) = F(\mathbf{x}_j\boldsymbol{\beta})$$

where F is some cumulative distribution. Two popular choices for $F(\cdot)$ are the normal and logistic, and the models are called the probit and logit (or logistic regression) models. The two parent commands for the maximum likelihood estimator of probit and logit are `probit` and `logit`. `logit` has a sibling, `logistic`, that provides the same estimates but displays results in a slightly different way. There is also an exact logistic estimator; see **[U] 27.11 Exact estimators**.

A third choice for $F(\cdot)$ is the complementary log–log function. Maximum likelihood estimates are obtained by Stata's `cloglog` command.

Do not read anything into the names logit and logistic. Logit and logistic have two interchanged definitions in two scientific camps. In the medical sciences, logit means the minimum χ^2 estimator, and logistic means maximum likelihood. In the social sciences, it is the other way around. From our experience, it appears that neither reads the other's literature, because both assert that logit means one thing and logistic the other. Our solution is to provide both `logit` and `logistic`, which do the same thing, so that each camp can latch on to the maximum likelihood command under the name each expects.

There are two slight differences between `logit` and `logistic`. `logit` reports estimates in the coefficient metric, whereas `logistic` reports exponentiated coefficients—odds ratios. This is in accordance with the expectations of each camp and makes no substantial difference. The other difference is that `logistic` has a family of post-`logistic` commands that you can run to explore the nature of the fit. Actually, that is not exactly true because all the commands for use after `logistic` can also be used after `logit`.

If you have not already selected `logit` or `logistic` as your favorite, we recommend that you try `logistic`. Logistic regression (logit) models are more easily interpreted in the odds-ratio metric.

`binreg` can be used to model either individual-level or grouped data in an application of the generalized linear model. The family is assumed to be binomial, and each link provides a distinct parameter interpretation. Also, `binreg` offers several options for setting the link function according to the desired biostatistical interpretation. The available links and interpretation options are the following:

Option	Implied link	Parameter
`or`	`logit`	Odds ratios = exp(β)
`rr`	`log`	Risk ratios = exp(β)
`hr`	`log complement`	Health ratios = exp(β)
`rd`	`identity`	Risk differences = β

`reri` can be used to assess two-way interactions in an additive model of relative risk. It reports the relative excess risk due to interaction, attributable proportion, and synergy index. `reri` supports binomial generalized linear and logistic models, as well as Poisson, negative binomial, Cox, parametric survival, and interval-censored parametric and nonparametric survival models.

Related to logit, the skewed logit estimator scobit adds a power to the logit link function and is estimated by Stata's `scobit` command.

`hetprobit` fits heteroskedastic probit models. In these models, the variance of the error term is parameterized.

Also, Stata's biprobit command fits bivariate probit models, meaning models with two correlated outcomes. biprobit also fits partial-observability models in which only the outcomes $(0,0)$ and $(1,1)$ are observed.

27.4.2 Conditional logistic regression

clogit is Stata's conditional logistic regression estimator. In this model, observations are assumed to be partitioned into groups, and a predetermined number of events occur in each group. The model measures the risk of the event according to the observation's covariates, $\mathbf{x}_j$. The model is used in matched case–control studies (clogit allows $1:1$, $1:k$, and $m:k$ matching) and is used in natural experiments whenever observations can be grouped into pools in which a fixed number of events occur. clogit is also used to fit logistic regression with fixed group effects.

27.4.3 ROC analysis

ROC stands for "receiver operating characteristics". ROC deals with specificity and sensitivity, the number of false positives and undetected true positives of a diagnostic test. The term "ROC" dates back to the early days of radar when there was a knob on the radar receiver labeled "ROC". If you turned the knob one way, the receiver became more sensitive, which meant it was more likely to show airplanes that really were there and, simultaneously, more likely to show returns where there were no airplanes (false positives). If you turned the knob the other way, you suppressed many of the false positives, but unfortunately, you also suppressed the weak returns from real airplanes (undetected positives). These days, in the statistical applications we imagine, one does not turn a knob but instead chooses a value of the diagnostic test, above which is declared to be a positive and below which, a negative.

ROC analysis is applied to binary outcomes such as those appropriate for probit or logistic regression. After fitting a model, one can obtain predicted probabilities of a positive outcome. One chooses a value, above which the predicted probability is declared a positive and below which, a negative.

ROC analysis is about modeling the tradeoff of sensitivity and specificity as the threshold value is chosen.

Stata's suite for ROC analysis consists of six commands: roctab, roccomp, rocfit, rocgold, rocreg, and rocregplot.

roctab provides nonparametric estimation of the ROC curve and produces Bamber and Hanley CIs for the area under the curve.

roccomp provides tests of equality of ROC areas. It can estimate nonparametric and parametric binormal ROC curves.

rocfit fits maximum likelihood models for a single classifier, an indicator of the latent binormal variable for the true status.

rocgold performs tests of equality of ROC areas against a "gold standard" ROC curve and can adjust significance levels for multiple tests across classifiers via Šidák's method.

rocreg performs ROC regression; it can adjust both sensitivity and specificity for prognostic factors such as age and gender. It is by far the most general of all the ROC commands.

rocregplot graphs ROC curves as modeled by rocreg. ROC curves can be drawn across covariate values, across classifiers, and across both.

See [R] **roc**.

27.5 Fractional outcomes

Fractional response data occur when the outcome of interest is measured as a fraction, proportion, or rate. Two widely used methods for modeling these outcomes are beta regression and fractional regression.

betareg can be used to estimate the parameters of a beta-regression model for fractional responses that are strictly greater than zero and less than one.

fracreg can be used to estimate the parameters of a fractional logistic model, a fractional probit model, or a fractional heteroskedastic probit model for fractional responses that are greater than or equal to zero and less than or equal to one.

Both commands use quasimaximum likelihood estimation. When the dependent variable is between zero and one, betareg provides more flexibility than fracreg in the distribution of the conditional mean of the dependent variable.

27.6 Ordinal outcomes

For ordered outcomes, Stata provides ordered logit, ordered probit, zero-inflated ordered probit, and rank-ordered logit, as well as rank-ordered logit regression.

oprobit and ologit provide maximum-likelihood ordered probit and logit. These are generalizations of probit and logit models known as the proportional odds model and are used when the outcomes have a natural ordering from low to high. The idea is that there is an unmeasured $z_j = \mathbf{x}_j\boldsymbol{\beta}$, and the probability that the kth outcome is observed is $\Pr(c_{k-1} < z_j < c_k)$, where $c_0 = -\infty$, $c_k = +\infty$, and $c_1, \ldots, c_{k-1}$ along with $\boldsymbol{\beta}$ are estimated from the data.

hetoprobit fits heteroskedastic ordered probit models to ordinal outcomes. It is a generalization of an ordered probit model that allows the variance to be modeled as a function of independent variables and to differ between subjects or population groups.

zioprobit fits zero-inflated ordered probit models, and ziologit fits zero-inflated ordered logit models. They are used to model an ordered outcome with a higher fraction of observations in the lowest category than would be expected from an ordered probit or ordered logit model. Typically, the lowest value is represented by zero—hence the name, "zero inflated". In these models, the outcome is a result of two processes. In the zero-inflated ordered probit model, a probit process first describes the presence of excess zeros or "nonparticipants". Second, an ordered probit process, conditional on "participation" from the probit process, describes the ordered outcome. Zero-inflated ordered logit is similar, except excess zeros are modeled with a logit process and an ordered logit process describes the ordered outcome. The logit version can optionally report odds ratios.

cmrologit fits the rank-ordered logit model for rankings. This model is also known as the Plackett–Luce model, the exploded logit model, and choice-based conjoint analysis.

cmroprobit fits the probit model for rankings, a more flexible estimator than cmrologit because cmroprobit allows covariances among the rankings.

27.7 Categorical outcomes

For categorical outcomes, Stata provides multinomial logistic regression, multinomial probit regression, stereotype logit regression, McFadden's choice model (conditional fixed-effects logistic regression), nested logistic regression, multinomial probit choice model, and mixed logit choice model.

mlogit fits maximum-likelihood multinomial logistic models, also known as polytomous logistic regression. mprobit is similar but instead is a generalization of the probit model. Both models are intended for use when the outcomes have no natural ordering and you know only the characteristics of the outcome chosen (and, perhaps, the chooser).

slogit fits the stereotype logit model for data that are not truly ordered, as data are for ologit, but for which you are not sure that they are unordered, in which case mlogit would be appropriate.

cmclogit fits McFadden's choice model, also known as conditional logistic regression. In the context denoted by the name McFadden's choice model, the model is used when the outcomes have no natural ordering, just as in multinomial logistic regression, but the characteristics of the outcomes chosen and not chosen are known (along with, perhaps, the characteristics of the chooser).

In the context denoted by the name conditional logistic regression—mentioned above—subjects are members of pools, and one or more are chosen, typically to be infected by some disease or to have some other unfortunate event befall them. Thus, the characteristics of the chosen and not chosen are known, and the issue of the characteristics of the chooser never arises. Either way, it is the same model.

In their choice-model interpretations, mlogit and cmclogit assume that the odds ratios are independent of other alternatives, known as the independence of irrelevant alternatives (IIA) assumption. This assumption is often rejected by the data, and the nested logit model relaxes this assumption. nlogit is also popular for fitting the random utility choice model.

cmmprobit is for use with outcomes that have no natural ordering and with regressors that are alternative specific. cmmixlogit is a generalization of mlogit that allows for correlation of choices across outcomes. Unlike mlogit, cmmprobit and cmmixlogit do not assume the IIA. The random coefficients that are used by cmmixlogit to relax the IIA also directly model the heterogeneity in choices given covariates.

27.8 Count outcomes

These models concern dependent variables that count the occurrences of an event. In this category, we include Poisson and negative binomial regression. For the Poisson model,

$$E(\text{count}) = E_j \exp(\mathbf{x}_j\boldsymbol{\beta})$$

where E_j is the exposure time. poisson fits this model. There is also an exact Poisson estimator; see **[U] 27.11 Exact estimators**.

Negative binomial regression refers to estimating with data that are a mixture of Poisson counts. One derivation of the negative binomial model is that individual units follow a Poisson regression model but that there is an omitted variable that follows a gamma distribution with parameter α. Negative binomial regression estimates $\boldsymbol{\beta}$ and α. nbreg fits such models. A variation on this, unique to Stata, allows you to model α. gnbreg fits those models.

Sometimes, the value of the outcome variable is not observed when it falls outside a known range, and it is observed inside that range. This limitation comes in two types—censoring and truncation. It is called censoring when we have an observation for the outcome but know only that the value of the outcome is outside the range. It is called truncation when we do not even have an observation when the value of the outcome is outside the range. The cpoisson command can be used to fit models for censored count data. Commands tpoisson and tnbreg can be used to fit models for truncated count data.

Zero inflation refers to count models in which the number of zero counts is more than would be expected in the regular model. The excess zeros are explained by a preliminary probit or logit process. If the preliminary process produces a positive outcome, the usual counting process occurs, and otherwise, the count is zero. Thus, whenever the preliminary process produces a negative outcome, excess zeros are produced. The `zip` and `zinb` commands fit such models.

27.9 Generalized linear models

The generalized linear model is

$$g\{E(y_j)\} = \mathbf{x}_j\boldsymbol{\beta}, \qquad y_j \sim F$$

where $g(\cdot)$ is called the link function and F is a member of the exponential family, both of which you specify before estimation. `glm` fits this model.

The GLM framework encompasses a surprising array of models known by other names, including linear regression, Poisson regression, exponential regression, and others. Stata provides dedicated estimation commands for many of these. For instance, Stata has `regress` for linear regression, `poisson` for Poisson regression, and `streg` for exponential regression, and that is not all the overlap.

`glm` by default uses maximum likelihood estimation and alternatively estimates via iterated reweighted least squares (IRLS) when the `irls` option is specified. For each family, F, there is a corresponding link function, $g(\cdot)$, called the canonical link, for which IRLS estimation produces results identical to maximum likelihood estimation. You can, however, match families and link functions as you wish, and when you match a family to a link function other than the canonical link, you obtain a different but valid estimator of the standard errors of the regression coefficients. The estimator you obtain is asymptotically equivalent to the maximum likelihood estimator, which, in small samples, produces slightly different results.

For example, the canonical link for the binomial family is logit. `glm, irls` with that combination produces results identical to the maximum-likelihood `logit` (and `logistic`) command. The binomial family with the probit link produces the probit model, but probit is not the canonical link here. Hence, `glm, irls` produces standard error estimates that differ slightly from those produced by Stata's maximum-likelihood `probit` command.

Many researchers feel that the maximum-likelihood standard errors are preferable to IRLS estimates (when they are not identical), but they would have a difficult time justifying that feeling. Maximum likelihood probit is an estimator with (solely) asymptotic properties; `glm, irls` with the binomial family and probit link is an estimator with (solely) asymptotic properties, and in finite samples, the standard errors differ a little.

Still, we recommend that you use Stata's dedicated estimators whenever possible. IRLS (the theory) and `glm, irls` (the command) are all encompassing in their generality, meaning that they rarely use the right jargon or provide things in the way you wish they would. The narrower commands, such as `logit`, `probit`, and `poisson`, focus on the issue at hand and are invariably more convenient.

`glm` is useful when you want to match a family to a link function that is not provided elsewhere.

`glm` also offers several estimators of the variance–covariance matrix that are consistent, even when the errors are heteroskedastic or autocorrelated. Another advantage of a `glm` version of a model over a model-specific version is that many of these VCE estimators are available only for the `glm` implementation. You can also obtain the ML–based estimates of the VCE from `glm`.

27.10 Choice models

Choice models are models for data with outcomes that are choices. For instance, we could model choices made by consumers who select a breakfast cereal from several different brands. Stata's choice model commands come in two varieties—-commands for modeling for discrete choices and commands for modeling rank-ordered alternatives. When each individual selects a single alternative, say, a shopper purchasing one box of cereal, the data are discrete choice data. When each individual ranks the choices, say, that shopper orders cereals from most favorite to least favorite, the data are rank-ordered data.

Commands for binary outcomes, categorical outcomes, panel data, multilevel models, Bayesian estimation, and more can be useful in modeling choice data in addition to other types of data; see [CM] **Intro 4**. The commands described below are designed specifically for choice data. Each of these commands allows alternative-specific covariates—covariates that differ across alternatives (cereals in our example) and possibly across cases (individuals). In addition, these models properly account for unbalanced data in which some individuals choose from only a subset of the alternatives.

27.10.1 Models for discrete choices

For discrete choice data, Stata provides conditional logit (McFadden's choice), multinomial probit, mixed logit, panel-data mixed logit, and nested logit regression. For an overview of these models, see [CM] **Intro 5**.

`cmclogit` fits McFadden's choice model, also known as conditional logistic regression. `cmclogit` relies on the independence of irrelevant alternatives (IIA) assumption, which implies that the relative probability of selecting alternatives should not change if we introduce or eliminate another alternative; see [CM] **Intro 8**.

The mixed logit model, the multinomial probit model, and the nested logit model relax the IIA assumption in different ways.

`cmmixlogit` fits a mixed logit regression for choice models. This model allows random coefficients on one or more of the alternative-specific predictors in the model. Through these random coefficients, the model allows correlation across alternatives and, thus, relaxes the IIA assumption. `cmxtmixlogit` extends this model for panel data.

`cmmprobit` fits a multinomial probit choice model. Like `cmclogit`, this command estimates fixed coefficients for all predictors. It does not require an IIA assumption because it directly models the correlation between the error terms for the different alternatives.

`nlogit` fits a nested logit choice model. With this model, similar alternatives—alternatives whose errors are likely to be correlated—can be grouped into nests. This model then accounts for correlation of alternatives within the same nest.

27.10.2 Models for rank-ordered alternatives

For rank-ordered alternatives, Stata provides the rank-ordered logit and rank-ordered probit model. For an overview of these models, see [CM] **Intro 6**.

`cmrologit` fits the rank-ordered logit model. This model is also known as the Plackett–Luce model, the exploded logit model, and choice-based conjoint analysis. This model requires the IIA assumption. It is unique because alternatives are not specified. They are instead identified only by the characteristics in alternative-specific covariates.

cmroprobit fits the rank-ordered probit model, an extension of the multinomial probit choice model for rank-ordered alternatives. It allows both alternative-specific and case-specific predictors. It does not assume IIA; instead, it models the correlation of errors across alternatives.

27.11 Exact estimators

Exact estimators refer to models that, rather than being estimated by asymptotic formulas, are estimated by enumerating the conditional distribution of the sufficient statistics and then computing the maximum likelihood estimate using that distribution. Standard errors cannot be estimated, but CIs can be and are obtained from the enumerations.

exlogistic fits logistic models of binary data in this way.

expoisson fits Poisson models of count data in this way.

In small samples, exact estimates have better coverage than the asymptotic estimates, and exact estimates are the only way to obtain estimates, tests, and CIs of covariates that perfectly predict the observed outcome.

27.12 Models with endogenous covariates

A covariate is endogenous if it is correlated with the unobservable components of a model. Endogeneity encompasses cases such as measurement error, omitted variables correlated with included regressors, and simultaneity. Stata offers several commands to address endogeneity depending on your outcome of interest and how you wish to model the correlation that generates the endogeneity problem.

Solutions to endogeneity rely on the use of instrumental variables. Instrumental variables are uncorrelated with the unobservable components of a model and are related to the outcome of interest only through their relationships with the endogenous variables.

Instrumental-variable models use instrumental variables to model endogeneity. Alternatively, a control function approach can be used. In this case, instrumental variables are used to directly model the correlation between unobservable components in the model.

ivregress fits linear outcome models with endogenous variables using the two-stage least-squares form of instrumental variables, the limited-information form of maximum likelihood, and a version of the generalized method of moments (GMM). The three estimators differ in the efficiency and robustness to additional assumptions such as constraints on the variances of the error terms.

ivprobit fits a probit outcome model where one or more of the covariates are endogenously determined. ivfprobit is like ivprobit but fits a model for a fractional outcome, such as a rate or proportion. ivtobit is like ivregress but allows for censored outcomes. ivpoisson fits a Poisson outcome model where one or more of the covariates are endogenously determined. It can also be used for modeling nonnegative continuous outcomes instead of counts. ivqregress fits a quantile regression model where one or more of the covariates are endogenously determined.

The GMM estimator implemented in ivregress is a special case of the estimators implemented in gmm. For other functional forms, you can write your own moment-evaluator program or supply the moment conditions as substitutable expressions to gmm; see **[U] 27.24 Generalized method of moments (GMM)**.

cfregress fits linear models with endogenous regressors using control functions. Endogenous variables are first modeled as a function of instruments using linear, probit, fractional probit, or Poisson regression. The residuals, or generalized residuals, from these first-stage regressions are then included in the main equation as control functions to make regression estimates robust to endogeneity. cfprobit is like cfregress but fits a probit outcome model for binary dependent variables.

The extended regression commands fit models with endogenous covariates that are binary, ordinal, or censored, as well as continuous. eregress fits a linear model with endogenous covariates, eintreg fits tobit and interval regression models with endogenous covariates, eprobit fits a probit model with endogenous covariates, and eoprobit fits an ordered probit model with endogenous covariates. You may also use these commands to accommodate endogenous sample selection (see **[U] 27.13 Models with endogenous sample selection**) and treatment effects (see **[U] 27.20 Causal inference**) in combination with endogenous covariates.

For systems of linear equations with endogenous covariates, the three-stage least-squares (3SLS) estimator in reg3 can produce constrained and unconstrained estimates. Structural equation models discussed in **[U] 27.25 Structural equation modeling (SEM)** and GMM estimators discussed in **[U] 27.24 Generalized method of moments (GMM)** are also widely used for such systems.

27.13 Models with endogenous sample selection

When unobservable factors that affect who is included in a sample are correlated with unobservable factors that affect the outcome, we say that there is endogenous sample selection. When present, endogenous sample selection should be modeled; consider using one of the commands discussed below.

What has become known as the Heckman model refers to linear regression in the presence of endogenous sample selection: $y_j = \mathbf{x}_j\boldsymbol{\beta}+\epsilon_j$ is not observed unless some event occurs that itself has probability $p_j = F(\mathbf{z}_j\boldsymbol{\gamma} + \nu_j)$, where ϵ and ν might be correlated and $\mathbf{z}_j$ and $\mathbf{x}_j$ may contain variables in common. heckman fits such models by maximum likelihood or Heckman's original two-step procedure.

This model has been generalized to replace the linear regression equation with another probit equation, and that model is fit by heckprobit. The command heckoprobit fits an ordered probit model in the presence of sample selection. Finally, heckpoisson is used to model count data subject to endogenous sample selection.

Stata's extended regression commands allow you to model endogenous sample selection along with endogenous covariates and treatment effects. These commands are discussed in **[U] 27.12 Models with endogenous covariates**.

27.14 Time-series models

ARIMA refers to models with autoregressive integrated moving-average processes, and Stata's arima command fits models with ARIMA disturbances via the Kalman filter and maximum likelihood. These models may be fit with or without covariates. arima also fits ARMA models.

ARFIMA, or autoregressive fractionally integrated moving average, handles long-memory processes. ARFIMA generalizes the ARMA and ARIMA models. ARMA models assume short memory; after a shock, the process reverts to its trend relatively quickly. ARIMA models assume shocks are permanent and memory never fades. ARFIMA provides a middle ground in the length of the process's memory. The arfima command fits ARFIMA models. In addition to one-step and dynamic forecasts, arfima can predict fractionally integrated series.

UCM, or unobserved components model, decomposes a time series into trend, seasonal, cyclic, and idiosyncratic components after controlling for optional exogenous variables. UCM provides a flexible and formal approach to smoothing and decomposition problems. The `ucm` command fits UCM models.

The estimated parameters of ARIMA, ARFIMA, and UCM are sometimes more easily interpreted in terms of the implied spectral density. `psdensity` transforms results.

Band-pass and high-pass filters are also used to decompose a time series into trend and cyclic components, even though the `tsfilter` commands are not estimation commands. Provided are Baxter–King, Butterworth, Christiano–Fitzgerald, and Hodrick–Prescott filters.

Stata's `prais` command performs regression with AR(1) disturbances using the Prais–Winsten or Cochrane–Orcutt transformation. Both two-step and iterative solutions are available, as well as a version of the Hildreth–Lu search procedure.

`newey` produces linear regression estimates with the Newey–West variance estimates that are robust to heteroskedasticity and autocorrelation of specified order.

Stata provides estimators for ARCH, GARCH, univariate, and multivariate models. These models are for time-varying volatility. ARCH models allow for conditional heteroskedasticity by including lagged variances. GARCH models also include lagged second moments of the innovations (errors). ARCH stands for "autoregressive conditional heteroskedasticity". GARCH stands for "generalized ARCH".

`arch` fits univariate ARCH and GARCH models, and the command provides many popular extensions, including multiplicative conditional heteroskedasticity. Errors may be normal or Student's t or may follow a generalized error distribution. Robust standard errors are optionally provided.

`mgarch` fits multivariate ARCH and GARCH models, including the diagonal vech model and the constant, dynamic, and varying conditional correlation models. Errors may be multivariate normal or multivariate Student's t. Robust standard errors are optionally provided.

Stata provides VAR, SVAR, instrumental-variables SVAR, and VEC estimators for modeling multivariate time series. VAR, SVAR, and instrumental-variables SVAR deal with stationary series. SVAR places additional constraints on the VAR model that identifies the impulse–response functions. Instrumental-variables SVAR uses instruments to identify the impulse–response functions. VEC is for cointegrating VAR models. VAR stands for "vector autoregression"; SVAR, for "structural VAR"; and VEC, for "vector error-correction" model.

`var` fits VAR models, `svar` fits SVAR models, `ivsvar` fits instrumental-variables SVAR models, and `vec` fits VEC models. These commands share many of the same features for specification testing, forecasting, and parameter interpretation; see [TS] **var intro** for `var`, `svar`, and `ivsvar`; [TS] **vec intro** for `vec`; and [TS] **irf** for all four impulse–response functions and forecast-error variance decomposition. For lag-order selection, residual analysis, and Granger causality tests, see [TS] **var intro** (for `var`, `svar`, and `ivsvar`) and [TS] **vec intro**.

`lpirf` and `ivlpirf` estimate impulse–response functions via local projections. Local projections provide a flexible alternative to the model-based impulse–response estimates obtained after fitting a VAR model. Local projections simplify estimation and hypothesis testing, and the corresponding CIs can have better small-sample properties than those of the VAR estimates. When the impulse variable of interest is an endogenous regressor, `ivlpirf` accounts for the endogeneity by using instrumental variables.

sspace estimates the parameters of multivariate state-space models using the Kalman filter. The state-space representation of time-series models is extremely flexible and can be used to estimate the parameters of many different models, including vector autoregressive moving-average (VARMA) models, dynamic-factor (DF) models, and structural time-series (STS) models. It can also solve some stochastic dynamic-programming problems.

dfactor estimates the parameters of dynamic-factor models. These flexible models for multivariate time series provide for a vector-autoregressive structure in both observed outcomes and unobserved factors. They also allow exogenous covariates for observed outcomes or unobserved factors.

Sometimes time-series data are characterized by shifts in the mean or variance. Linear autoregressive models may not adequately capture these peculiarities of the data. Stata provides Markov-switching and threshold models to fit such series.

Markov-switching models are used for series that transition over a finite set of unobserved states where the transitions occur according to a Markov process. The time of transition from one state to another and the duration between changes in state are random. By contrast, threshold models are used for series that transition over regions determined by threshold values. You can use the mswitch command to fit Markov-switching dynamic-regression (MSDR) and Markov-switching autoregression (MSAR) models. MSDR models can accommodate higher autoregressive lags than MSAR models because the state vector does not depend on the autoregressive lags in an MSDR model. You can use threshold to fit threshold regression models.

Bayesian estimation of the VAR models is available by using the bayes: var command. Bayesian estimation allows you to incorporate external information about model parameters often available in practice and provides more stable inference in the presence of many model parameters relative to the size of the data; see *Advantages of Bayesian VAR models* in [BAYES] **bayes: var**. After estimation using bayes: var, you can obtain Bayesian forecasts by using bayesfcast and perform IRF and FEVD analysis by using bayesirf.

27.15 Panel-data models

Commands in this class begin with the letters xt. You must xtset your data before you can use an xt command.

27.15.1 Continuous outcomes with panel data

xtreg fits models of the form

$$y_{it} = \mathbf{x}_{it}\boldsymbol{\beta} + \nu_i + \epsilon_{it}$$

xtreg can produce the between-regression estimator, the within-regression (fixed-effects) estimator, the generalized least-squares (GLS) random-effects (matrix-weighted average of between and within results) estimator, or the correlated random-effects estimator. It can also produce the maximum-likelihood random-effects estimator. wildbootstrap xtreg also produces the within-regression estimator but with wild cluster bootstrap p-values and CIs for robust inference.

xtgee fits population-averaged models, and it optionally provides robust estimates of variance. Moreover, xtgee allows other correlation structures. One of particular interest to those with a lot of data goes by the name "unstructured". The within-panel correlations are simply estimated in an unconstrained way. **[U] 27.15.4 Generalized linear models with panel data** will discuss this estimator further because it is not restricted to linear regression models.

xtfrontier fits stochastic production or cost frontier models for panel data. You may choose from a time-invariant model or a time-varying decay model. In both models, the nonnegative inefficiency term is assumed to have a truncated-normal distribution. In the time-invariant model, the inefficiency term is constant within panels. In the time-varying decay model, the inefficiency term is modeled as a truncated-normal random variable multiplied by a specific function of time. In both models, the idiosyncratic error term is assumed to have a normal distribution. The only panel-specific effect is the random inefficiency term.

xtheckman fits random-effects models that account for endogenous sample selection. Random effects are included in the equation for the main outcome and in the selection equation and are allowed to be correlated.

xtivreg contains the between-2SLS estimator, the within-2SLS estimator, the first-differenced-2SLS estimator, and two GLS random-effects-2SLS estimators to handle cases in which some of the covariates are endogenous.

xteregress fits random-effects models that account for any combination of endogenous covariates, endogenous sample selection, and nonrandom treatment assignment.

xtdidregress estimates the average treatment effect on the treated (ATET) from observational data by difference in differences (DID) or difference in difference in differences (DDD). The ATET of a binary or continuous treatment on a continuous outcome is estimated by fitting a linear model with time and panel fixed effects. xthdidregress is an extension of xtdidregress that, instead of one ATET, allows for multiple ATETs that vary over time and over treatment cohorts. Treatment cohorts are groups subject to treatment at different points in time.

xthtaylor uses instrumental-variables estimators to estimate the parameters of panel-data random-effects models of the form

$$y_{it} = \mathbf{X}_{1it}\boldsymbol{\beta}_1 + \mathbf{X}_{2it}\boldsymbol{\beta}_2 + \mathbf{Z}_{1i}\boldsymbol{\delta}_1 + \mathbf{Z}_{2i}\boldsymbol{\delta}_2 + u_i + e_{it}$$

The individual effects u_i are correlated with the explanatory variables $\mathbf{X}_{2it}$ and $\mathbf{Z}_{2i}$ but are uncorrelated with $\mathbf{X}_{1it}$ and $\mathbf{Z}_{1i}$, where $\mathbf{Z}_1$ and $\mathbf{Z}_2$ are constant within the panel.

xtgls produces GLS estimates for models of the form

$$y_{it} = \mathbf{x}_{it}\boldsymbol{\beta} + \epsilon_{it}$$

where you may specify the variance structure of ϵ_{it}. If you specify that ϵ_{it} is independent for all i's and t's, xtgls produces the same results as regress up to a small-sample degrees-of-freedom correction applied by regress but not by xtgls.

You may choose among three variance structures concerning i and three concerning t, producing a total of nine different models. Assumptions concerning i deal with heteroskedasticity and cross-sectional correlation. Assumptions concerning t deal with autocorrelation and, more specifically, AR(1) serial correlation.

In the jargon of GLS, the random-effects model fit by xtreg has exchangeable correlation within i—xtgls does not model this particular correlation structure. xtgee, however, does.

Alternative methods report the OLS coefficients and a version of the GLS variance–covariance estimator. xtpcse produces panel-corrected standard error (PCSE) estimates for linear cross-sectional time-series models, where the parameters are estimated by OLS or Prais–Winsten regression. When you are computing the standard errors and the variance–covariance estimates, the disturbances are, by default, assumed to be heteroskedastic and contemporaneously correlated across panels.

xtrc fits Swamy's random-coefficients linear regression model. In this model, rather than only the intercept varying across groups, all the coefficients are allowed to vary.

See [U] 27.16 Multilevel mixed-effects models for a generalization of xtreg and xtrc that allows for multiple levels of panels, random coefficients, and variance-component estimation in general. xtrc is a special case of mixed.

27.15.2 Censored outcomes with panel data

xttobit fits a random-effects tobit model and generalizes that to observation-specific censoring.

xtintreg performs random-effects interval regression and generalizes that to observation-specific censoring. Interval regression, in addition to allowing open-ended intervals, allows closed intervals.

xteintreg fits random-effects interval regression models that account for any combination of endogenous covariates, endogenous sample selection, and nonrandom treatment assignment.

These models are generalizable to multilevel data; see [U] 27.16 Multilevel mixed-effects models.

27.15.3 Discrete outcomes with panel data

xtprobit fits random-effects probit regression via maximum likelihood. It also fits population-averaged models via GEE.

xtlogit fits random-effects logistic regression models via maximum likelihood. It also fits conditional fixed-effects models via maximum likelihood and population-averaged models via GEE.

xtcloglog estimates random-effects complementary log–log regression via maximum likelihood. It also fits population-averaged models via GEE.

xteprobit fits random-effects probit models that account for any combination of endogenous covariates, endogenous sample selection, and nonrandom treatment assignment.

xtologit and xtoprobit are multiple-outcome models. xtologit fits a random-effects ordered logistic model, and xtoprobit fits a random-effects ordered probit model.

xteoprobit fits random-effects ordered probit models that account for any combination of endogenous covariates, endogenous sample selection, and nonrandom treatment assignment.

xtmlogit fits random-effects multinomial logistic regression models via maximum likelihood. It also fits conditional fixed-effects models via maximum likelihood.

xtpoisson fits two different random-effects Poisson regression models via maximum likelihood. The two distributions for the random effects are gamma and normal. xtpoisson also fits conditional fixed-effects models, and it fits population-averaged models via GEE.

xtnbreg fits random-effects negative binomial regression models via maximum likelihood (the distribution of the random effects is assumed to be beta). xtnbreg also fits conditional fixed-effects models, and it fits population-averaged models via GEE.

xtprobit, xtlogit, xtcloglog, xtpoisson, and xtnbreg are nothing more than xtgee with the appropriate family and link and an exchangeable error structure. See [U] 27.15.4 Generalized linear models with panel data.

These models are generalizable to multilevel data; see [U] 27.16 Multilevel mixed-effects models.

27.15.4 Generalized linear models with panel data

[U] 27.9 Generalized linear models discussed the model

$$g\{E(y_j)\} = \mathbf{x}_j\boldsymbol{\beta}, \qquad y_j \sim F$$

where $g(\cdot)$ is the link function and F is a member of the exponential family, both of which you specify before estimation.

There are two ways to extend the generalized linear model to panel data. They are the generalized linear mixed model (GLMM) and generalized estimation equations (GEE).

GEE uses a working correlation structure to model within-panel correlation. GEEs may be fit with the `xtgee` command.

For generalized linear models with multilevel data, including panel data, see [U] 27.16 Multilevel mixed-effects models.

27.15.5 Survival models with panel data

`xtstreg` fits a random-effects parametric survival-time model by maximum likelihood. The conditional distribution of the response given the random effects is assumed to be exponential, Weibull, lognormal, loglogistic, or gamma. Depending on the selected distribution, `xtstreg` can fit models using a proportional hazards (PH) or accelerated failure-time (AFT) parameterization. Unlike the other panel-data commands, `xtstreg` requires that the data be `xtset` and `stset`.

These models are generalizable to multilevel data; see [U] 27.16 Multilevel mixed-effects models.

27.15.6 Dynamic and autoregressive panel-data models

`xtregar` can produce the within estimator and a GLS random-effects estimator when the ϵ_{it} are assumed to follow an AR(1) process.

`xtabond` is for use with dynamic panel-data models (models in which there are lagged dependent variables) and can produce the one-step, one-step robust, and two-step Arellano–Bond estimators. `xtabond` can handle predetermined covariates, and it reports both the Sargan and autocorrelation tests derived by Arellano and Bond.

`xtdpdsys` is an extension of `xtabond` and produces estimates with smaller bias when the coefficients of the AR process are large. `xtdpdsys` is also more efficient than `xtabond`. Whereas `xtabond` uses moment conditions based on the differenced errors, `xtdpdsys` uses moment conditions based on both the differenced errors and their levels.

`xtdpd` is an extension of `xtdpdsys` and can be used to estimate the parameters of a broader class of dynamic panel-data models. `xtdpd` can be used to fit models with serially correlated idiosyncratic errors, whereas `xtdpdsys` and `xtabond` assume no serial correlation. `xtdpd` can also be used with models where the structure of the predetermined variables is more complicated than that assumed by `xtdpdsys` or `xtabond`.

`xtvar` is an extension of multivariate time-series regression for dynamic panel data. The parameters fit by `xtvar` are analogous to those of a VAR model. Therefore, although the estimation techniques are more similar to those of other dynamic panel-data models, the postestimation tools for testing, interpretation, and diagnostics are the same as those for multivariate time-series models. For instance, impulse–response functions (see [TS] **irf**) are useful for interpreting results.

27.15.7 Bayesian estimation

Bayesian estimation for some of the random-effects panel-data models is available via the `bayes` prefix command. See *Bayesian panel-data commands* in [BAYES] **Bayesian estimation** for the supported commands. You may be interested in Bayesian estimation, for instance, if you would like to incorporate external information about model parameters often available in practice or when you have small datasets and many parameters to estimate. Bayesian estimation is particularly useful if you are interested in estimating random effects because it provides an entire posterior distribution that incorporates all sources of variability in the model parameter estimates for each random effect. In addition, you can use the `bayespredict` command to compute predictions and their variability without relying on the assumption of asymptotic normality of the model parameter estimates. See *Panel-data models* in [BAYES] **bayes**.

27.16 Multilevel mixed-effects models

In multilevel data, observations—subjects, for want of a better word—can be divided into groups that have something in common. Perhaps the subjects are students, and the groups attended the same high school, or they are patients who were treated at the same hospital, or they are tractors that were manufactured at the same factory. Whatever they have in common, it may be reasonable to assume that the shared attribute affects the outcome being modeled.

With regard to students and high school, perhaps you are modeling later success in life. Some high schools are better (or worse) than others, so it would not be unreasonable to assume that the identity of the high school had an effect. With regard to patients and hospital, the argument is much the same if the outcome is subsequent health: some hospitals are better (or worse) than others, at least with respect to particular health problems. With regard to tractors and factory, it would hardly be surprising if tractors from some factories were more reliable than tractors from other factories.

Described above is two-level data. The first level is the student, patient, or tractor, and the second level is the high school, hospital, or factory. Observations are said to be nested within groups: students within a high school, patients within a hospital, or tractors within a factory.

Even though the effect on outcome is not directly observed, one can control for the effect if one is willing to assume that the effect is the same for all observations within a group and that, across groups, the effect is a random draw from a statistical distribution that is uncorrelated with the overall residual of the model and other group effects.

We have just described multilevel models.

A more complicated scenario might have three levels: students nested within teachers within a high school, patients nested within doctors within a hospital, or tractors nested within an assembly line within a factory.

An alternative to three-level hierarchical data is crossed data. We have workers and their occupation and the industry in which they work.

Stata provides a suite of multilevel estimation commands. The estimation commands are the following:

Command	Outcome variable	Equivalent to
mixed	continuous	linear regression
menl	continuous	nonlinear regression
metobit	censored	tobit regression
meintreg	censored	interval regression
meprobit	binary	probit regression
melogit	binary	logistic regression
mecloglog	binary	complementary log–log regression
meoprobit	ordered categorical	ordered probit regression
meologit	ordered categorical	ordered logistic regression
mepoisson	count	Poisson regression
menbreg	count	negative binomial regression
mestreg	survival-time	parametric survival-time regression
meglm	various	generalized linear models

The above estimators provide random intercepts and random coefficients and allow constraints to be placed on coefficients and on variance components. (menl does not allow constraints.)

See the *Stata Multilevel Mixed-Effects Reference Manual*; in particular, see [ME] **me**.

27.17 Survival analysis models

Commands are provided to fit Cox proportional hazards models, competing-risks regression, and several parametric survival models, including exponential, Weibull, Gompertz, lognormal, loglogistic, and generalized gamma. The command for Cox regression is stcox. Cox regressions may be fit to left- or right-censored survival-time data. For interval-censored survival-time data, stintcox may be used to fit semiparametric Cox proportional hazards models, and stmgintcox may be used to fit marginal Cox proportional hazards models to multiple-event data. Parametric models may be fit to right-censored survival-time data by using the streg command and to interval-censored survival-time data by using the stintreg command.

stcox and streg support single- or multiple-failure-per-subject data. The command for competing-risks regression, stcrreg, and stintreg support only single-failure data. Conventional, robust, bootstrap, and jackknife standard errors are available with all four commands, with the exception that for stcrreg, robust standard errors are the conventional standard errors.

Both the Cox model and the parametric models (as fit using Stata) allow for two additional generalizations. First, the models may be modified to allow for latent random effects, or frailties. Second, the models may be stratified in that the baseline hazard function may vary completely over a set of strata. The parametric models also allow for the modeling of ancillary parameters.

Competing-risks regression, as fit using Stata, is a useful alternative to Cox regression for datasets where more than one type of failure occurs, in other words, for data where failure events compete with one another. In such situations, competing-risks regression allows you to easily assess covariate effects on the incidence of the failure type of interest without having to make strong assumptions concerning the independence of failure types.

`stcox`, `stcrreg`, and `streg` require that the data be `stset` so that the proper response variables can be established. After you `stset` the data, the time/censoring response is taken as understood, and you need supply only the regressors (and other options) to `stcox`, `stcrreg`, and `streg`. With `stcrreg`, one required option deals with specifying which events compete with the failure event of interest that was previously `stset`. `stintcox`, `stintreg`, and `stmgintcox` require that you specify the interval-censored time variables with the command and thus ignore any `st` settings.

Stata also provides commands to estimate average treatment effects and average treatment effects on the treated from observational survival-time data. See **[U] 27.20 Causal inference**.

We discuss panel-data survival-time models in **[U] 27.15.5 Survival models with panel data**. These models generalize to multilevel data; see **[U] 27.16 Multilevel mixed-effects models**.

27.18 Meta-analysis

Meta-analysis is a statistical method for combining the results from several different studies that answer similar research questions. The goal of meta-analysis is to compare the study results and, if possible, provide a unified conclusion based on an overall estimate of the effect of interest. Stata provides a suite of commands for conducting meta-analysis.

Study-specific effect sizes and their corresponding standard errors are the two main components of meta-analysis. They are specified during the declaration step ([META] **meta data**) using `meta set` or `meta esize`; see [META] **meta set** and [META] **meta esize**.

Basic meta-analysis summary, which includes the overall effect-size estimate and its CI and heterogeneity statistics, can be displayed in a table ([META] **meta summarize**) or on a forest plot ([META] **meta forestplot**). Three meta-analysis models—random-effects, fixed-effects, and common-effect—and several estimation methods, such as restricted maximum likelihood and Mantel–Haenszel, are supported.

Heterogeneity or between-study variation arises frequently in meta-analysis. It can be explored graphically using subgroups in forest plots or using Galbraith or L'Abbé plots. See the `subgroup()` option in [META] **meta forestplot**, and see [META] **meta galbraithplot** and [META] **meta labbeplot**. It can be examined analytically via meta-regression and subgroup analysis. See [META] **meta regress** and the `subgroup()` option in [META] **meta summarize**. You can also use `meta summarize` or `meta forestplot` to perform cumulative meta-analysis by specifying the `cumulative()` option with the command. Leave-one-out meta-analysis can be done by specifying the `leaveoneout` option with these commands.

The presence of publication bias is another concern in meta-analysis. It typically arises when the decision of whether to publish the results of a study depends on the statistical significance of its results. Smaller studies with nonsignificant findings are commonly more prone to publication bias. Standard and contour-enhanced funnel plots ([META] **meta funnelplot**), tests for funnel-plot asymmetry ([META] **meta bias**), and the trim-and-fill method ([META] **meta trimfill**) can all be used to explore publication bias and assess its impact on meta-analysis results. More generally, `meta funnelplot` and `meta bias` are used to explore the so-called small-study effects, or the tendency of smaller studies to report different, often larger, effect sizes compared with larger studies.

When a study reports multiple effect sizes, you may use `meta mvregress` to perform multivariate meta-analysis while accounting for the dependence among the effect sizes. You may also incorporate covariates in your model and conduct a multivariate meta-regression to explore the multivariate heterogeneity of the effect sizes.

Additionally, if the dependence among effect sizes stems from a hierarchical or multilevel structure, you may use `meta meregress` to perform multilevel meta-analysis. With `meta meregress`, you can fit models with random intercepts and random slopes. If, however, you are interested in fitting only random-intercepts meta-analysis models, you can use `meta multilevel`, which provides a simpler syntax.

Also available in the `meta` suite are postestimation tools, such as bubble plots and various predictions. See [META] **meta regress postestimation**, [META] **meta mvregress postestimation**, and [META] **meta me postestimation**.

27.19 Spatial autoregressive models

Stata's Sp estimation commands fit spatial autoregressive (SAR) models, also known as simultaneous autoregressive models. The commands allow spatial lags of the dependent and independent variables and spatial autoregressive errors. In time-series analysis, lags refer to recent times. In spatial analysis, lags mean nearby areas.

An essential part of the model specification for SAR models is the formulation of spatial lags. Spatial lags are specified using spatial weighting matrices. Because of the potentially large dimensions of the weighting matrices, Stata provides commands for creating, using, and saving spatial weighting matrices.

Spatial models estimate indirect or spillover effects from one spatial unit (area) to another. The models estimate direct effects, too, just as nonspatial models would. Direct effects are the effects within a spatial unit. Viewing estimates of the direct effects, indirect effects, and total effects is done by running `estat impact` after any of the Sp estimation commands. `estat impact` makes interpreting results easy.

Datasets for SAR models contain observations on geographical areas or other units; the only requirement is some measure of distance that distinguishes which units are close to each other. Spatial data for geographic areas are typically based on shapefiles. The Sp system converts standard-format shapefiles to Stata `.dta` files so they can be merged with other Stata `.dta` datasets.

The Sp system will also work without shapefiles. Data can contain (x, y) coordinates, or data need not be geographic at all. For example, Sp can be used to analyze social networks.

Read [SP] **Intro** and the introductory sections that follow it for an overview of SAR models and a tutorial with examples for preparing your data and creating spatial weighting matrices.

The available Sp estimation commands are as follows:

Command	Description	Equivalent to
`spregress, gs2sls`	SAR with GS2SLS estimator	`regress`
`spregress, ml`	SAR with ML estimator	`regress`
`spivregress`	SAR with endogenous regressors	`ivregress`
`spxtregress, fe`	fixed-effects SAR for panel data	`xtreg, fe`
`spxtregress, re`	random-effects SAR for panel data	`xtreg, re`
`spxtregress, re sarpanel`	random-effects SAR alternative	

spregress, gs2sls and spivregress will fit multiple spatial lags of the dependent variable, multiple spatial autoregressive error terms, and multiple spatial lags of covariates. The other Sp estimation commands will fit only one spatial lag of the dependent variable and only one spatial autoregressive error term, but will allow multiple spatial lags of covariates.

27.20 Causal inference

Many research questions focus on causality. We wish to draw causal inferences when we ask what would happen to an outcome of interest when a change is made to another variable, often called a treatment variable. Under proper assumptions, many of Stata's estimation commands can be used for causal inference; see [CAUSAL] **Intro** for more information. Stata also offers estimation commands specifically designed for estimating treatment effects when causal inference is the research goal.

teffects, stteffects, eteffects, mediate, didregress, hdidregress, xtdidregress, xthdidregress, telasso, and cate estimate treatment effects from observational data.

A treatment effect is the change in an outcome caused by an individual getting one treatment instead of another. We can estimate average treatment effects, but not individual-level treatment effects, because we observe each individual getting only one or another treatment.

teffects, stteffects, eteffects, and telasso use methods that specify what the individual-level outcomes would be for each treatment level, even though only one of them can be realized. This approach is known as the potential-outcome framework. See [CAUSAL] **teffects intro** for a basic introduction to the key concepts associated with observational data analysis. See [CAUSAL] **teffects intro advanced** for a more advanced introduction that provides the intuition behind the potential-outcome framework. [CAUSAL] **stteffects intro** extends the concepts in the two earlier introductions to survival-time data.

mediate takes the potential-outcomes approach to causal mediation analysis. This estimator allows you to estimate the direct effect that a treatment has on the outcome as well as the indirect effect through a mediator variable.

didregress and xtdidregress can also be understood within the potential-outcome framework; however, these estimators differ from teffects, stteffects, eteffects in that they include group and time effects in the model. Including group and time effects controls for group and time unobservables that might bias effect estimates.

hdidregress and xthdidregress estimate treatment effects that may vary over time and over treatment cohorts. Treatment cohorts are groups subject to treatment at different points in time. Both of these commands are extensions of didregress and xtdidregress, but unlike the former they estimate multiple ATETs instead of only one. hdidregress and xthdidregress are commands for heterogeneous treatment-effect estimation.

Suppose we want to use observational data to learn about the effect of exercise on blood pressure. The potential-outcome framework provides the structure to estimate what would be the average effect of everyone exercising instead of everyone not exercising, an effect known as average treatment effect (ATE). Similarly, we can estimate the average effect, among those who exercise, of exercising instead of not exercising, which is known as the average treatment effect on the treated (ATET). Finally, we could estimate the average blood pressure that would be obtained if everyone exercised or if no one exercised, parameters known as potential-outcome means (POMs).

teffects can estimate the ATE, the ATET, and the POMs. The estimators implemented in teffects impose the structure of the potential-outcome framework on the data in different ways.

- Regression-adjustment estimators use models for the potential outcomes. See [CAUSAL] **teffects ra**.
- Inverse-probability-weighted estimators use models for treatment assignment. See [CAUSAL] **teffects ipw**.
- Augmented inverse-probability-weighted estimators and inverse-probability-weighted regression-adjustment estimators use models for the potential outcomes and for treatment assignment. These estimators have the double-robust property; they correctly estimate the treatment effect even if only one of the two models is correctly specified. See [CAUSAL] **teffects aipw** and [CAUSAL] **teffects ipwra**.
- Nearest-neighbor matching (NNM) and propensity-score matching (PSM) estimators compare the outcomes of individuals who are as similar as possible except that one gets the treatment and the other does not. NNM uses a nonparametric similarity measure, while PSM uses estimated treatment probabilities to measure similarity. See [CAUSAL] **teffects nnmatch** and [CAUSAL] **teffects psmatch**.

`stteffects` can estimate the ATE, the ATET, and the POMs. The estimators implemented in `stteffects` impose the structure of the potential-outcome framework on the data in different ways.

- Regression-adjustment estimators use models for the potential outcomes, and censoring is adjusted for the log-likelihood function. See [CAUSAL] **stteffects ra**.
- Inverse-probability-weighted estimators use models for treatment assignment and for the censoring time. See [CAUSAL] **stteffects ipw**.
- Inverse-probability-weighted regression-adjustment (IPWRA) estimators use models for the potential outcomes and for treatment assignment. IPWRA estimators can adjust for censoring in the outcome model or with a separate censoring model. These estimators have the double-robust property: they correctly estimate the treatment effect even if only the outcome model or the treatment-assignment model is correctly specified. If a censoring model is specified, both the treatment-assignment model and the censoring model must be correctly specified for the estimator to be double robust. See [CAUSAL] **stteffects ipwra**.
- Weighted regression-adjustment estimators model the outcome and the time to censoring. See [CAUSAL] **stteffects wra**.

`teffects` and `stteffects` can estimate treatment effects from multivalued treatments; see [CAUSAL] **teffects multivalued**.

`telasso` estimates the ATE, the ATET, and the POMs from observational data by augmented inverse-probability weighting while using lasso methods to select from potential control variables to be included in the model.

The `cate` suite of commands is useful for estimating the average treatment effects conditional on a set of variables, known as conditional average treatment effects (CATEs). `cate` provides three different CATE estimates: individualized average treatment effects (IATEs), group average treatment effects (GATEs), and sorted group average treatment effects (GATESs). IATEs are treatment effects conditional on observation-level characteristics. There is one IATE for each observation in the data. GATEs are treatment effects conditional on prespecified groups. There is a treatment effect for each group. GATESs compute average treatment effects for a prespecified number of groups. The groups are determined by quantiles of individual-level treatment-effects values. Estimating CATE allows us to study the treatment-effect heterogeneity and evaluate the treatment-assignment policy.

`mediate` decomposes the effect of the treatment on the outcome into direct effects, meaning how the treatment directly affects the outcome, and indirect effects, meaning how the treatment indirectly affects the outcome through a mediator. `mediate` estimates the average direct treatment effect (ADTE), average

indirect treatment effect (AITE), average direct treatment effect with respect to treatment (ADTET), average indirect treatment effect with respect to controls (AITEC), total average treatment effect (ATE), and the POMs.

didregress and xtdidregress estimate the ATET from observational data by difference in differences (DID) or difference in difference in differences (DDD). The ATET of a binary or continuous treatment on a continuous outcome is estimated by fitting a linear model with time and group fixed effects for didregress and time and panel fixed effects for xtdidregress. didregress is for repeated cross-sections in which different groups of individuals are observed at each time period. xtdidregress is for panel data. hdidregress and xthdidregress extend didregress and xtdidregress to estimate ATETs that may vary over time and over treatment cohorts. Treatment cohorts are groups subject to treatment at different points in time.

It is not appropriate to use teffects, stteffects, telasso, didregress, hdidregress, xtdidregress, or xthdidregress when a treatment is endogenously determined (the potential outcomes are not conditionally independent). When the treatment is endogenous, an endogenous treatment-effects model can be used to estimate the ATE. These models consider the effect of an endogenously determined binary treatment variable on the outcome.

eteffects can estimate the ATE, the ATET, and the POMs. It fits endogenous treatment-effects models by using either a linear or a nonlinear (probit, fractional probit, or exponential) model for the outcome. eteffects implements control-function regression-adjustment estimators.

etregress and etpoisson also fit endogenous treatment-effects models and can be used to estimate the ATE and the ATET. See [CAUSAL] **etregress** and [CAUSAL] **etpoisson**. etregress fits an endogenous treatment-effects model by using a linear model for the outcome. etpoisson fits an endogenous treatment-effects model by using a nonlinear (exponential) model for the outcome.

When the outcome is censored, eintreg estimates effects of endogenously or exogenously assigned treatments. eregress, eprobit, and eoprobit estimate effects of endogenously or exogenously assigned treatments, when the outcome is continuous, binary, or ordinal, respectively. All four commands can account for endogenous sample selection and endogenous covariates in combination with endogenous or exogenous treatment. See **[U] 27.13 Models with endogenous sample selection** and **[U] 27.12 Models with endogenous covariates**.

27.21 Pharmacokinetic data

There are four estimation commands designed for analyzing pharmacokinetic data. See [R] **pk** for an overview of the pk system.

1. pkexamine calculates pharmacokinetic measures from time-and-concentration subject-level data. pkexamine computes and displays the maximum measured concentration, the time at the maximum measured concentration, the time of the last measurement, the elimination time, the half-life, and the area under the concentration-time curve (AUC).
2. pksumm obtains the first four moments from the empirical distribution of each pharmacokinetic measurement and tests the null hypothesis that the distribution of that measurement is normally distributed.
3. pkcross analyzes data from a crossover design experiment. When one is analyzing pharmaceutical trial data, if the treatment, carryover, and sequence variables are known, the omnibus test for separability of the treatment and carryover effects is calculated.

4. pkequiv performs bioequivalence testing for two treatments. By default, pkequiv computes a CI for the ratio of treatment geometric means, calculated using log-scaled data. pkequiv can also calculate CIs using the original data, such as the classic shortest CI and a CI based on Fieller's theorem. Also, pkequiv performs interval hypothesis tests for bioequivalence, such as Schuirmann's two one-sided tests.

See [ME] **menl** for fitting pharmacokinetic models using nonlinear mixed-effects models.

27.22 Multivariate analysis

Stata's multivariate capabilities can be found in the *Multivariate Statistics Reference Manual*.

1. mvreg fits multivariate regressions.
2. manova provides MANOVA and MANCOVA (multivariate ANOVA and ANCOVA). The command fits MANOVA and MANCOVA models, one-way and up—including two-way factorial, three-way factorial, etc.—and it fits nested and mixed-design models.
3. canon estimates canonical correlations and their corresponding loadings. Canonical correlation attempts to describe the relationship between two sets of variables.
4. pca extracts principal components and reports eigenvalues and loadings. Some people consider principal components a descriptive tool—in which case standard errors as well as coefficients are relevant—and others look at it as a dimension-reduction technique.
5. factor fits factor models and provides principal factors, principal-component factors, iterated principal-component factors, and maximum likelihood solutions. Factor analysis is concerned with finding few common factors $\hat{\mathbf{z}}_k$, $k = 1, \ldots, q$, that linearly reconstruct the original variables $\mathbf{y}_i$, $i = 1, \ldots, L$.
6. tetrachoric, in conjunction with pca or factor, allows you to perform PCA or factor analysis on binary data.
7. rotate provides a wide variety of orthogonal and oblique rotations after factor and pca. Rotations are often used to produce more interpretable results.
8. procrustes performs Procrustes analysis, one of the standard methods of multidimensional scaling. It can perform orthogonal or oblique rotations as well as translation and dilation.
9. mds performs metric and nonmetric multidimensional scaling for dissimilarity between observations with respect to a set of variables. A wide variety of dissimilarity measures are available and, in fact, are the same as those for cluster.
10. ca performs correspondence analysis, an exploratory multivariate technique for analyzing cross-tabulations and the relationship between rows and columns.
11. mca performs multiple correspondence analysis (MCA) and joint correspondence analysis (JCA).
12. mvtest performs tests of multivariate normality along with tests of means, covariances, and correlations.
13. cluster provides cluster analysis; both hierarchical and partition clustering methods are available. Strictly speaking, cluster analysis does not fall into the category of statistical estimation. Rather, it is a set of techniques for exploratory data analysis. Stata's cluster environment has many different similarity and dissimilarity measures for continuous and binary data.

14. discrim and candisc perform discriminant analysis. candisc performs linear discriminant analysis (LDA). discrim also performs LDA, and it performs quadratic discriminant analysis (QDA), kth nearest neighbor (KNN), and logistic discriminant analysis. The two commands differ in default output. discrim shows the classification summary, candisc shows the canonical linear discriminant functions, and both will produce either.

For multivariate linear models that can include observed and latent variables, see **[U] 27.25 Structural equation modeling (SEM)**. To fit item response theory models to binary, ordinal, and nominal items, and their combinations, see **[U] 27.28 Item response theory (IRT)**. For multivariate time-series models, see **[U] 27.14 Time-series models**. To fit a multivariate meta-regression, see [META] **meta mvregress**.

27.23 Maximum likelihood estimation

Many of Stata's estimation commands fit models by using maximum likelihood estimation. If Stata does not have a command for the model you wish to fit and if you can specify the likelihood for the model, then you can use the mlexp command or the ml suite of commands to perform maximum likelihood estimation. mlexp is an easy-to-use command that does not require any programming; it does, however, require that you can write the log likelihood for each observation and that the overall log likelihood is the sum of the individual log likelihoods. ml can fit classes of models that do not meet these requirements, such as models for panel data; however, ml does require some programming.

27.24 Generalized method of moments (GMM)

gmm fits models using generalized method of moments (GMM). With the interactive version of the command, you enter your moment equations directly into the dialog box or command line using substitutable expressions just like with nl or nlsur. The moment-evaluator program version gives you greater flexibility in exchange for increased complexity; with this version, you write a program that calculates the moments based on a vector of parameters passed to it.

gmm can fit both single- and multiple-equation models, and you can combine moment conditions of the form $E\{\mathbf{z}_i u_i(\boldsymbol{\beta})\} = \mathbf{0}$, where $\mathbf{z}_i$ is a vector of instruments and $u_i(\boldsymbol{\beta})$ is often an additive regression error term, as well as more general moment conditions of the form $E\{\mathbf{h}_i(\mathbf{z}_i; \boldsymbol{\beta})\} = \mathbf{0}$. In the former case, you specify the expression for $u_i(\boldsymbol{\beta})$ and use the instruments() and xtinstruments() options to specify $\mathbf{z}_i$. In the latter case, you specify the expression for $\mathbf{h}_i(\mathbf{z}_i; \boldsymbol{\beta})$; because that expression incorporates your instruments, you do not use the instruments() or xtinstruments() option.

gmm supports cross-sectional, time-series, and panel data. You can request weight matrices and VCEs that are suitable for independent and identically distributed errors, that are suitable for heteroskedastic errors, that are appropriate for clustered observations, or that are heteroskedasticity- and autocorrelation-consistent (HAC). For HAC weight matrices and VCEs, gmm lets you specify the bandwidth or request an automatic bandwidth selection algorithm.

27.25 Structural equation modeling (SEM)

SEM stands for "structural equation modeling". The sem and gsem commands fit SEM.

sem fits standard linear SEMs. gsem fits what we call generalized SEMs, generalized to allow for generalized linear responses and multilevel modeling.

Generalized linear means, among other types of responses, binary responses such as probit and logit, count responses such as Poisson and negative binomial, categorical responses such as multinomial logit, ordered responses such as ordered probit and ordered logit, censored responses such as tobit, and survival responses such as exponential and Weibull. Generalized linear includes linear responses.

Multilevel modeling allows for nested effects, such as patient within doctor and patients within doctor within hospital, and crossed effects, such as occupation and industry.

Let's start with `sem`. `sem` can fit models ranging from linear regression to measurement models to simultaneous equations, including confirmatory factor analysis (CFA) models, correlated uniqueness models, latent growth models, and multiple indicators and multiple causes (MIMIC) models. You can obtain standardized or unstandardized results, direct and indirect effects, goodness-of-fit statistics, modification indices, score tests, Wald tests, linear and nonlinear tests of estimated parameters, and linear and nonlinear combinations of estimated parameters with CIs. You can perform estimation across groups with easy model specification and easy-to-use tests for group invariance. This can all be done using raw or summary statistics data. In addition, `sem` optionally can use full information maximum-likelihood (FIML) estimation to handle observations containing missing values.

`gsem` extends the types of models that can be fit. Responses may be continuous, ordinal, count, categorical, or survival time, and `gsem` allows for multilevel modeling. Latent variables can be included at any level. This allows for fitting models with random intercepts and random slopes. These random effects may be nested or crossed.

There is considerable overlap in the capabilities of `sem` and `gsem`. Whenever there is overlap, `sem` is faster and sometimes easier to use.

The generalized response variables allowed by `gsem` permit fitting measurement models with different types of responses, latent growth models with different types of responses, and so on.

`gsem` can also fit item response theory (IRT) models, multilevel CFA models, models for latent class analysis (LCA), finite mixture models (FMMs), multilevel mixed-effects models, and multilevel structural equation models. See **[U] 27.28 Item response theory (IRT)**, **[U] 27.26 Latent class models**, and **[U] 27.27 Finite mixture models (FMMs)**.

Where appropriate, results can be reported in exponentiated form to provide odds ratios, incidence-rate ratios, and relative-risk ratios. You can also obtain predictions, likelihood-ratio tests, Wald tests, predictive margins, contrasts, and pairwise comparisons.

Whether fitting a model with `sem` or `gsem`, you can specify your model by typing the command or by using the SEM Builder to draw path diagrams.

For those of you unfamiliar with SEM, it is worth your time to learn about it if you ever fit linear regressions, logistic regressions, ordered logit regressions, ordered probit regressions, Poisson regressions, seemingly unrelated regressions, multivariate regressions, simultaneous systems, measurement-error models, selection models, endogenous treatment-effects models, tobit models, survival models, fractional response models, or multilevel mixed-effects models.

You may also want to learn about SEM if you are interested in GMM. `sem` and `gsem` fit many of the same models by maximum likelihood and quasimaximum likelihood that you can fit by GMM.

sem and gsem can be used to fit many models that can be fit by other Stata commands. The advantage of using sem and gsem is in the extensions they can provide. They allow for introduction of latent variables to account for measurement error, simultaneous equations with different types of responses, multilevel versions of popular models such as selection models, and more.

See the *Stata Structural Equation Modeling Reference Manual*; in particular, see [SEM] **Intro 5**.

27.26 Latent class models

Latent class models (LCMs) are used to identify and understand unobserved groups in a population. Individuals in the population are assumed to be divided among these unobserved subpopulations called classes. The classes are represented by one or more categorical latent variables. LCMs often include a group of observed variables that are thought of as being measurements or indicators of class membership. The parameters in the models for these observed variables are allowed to vary across classes. In addition to modeling the observed variables, we also model the probability of being in each class.

After fitting an LCM, we can estimate the proportion of individuals in the population who belong to each class. We can also predict each individual's probability of belonging to each class.

We use LCM to refer to any model that includes categorical latent variables. In some literature, LCMs are more narrowly defined to include only categorical latent variables and the binary or categorical observed measurement variables, but we do not make such a restriction. Other labels closely associated with LCMs are latent class analysis, latent cluster models, latent cluster analysis, latent profile models, latent profile analysis, and finite mixture models. Each of these models can be fit as an LCM in Stata. See [SEM] **Intro 5**.

You fit latent class models in Stata by specifying the lclass() option with gsem. See the *Stata Structural Equation Modeling Reference Manual*; in particular, see [SEM] **Intro 1**, [SEM] **Intro 2**, [SEM] **Intro 5**, [SEM] **Example 50g**, and [SEM] **Example 52g**.

27.27 Finite mixture models (FMMs)

Finite mixture models (FMMs) are used to classify observations, to adjust for clustering, and to model unobserved heterogeneity. In finite mixture modeling, the observed data are assumed to belong to unobserved subpopulations called classes, and mixtures of probability densities or regression models are used to model the outcome of interest.

You can use FMMs to estimate the means and variances of the underlying densities for each unobserved subpopulation. Along with densities, they allow mixtures of regression models for continuous, binary, ordinal, categorical, count, fractional, and survival outcomes, where parameters are allowed to vary across subpopulations. You also can use FMMs to estimate each subpopulation's proportion in the overall population. In addition, FMMs allow the inclusion of covariates that model the probability of being in each subpopulation.

You fit FMMs in Stata by specifying the fmm prefix with the number of subpopulations; see [FMM] **fmm estimation** for models that can be specified as FMMs.

The *Stata Finite Mixture Models Reference Manual* provides complete documentation of Stata's finite mixture modeling features. See [FMM] **fmm intro** for an overview of FMMs and an introductory example.

27.28 Item response theory (IRT)

Item response theory (IRT) is used in the design, analysis, scoring, and comparison of tests and similar instruments whose purpose is to measure a latent trait. Latent traits cannot be measured directly because they are unobservable, but they can be quantified with an instrument. An instrument is simply a collection of items designed to measure a person's level of the latent trait. For example, a researcher interested in measuring mathematical ability (latent trait) may design a test (instrument) consisting of 100 questions (items).

When designing the instrument or analyzing data from the instrument, the researcher is interested in how each individual item relates to the trait and how the group of items as a whole relates to the trait. IRT models allow us to study these relationships.

Stata provides a suite of IRT estimation commands to fit a variety of models for binary responses and categorical responses. Models can also be combined. The available commands are the following:

Command	Description	Response
`irt 1pl`	One-parameter logistic model	binary
`irt 2pl`	Two-parameter logistic model	binary
`irt 3pl`	Three-parameter logistic model	binary
`irt grm`	Graded response model	categorical
`irt nrm`	Nominal response model	categorical
`irt pcm`	Partial credit model	categorical
`irt gpcm`	Generalized partial credit model	categorical
`irt rsm`	Rating scale model	categorical
`irt hybrid`	Hybrid IRT model	combination

A major concept in IRT is the item characteristic curve (ICC). The ICC maps the relationship between the latent trait and the probability that a person "succeeds" on a given item (individual test question). `irtgraph icc` can be used to plot the ICCs for items after any of the models above.

`irtgraph tcc` is used to plot the test characteristic curve (TCC), which shows the relationship between the expected score on the whole test and the latent trait. Plots of the item information and test information can be obtained with `irtgraph iif` and `irtgraph tif`.

Researchers are often interested in determining whether an instrument measures the latent trait in the same way for different groups. Multiple-group IRT models allow parameters to differ across groups and can be fit by adding the `group()` option to any of the `irt` commands.

See [IRT] **irt** for more information.

27.29 Dynamic stochastic general equilibrium (DSGE) models

DSGE models are time-series models used in economics for policy analysis and forecasting. The models are derived from macroeconomic theory and include multiple equations. A key feature of these models is that expectations of future variables affect variables today; this distinguishes DSGE models from other multivariate time-series models. Another key feature is that, being derived from theory, the parameters can usually be interpreted in terms of that theory.

The `dsge` and `dsgenl` commands fit DSGE models. `dsgenl` fits nonlinear DSGE models, and `dsge` fits linear DSGE models. See the *Stata Dynamic Stochastic General Equilibrium Models Reference Manual*; in particular, [DSGE] **Intro 1**.

Bayesian estimation of DSGE models is available by using the `bayes: dsge` and `bayes: dsgenl` commands (see [BAYES] **bayes: dsge**, [BAYES] **bayes: dsgenl**, and [DSGE] **Intro 9**). Bayesian estimation allows you to incorporate external information about model parameters often available in practice; see [DSGE] **Intro 9b**. After estimation using `bayes: dsge` or `bayes: dsgenl`, you can perform IRF analysis by using [BAYES] **bayesirf**.

27.30 Lasso

Lasso simultaneously performs model selection and estimation. The set of candidate models for which you may consider using lasso is much larger than what can be evaluated with traditional model selection techniques, such as comparisons of Akaike or Bayesian information criteria. Because it allows simultaneous model selection and estimation and is feasible for very large models, lasso is one of the most popular and widely used machine learning tools.

Lasso is a solution to a penalized optimization problem for continuous, binary, count, and survival-time outcomes. Without the penalty, lasso would give the same solutions as traditional likelihood-based estimators. The penalty forces some of the variables to be excluded from the model. In other words, the penalty is what determines the model selection properties of the lasso. For more information on the lasso penalty, see [LASSO] **lasso**.

Related to lasso are the elastic net and the square-root lasso estimators. Both the elastic net and the square-root lasso have the model selection and estimation characteristics of lasso. The difference between lasso, elastic net, and square-root lasso is how they penalize the model. The elastic net penalty yields an estimator that works better than lasso when groups of variables are highly correlated. The square-root lasso is equivalent to the lasso but allows for easier computation of the penalty parameters. For more information on elastic net and square-root lasso, see [LASSO] **elasticnet** and [LASSO] **sqrtlasso**.

With Stata, you may use `lasso`, `elasticnet`, and `sqrtlasso` to implement the estimators mentioned above and to do out-of-sample predictions. You may also use these commands with random subsamples of the data used for training, validation, and prediction. You can use `splitsample` to easily split your data into such subsamples.

You can also go beyond prediction. You can use lasso to obtain inferences with double-selection lasso, partialing-out lasso, and cross-fit partialing-out lasso. These estimators allow you to estimate effects and perform tests on coefficients for a fixed and known set of covariates, while also performing model selection using lasso for a potentially large set of control variables. The following inferential lasso commands fit models with continuous, binary, and count outcomes:

Command	Description
`dsregress`	Double-selection lasso linear regression
`dslogit`	Double-selection lasso logistic regression
`dspoisson`	Double-selection lasso Poisson regression
`poregress`	Partialing-out lasso linear regression
`pologit`	Partialing-out lasso logistic regression
`popoisson`	Partialing-out lasso Poisson regression
`poivregress`	Partialing-out lasso instrumental-variables regression
`xporegress`	Cross-fit partialing-out lasso linear regression
`xpologit`	Cross-fit partialing-out lasso logistic regression
`xpopoisson`	Cross-fit partialing-out lasso Poisson regression
`xpoivregress`	Cross-fit partialing-out lasso instrumental-variables regression
`telasso`	Treatment-effects estimation using lasso

27.31 Survey data

Stata's svy command fits statistical models for complex survey data. svy is a prefix command, so to obtain linear regression, you type

```
. svy: regress ...
```

or to obtain probit regression, you type

```
. svy: probit ...
```

but you must first type a svyset command to define the survey design characteristics. Prefix svy works with many estimation commands, and everything is documented together in the *Stata Survey Data Reference Manual*.

svy supports the following variance-estimation methods:

- Taylor-series linearization
- Bootstrap
- Balanced repeated replication (BRR)
- Jackknife
- Successive difference replication (SDR)

See [SVY] **Variance estimation** for details.

svy supports the following survey design characteristics:

- With- and without-replacement sampling
- Observation-level sampling weights
- Stage-level sampling weights
- Stratification
- Poststratification
- Clustering
- Multiple stages of clustering without replacement
- BRR and jackknife replication weights

See [SVY] **svyset** for details. For an application of the svy prefix with stage-level sampling weights, see example 6 in [ME] **meglm**.

Subpopulation estimation is available for all estimation commands.

Tabulations and summary statistics are also available, including means, proportions, ratios, and totals over multiple subpopulations and direct standardization of means, proportions, and ratios.

See [SVY] **Survey**.

27.32 Multiple imputation

Multiple imputation (MI) is a statistical technique for estimation in the presence of missing data. If you estimate the parameters of y on x_1, x_2, and x_3 using any of the other Stata estimation commands, parameters are estimated on the data for which y, x_1, x_2, and x_3 contain no missing values. This process is known as listwise or casewise deletion because observations for which any of y, x_1, x_2, or x_3 contain

missing values are ignored or, said differently, deleted from consideration. MI is a technique to recover the information in those ignored observations when the missing values are missing at random (MAR) or missing completely at random (MCAR). Data are MAR if the probability that a value is missing may depend on observed data but not on unobserved data. Data are MCAR if the probability of missingness is not even a function of the observed data.

MI is named for the imputations it produces to replace the missing values in the data. MI does not just form replacement values for the missing data; it produces multiple replacements. The purpose is not to create replacement values as close as possible to the true ones but to handle missing data in a way resulting in valid statistical inference.

There are three steps in an MI analysis. First, one forms M imputations for each missing value in the data. Second, one fits the model of interest separately on each of the M resulting datasets. Finally, one combines those M estimation results into the desired single result.

The `mi` command does this for you. It can be used with most of Stata's estimation commands, including with survey, survival, and panel and multilevel models. See [MI] **Intro**.

27.33 Power, precision, and sample-size analysis

Sample-size determination is important for planning a study. It helps allocate the necessary resources to achieve the research objective of a study.

When a study uses hypothesis testing to make inference about parameters of interest, power and sample-size (PSS) analysis is used to investigate the optimal allocation of study resources to increase the likelihood of detecting the desired magnitude of the effect of interest. Additionally, for studies in which the data gathering process will take place over an extended period of time, it is common to conduct interim analyses as data trickle in, rather than a single analysis once all the data have been collected. A popular framework for conducting interim analyses while preserving type I error is the group sequential design. Group sequential designs allow researchers to stop a trial early, at one of these interim analyses, if they find compelling evidence that a treatment is effective or ineffective.

When a study uses CIs for inference, precision and sample-size (PrSS) analysis is used to estimate the required sample size to achieve the desired precision of a CI in a future study.

27.33.1 Power and sample-size analysis

PSS analysis is used to plan studies that will use hypothesis testing for inference. For example, suppose that we want to design a study to evaluate a new drug for lowering blood pressure. We want to test whether the mean blood pressure of the experimental group, which will receive the new drug, is the same as the mean blood pressure of the control group, which will receive the old drug. The post hoc analysis will use a two-sample t test to test the difference between the two means. How many subjects do we need to enroll in our study to detect a difference between means that is of clinical importance? PSS analysis can answer this question.

PSS analysis can also answer other questions that may arise during the planning stage of a study. For example, what is the power of a test given an available sample size, and how likely is it to detect an effect of interest given limited study resources? The answers to these questions may help reduce the cost of a study by preventing an overpowered study or may help avoid wasting resources on an underpowered study.

See [PSS-2] **Intro (power)** for more information about PSS analysis.

The power command performs PSS analysis. It provides PSS analysis for comparison of means, variances, proportions, correlations, and contingency tables. It also provides PSS analysis for simple and multiple linear regression and for survival analysis. One-sample, two-sample, and paired analyses of means, variances, proportions, and correlations are supported. Contingency table analyses may be performed for matched samples, $2 \times 2 \times K$ tables, or $2 \times J$ tables. For survival-time data, one-sample analysis is supported for Cox proportional hazards models; two-sample analysis is supported for parametric or nonparametric comparison of survivor functions.

The power command can also account for a cluster randomized design (CRD) for some analyses, such as one- and two-sample analyses of means and proportions. In a CRD, groups of subjects or clusters are randomized instead of individual subjects. As a result, observations within a cluster are usually correlated, which must be accounted for when performing PSS analysis.

You can also add your own PSS methods to the power command; see [PSS-2] ***power usermethod***.

power provides both tabular output and graphical output, or power curves; see [PSS-2] **power, table** and [PSS-2] **power, graph** for details.

See [PSS-2] **power** for a full list of supported methods and the description of the command.

You can work with power commands either interactively or via a convenient point-and-click interface; see [PSS-2] **GUI (power)** for details.

27.33.2 Precision and sample-size analysis

PrSS analysis is used to plan studies that will use CIs for inference. For example, suppose again that we want to design a study to evaluate a new drug for lowering blood pressure. We now want to estimate the difference in the mean blood pressure of the experimental group, which will receive the new drug, and the mean blood pressure of the control group, which will receive the old drug. We will compute a two-sided 95% CI for the difference between the two means. How many subjects do we need to enroll in our study to obtain a CI that is narrow enough to draw inferences that are meaningful? PrSS analysis can answer this question.

PrSS analysis can also answer other questions that may arise during the planning stage of a study. For example, what is the width of a CI that can be obtained given an available sample size, and how likely is it that we obtain a CI of a specific width given limited study resources? The answers to these questions may help reduce costs by limiting the number of subjects in a study. They may also help prevent completing a study only to find that it had too few subjects to obtain a CI narrow enough to be useful.

See [PSS-3] **Intro (ciwidth)** for more information about PrSS analysis.

The ciwidth command performs PrSS analysis. It provides PrSS analysis for CIs for a mean or a variance. It also provides PrSS analysis for the difference in two means from independent samples and the difference in two means from paired samples.

You can also add your own PrSS methods to the ciwidth command; see [PSS-3] ***ciwidth usermethod***.

ciwidth provides both tabular output and graphical output, or sample-size curves; see [PSS-3] **ciwidth, table** and [PSS-3] **ciwidth, graph** for details.

See [PSS-3] **ciwidth** for a full list of supported methods and the description of the command.

You can work with ciwidth commands either interactively or via a convenient point-and-click interface; see [PSS-3] **GUI (ciwidth)** for details.

27.33.3 Group sequential designs

Group sequential designs (GSDs) are a type of adaptive design that allow researchers to stop a trial early if they find compelling evidence that a treatment is effective or ineffective. Suppose that we want to design a study to test whether the chemotherapy medicine sunitinib is effective for treating tumors. Also, suppose that we anticipate data collection to take place over three years. Rather than performing a single analysis once all the data have been collected, we can perform interim analyses as data trickle in. Suppose we perform the interim analyses every six months; for each interim analysis, we can test whether we have enough evidence to claim that sunitinib is effective or ineffective. If we find strong evidence of efficacy at the first interim analysis, we can terminate the study and proceed to applying for regulatory approval sooner rather than later. On the other hand, if we find strong evidence of inefficacy, we can terminate the trial because of futility and avoid exposing additional participants to this inadequate treatment. GSDs provide criteria for making these decisions at each interim analysis.

GSDs allow us to test for efficacy and futility at each interim analysis. With the `gsbounds` command, we can compute stopping boundaries for GSDs, and with the `gsdesign` commands, we can also compute sample sizes for the interim analyses. Stopping boundaries and sample sizes can be obtained for a one-sample mean or proportion test, two-sample means or proportions test, and a log-rank test.

You can also add your own GSD methods to the `gsdesign` command; see [ADAPT] ***gsdesign user-method***.

The `gsbounds` command and `gsdesign` suite of commands provide both tabular output and graphical output. See [ADAPT] **gsdesign** for a full list of supported methods and the description of the suite of commands.

27.34 Bayesian analysis

Bayesian analysis is a statistical analysis that answers research questions about unknown parameters of statistical models by using probability statements. Bayesian analysis rests on the assumption that all model parameters are random quantities and are subject to prior knowledge. This assumption is in sharp contrast with more traditional, frequentist analysis where all parameters are considered unknown but fixed quantities.

Bayesian analysis is based on modeling and summarizing the posterior distribution of parameters conditional on the observed data. The posterior distribution is composed of a likelihood distribution of the data and the prior distribution of the model parameters. Many posterior distributions do not have a closed form and must be approximated using, for example, Markov chain Monte Carlo (MCMC) methods such as Metropolis–Hastings (MH) methods, the Gibbs method, or sometimes their combination. The convergence of MCMC must be verified before any inference can be made. Once convergence is established, model checking can be performed by comparing various aspects of the distribution of the observed data with those of data that are simulated based on the fitted Bayesian model.

In Bayesian analysis, marginal posterior distributions of parameters are used for inference. They are summarized using point estimators, such as posterior mean and median, and using interval estimators, such as equal-tailed credible intervals and highest-posterior density intervals.

Stata provides a suite of commands for conducting Bayesian analysis. Bayesian estimation ([BAYES] **Bayesian estimation**) consists of the `bayes` prefix for fitting a variety of Bayesian regression models and the `bayesmh` command for fitting general Bayesian models. Both commands offer three MCMC sampling methods: an adaptive MH sampling, a Gibbs sampling, or a combination of the two. You can choose from a variety of supported Bayesian models, including panel-data, mul-

tilevel, and time-series models, or you can program your own Bayesian models; see [BAYES] **bayes**, [BAYES] **bayesmh**, and [BAYES] **bayesmh evaluators**. You can also perform Bayesian variable selection; see [BAYES] **bayesselect**.

Convergence of MCMC can be assessed visually using `bayesgraph`, and Gelman–Rubin convergence diagnostics can be computed using `bayesstats grubin`. Model checking can be performed using `bayespredict` and `bayesstats ppvalues`. Marginal summaries can be obtained using `bayesstats summary`, and hypothesis testing can be performed using `bayestest`; see [BAYES] **Bayesian postestimation**. Special-interest postestimation commands are also available to produce Bayesian forecasts ([BAYES] **bayesfcast**) after VAR models ([BAYES] **bayes: var**), and IRF analysis is available after VAR and linear and nonlinear DSGE models ([BAYES] **bayes: dsge** and [BAYES] **bayes: dsgenl**.

See [BAYES] **Bayesian commands** for more information about commands and for a quick *Overview example*.

27.35 Bayesian model averaging

Instead of fitting a single model, you can use Bayesian model averaging (BMA) to combine the results from multiple plausible models according to Bayesian principles to account for model uncertainty. See *Brief motivation* in *Remarks and examples* in [BMA] **Intro**.

In the regression framework, model uncertainty amounts to the uncertainty of which predictors should be included in the regression model. The `bmaregress` command performs BMA for a linear regression and can be used for inference, prediction, or model selection; see [BMA] **bmaregress**.

After using `bmaregress`, you can check for convergence with `bmagraph pmp` and use it and `bmastats models` to examine which models are more likely given the assumed prior and observed data, that is, have higher posterior model probabilities; see [BMA] **bmagraph pmp** and [BMA] **bmastats models**. You can use the `bmastats pip` command to identify important predictors—predictors that have a high probability of being included in a model based on the prior information and observed data; see [BMA] **bmastats pip**. You can use the `bmagraph varmap` command to more conveniently visualize both the influential models and predictors; see [BMA] **bmagraph varmap**. And you can use `bmastats jointness` to explore the joint importance of predictors across the considered models—whether variables tend to appear together in the models or separately; see [BMA] **bmastats jointness**. `bmastats msize` and `bmagraph msize` can be used to explore the summaries and the distribution of the model size to explore the complexity of a BMA model; see [BMA] **bmastats msize** and [BMA] **bmagraph msize**.

The above features allow you to perform model-choice analysis, but you can also use BMA for prediction. The `bmapredict` command computes various posterior predictive summaries such as predictive means and credible intervals, simulates a new outcome, and generates outcome replications; see [BMA] **bmapredict**. You can then use the `bmastats lps` command to evaluate the predictive performance of your BMA model by using the log predictive-score; see [BMA] **bmastats lps**.

Finally, when parameter averaging is applicable, you can perform inference for the regression coefficients. As in standard Bayesian analysis, your coefficient estimate is not just a single value but an entire distribution. In BMA analysis, this distribution additionally accounts for model uncertainty. You can use the `bmagraph coefdensity` command to explore this distribution; see [BMA] **bmagraph coefdensity**. More generally, you can use the `bmacoefsample` command to simulate an MCMC sample of regression coefficients and other model parameters (see [BMA] **bmacoefsample**) and, after that, use many of the standard Bayesian tools for inference; see [BAYES] **bayesstats summary** and [BAYES] **bayesgraph** for details.

See the full list of postestimation features in [BMA] **BMA postestimation**.

See [BMA] **Intro** and [BMA] **BMA commands** for more information about BMA and Stata commands for BMA analysis.

27.36 H2O machine learning

Machine learning methods are often used to solve research and business problems focused on prediction when the problems require more sophisticated modeling approaches than, for instance, linear regression or generalized linear models. Ensemble decision tree methods, which combine multiple decision trees to improve predictive performance, are popular and effective machine learning methods for solving such problems. H2O is a scalable and distributed machine learning and predictive analytics platform that allows you to perform data analysis and machine learning, including ensemble decision tree methods such as random forest and gradient boosting machine.

The `h2oml` suite of Stata commands is a wrapper for H2O and provides end-to-end support for H2O machine learning analysis using ensemble decision tree methods. In addition to `h2oml`, the `_h2oframe` command provides several key subcommands that connect Stata to an H2O cluster, import a Stata dataset into an H2O frame, and provide various H2O data management; see [H2OML] **H2O setup**.

`h2oml` *gbm* and `h2oml` *rf* provide the suite of estimation commands that implement gradient boosting and random forest regression, binary classification, and multiclass classification. `h2oml gbregress` and `h2oml rfregress` perform respective gradient boosting and random forest regressions for continuous and count responses; `h2oml gbbinclass` and `h2oml rfbinclass` perform gradient boosting and random forest classifications for binary responses; and `h2oml gbmulticlass` and `h2oml rfmulticlass` perform gradient boosting and random forest classifications for categorical responses (with more than two categories).

Each of these estimation commands allows you to use a validation frame or perform cross-validation to control for overfitting. They allow you to tune a variety of hyperparameters and to stop early for better model performance. Many commands also offer specialized options. For instance, `h2oml gbregress` allows you to choose from loss functions including quantile, Huber, and Tweedie. See [H2OML] ***h2oml gbm*** and [H2OML] ***h2oml rf*** for details.

After estimation, the `h2omlest` suite of commands can be used to manage estimation results. For instance, `h2omlest store` can be used to store the current estimation results for later use.

A number of postestimation commands are available to obtain tuning and estimation summaries. For instance, `h2omlestat gridsummary` is useful to view the results after tuning and select an alternative model that is more parsimonious. And `h2omlgraph scorehistory` can be used to display various validation curves to help monitor overfitting.

For binary and multiclass classifications, several commands can be used to explore model performance such as the `h2omlestat confmatrix` command, which displays the confusion matrix. Additionally, `h2omlgraph prcurve` and `h2omlgraph roc` can be used to plot precision–recall and receiver operating characteristic (ROC) curves after binary classification, and `h2omlestat hitratio` can be used to produce a hit-ratio table after multiclass classification.

The ultimate goal of machine learning is to obtain accurate prediction of the response on the new data. To achieve this goal, we often evaluate the model predictive performance by using an external, testing dataset. The `h2omlpostestframe` command provides a convenient way to specify the desired testing frame to be used in all subsequent postestimation analyses.

Depending on the estimation method, regression or classification, the `h2omlpredict` command produces predictions of continuous and count responses or class probabilities and classes.

Machine learning methods are often treated as a black box, meaning that little attempt is made to understand the obtained predictions. To rectify this, `h2oml` provides several postestimation commands to help explain predictions. The `h2omlgraph varimp` command can be used to assess the overall importance of predictors in the model, whereas the `h2omlgraph shapvalues` and `h2omlgraph shapsummary` commands can be used to explore the impact of predictors on individual predictions.

Finally, the `h2omltree` command can be used to save a specific decision tree in a DOT file and plot it by using the open-source software Graphviz; see [H2OML] **DOT extension**.

For more details about postestimation commands, see [H2OML] **h2oml postestimation**.

For more information about the `h2oml` command and its use with real-world data, see [H2OML] **h2oml**.

27.37 Reference

Gould, W. W. 2011. Use poisson rather than regress; tell a friend. *The Stata Blog: Not Elsewhere Classified*. https://blog.stata.com/2011/08/22/use-poisson-rather-than-regress-tell-a-friend/.

28 Commands everyone should know

Putting aside the statistical commands that might particularly interest you, here is a list of commands that everyone should know:

Getting help	
`help`, `net search`, `search`	**[U] 4 Stata's help and search facilities**
Keeping Stata up to date	
`ado`, `net`, `update`	**[U] 29 Using the internet to keep up to date**
`ado update`	[R] **ado update**
Operating system interface	
`pwd`, `cd`	[D] **cd**
Using and saving data from disk	
`save`	[D] **save**
`use`	[D] **use**
`compress`	[D] **compress**
Inputting data into Stata	**[U] 22 Entering and importing data**
`import`	[D] **import**
`edit`	[D] **edit**
Basic data reporting	
`describe`	[D] **describe**
`codebook`	[D] **codebook**
`list`	[D] **list**
`browse`	[D] **edit**
`count`	[D] **count**
`inspect`	[D] **inspect**
`table`	[R] **table**
`tabulate`	[R] **tabulate oneway** and [R] **tabulate twoway**
`summarize`	[R] **summarize**
Data manipulation	**[U] 13 Functions and expressions**
`append`, `merge`	**[U] 23 Combining datasets**
`generate`, `replace`	[D] **generate**
`egen`	[D] **egen**
`rename`	[D] **rename**, [D] **rename group**
`clear`	[D] **clear**
`drop`, `keep`	[D] **drop**
`sort`	[D] **sort**
`encode`, `decode`	[D] **encode**
`order`	[D] **order**
`by`	**[U] 11.5 by varlist: construct**
`reshape`	[D] **reshape**
`frames`	[D] **frames**

Graphing data	
`graph`	*Stata Graphics Reference Manual*
Keeping track of your work	
`log`	**[U] 15 Saving and printing output—log files**
`notes`	[D] **notes**
various	*Stata Reporting Reference Manual* and *Stata Customizable Tables and Collected Reference Manual*
Convenience	
`display`	[R] **display**

29 Using the internet to keep up to date

Contents

29.1 Overview

Stata can read files over the internet. Just to prove that to yourself, type the following:

```
. use https://www.stata.com/manual/chapter28, clear
```

You have just reached out and gotten a dataset from our website. The dataset is not in HTML format, nor does this have anything to do with your browser. We just copied the Stata data file `chapter28.dta` onto our server, and now people all over the world can use it. If you have a website, you can do the same thing. It is a convenient way to share datasets with colleagues.

Now type the following:

```
. update query
```

We promise that nothing bad will happen. `update` will read a short file from www.stata.com that will allow Stata to report whether your copy of Stata is up to date. Is your copy up to date? Now you know. If it is not, we will show you how to update it—it is no harder than typing `update`.

Now type the following:

```
. net from https://www.stata.com
```

That will go to www.stata.com and tell you what is available from our user-download site. The material there is not official, but it is useful. More useful is to type

```
. search kernel regression, net
```

or equivalently,

```
. net search kernel regression
```

That will search the entire web for additions to Stata having to do with kernel regression, whether the additions are from the *Stata Journal*, Statalist, archive sites, or private user sites.

To summarize: Stata can read files over the internet:

1. You can share datasets, do-files, etc., with colleagues all over the world. This requires no special expertise, but you do need to have a website.
2. You can update Stata; it is free and easy.
3. You can find and add new features to Stata; it is also free and easy.

Finally, you can create a site to distribute new features for Stata.

29.2 Sharing datasets (and other files)

There is just nothing to it: you copy the file as-is (in binary) onto the server and then let your colleagues know the file is there. This works for `.dta` files, `.do` files, `.ado` files, and, in fact, all files.

On the receiving end, you can `use` the file (if it is a `.dta` dataset) or you can copy it:

```
. use https://www.stata.com/manual/chapter28, clear
. copy https://www.stata.com/manual/chapter28.dta mycopy.dta
```

Stata includes a copy-file command and it works over the internet just as `use` does; see [D] **copy**.

29.3 Official updates

Although we follow no formal schedule for the release of updates, we typically provide updates to Stata approximately once a month. You do not have to update that often, although we recommend that you do. There are two ways to check whether your copy of Stata is up to date:

select	or type
Help > Check for updates	`. update query`

After that if an update is available, you should

click on	or type
Install available updates	`. update all`

After you have updated your Stata, to find out what has changed

select	or type
Help > What's new?	`. help whatsnew`

29.3.1 Frequently asked questions about updating

1. Could something go wrong and make my Stata become unusable?

   No. The updates are copied to a temporary place on your computer, Stata examines them to make sure they are complete before copying them to the official place. Thus either the updates are installed or they are not.

2. I do not have access to the internet from within Stata. Is there a way to update Stata manually?

   Yes. Open your web browser to https://www.stata.com/support/updates/ and follow the instructions on that page.

29.4 Downloading and managing additions by users

Try the following:

select
Help > SJ and community-contributed features

or type
`. net from https://www.stata.com`

and click on one of the links.

29.4.1 Downloading files

We are not the only ones developing additions to Stata. Stata is supported by a large and highly competent user community. An important part of this is the *Stata Journal* (SJ). The *Stata Journal* is a refereed, quarterly journal containing articles of interest to Stata users. For more details and subscription information, visit the *Stata Journal* website at https://www.stata-journal.com.

The *Stata Journal* is a printed and electronic journal with corresponding software. If you want the journal, you must subscribe, but the software is available for free; see the instructions below.

Installing software from the Stata Journal

1. From within Stata, select **Help > SJ and community-contributed features**.
2. Click on *Stata Journal*.
3. Click on *sj10-4*.
4. Click on *st0015_6*.
5. Click on *click here to install*.

or

1. Type `. net from https://www.stata-journal.com/software`
2. Type `. net cd sj10-4`
3. Type `. net describe st0015_6`
4. Type `. net install st0015_6`

The above could be shortened to

```
. net from https://www.stata-journal.com/software/sj10-4
. net describe st0015_6
. net install st0015_6
```

You could also type

```
. net sj 10-4
. net describe st0015_6
. net install st0015_6
```

29.4.2 Managing files

You now have the `concord` command, because we just downloaded and installed it. Convince yourself of this by typing

```
. help concord
```

and you might try it out, too. Let's now list the additions you have installed—that is probably just `concord`—and then get rid of `concord`.

In command mode, you can type

```
. ado dir
[1] package st0015_6 from https://www.stata-journal.com/software/sj10-4
     SJ10-4 st0015_6. Update: Concordance correlation...
```

If you had more additions installed, they would be listed. Now knowing that you have *st0015_6* installed, you can obtain a more thorough description by typing

```
. ado describe st0015_6
  (output omitted)
```

You can erase *st0015_6* by typing

```
. ado uninstall st0015_6
package package st0015_6 from https://www.stata-journal.com/software/sj10-4
     SJ10-4 st0015_6. Update: Concordance correlation...
(package uninstalled)
```

You can do all of this from the point-and-click interface, too. Pull down **Help** and select **SJ and community-contributed features** and then click on *List*. From there, you can click on *st0015_6* to see the detailed description of the package and from there you can click on *click here to uninstall* if you want to erase it.

For more information on the `ado` command and the corresponding menu, see [R] **net**.

29.4.3 Finding files to download

There are two ways to find useful files to download. One is simply to thumb through sites. That is inefficient but entertaining. If you want to do that,

1. Select **Help > SJ and community-contributed features**.
2. Click on *Other Locations*.
3. Click on *links*.

What you are doing is starting at our download site and then working out from there. We maintain a list of other sites and those sites will have more links. You can do this from command mode, too:

```
. net from https://www.stata.com
. net cd links
```

The efficient way to find files is to search; that is, use Stata's `search` command:

```
. search concordance correlation
```

Equivalently, you could select **Help > Search...**. Either way, you will learn about *st0015_6* and you can even click to install it.

29.4.4 Updating additions by users

After you have installed some community-contributed features, you should periodically check whether any updates or bug fixes are available for those commands. You can do this with the `ado update` command. Simply type `ado update` to see if any updates are available, and if they are, type `ado update, update` to obtain the updates. See [R] **ado update** for more details.

29.4.5 Video example

How to download and install user-written commands in Stata

29.5 Making your own download site

There are two reasons you may wish to create your own download site:

1. You have datasets and the like, you want to share them with colleagues, and you want to make it easier for colleagues to download the files.
2. You have written Stata programs, etc., that you wish to share with the Stata user community.

Before you create your own download site, you may wish to submit a command you have written to the Statistical Software Components (SSC) Archive. The SSC Archive contains the largest repository of community-contributed Stata software on the web. Stata has a command (see [R] **ssc**) that makes it easy to find and install packages from the SSC.

For information about submitting a command you have written to the SSC, see http://repec.org/bocode/s/sscsubmit.html.

If you do wish to create your own download site, making one is easy; the full instructions are found in [R] **net**.

At the beginning of this chapter, we pretended that you had a dataset you wanted to share with colleagues. We said you just had to copy the dataset onto your server and then let your colleagues know the dataset is there.

Let's now pretend that you had two datasets, `ds1.dta` and `ds2.dta`, and you wanted your colleagues to be able to learn about and fetch the datasets by using the `net` command or by pulling down **Help** and selecting **SJ and community-contributed commands**.

First, you would copy the datasets to your home page just as before. Then you would create three more files, one to describe your site named `stata.toc` and two more to describe each "package" you want to provide:

begin `stata.toc`

```
v 3
d My name and affiliation (or whatever other title I choose)
d Datasets for the PAR study
p ds1 The base dataset
p ds2 The detail dataset
```

end `stata.toc`

begin ds1.pkg
```
v 3
d ds1.  The base dataset
d My name or whatever else I wanted to put
d This dataset contains the baseline values for ...
d Distribution-Date: 26sep2024
p ds1.dta
```
end ds1.pkg

begin ds2.pkg
```
v 3
d ds1.  The detail dataset
d My name or whatever else I wanted to put
d This dataset contains the follow-up information ...
d Distribution-Date: 26sep2024
p ds2.dta
```
end ds2.pkg

The `Distribution-Date` line in the description should be changed whenever you change your package. This line is used by `ado update` to determine if a user who has installed your package needs to update it.

Here is what users would see when they went to your site:

```
. net from http://www.myuni.edu/hande/~aparker
------------------------------------------------------------------------------
http://www.myuni.edu/hande/~aparker
My name and whatever else I wanted to put
------------------------------------------------------------------------------

Datasets for the PAR study

PACKAGES you could -net describe-:
    ds1               The base dataset
    ds2               The detail dataset
------------------------------------------------------------------------------


. net describe ds1
------------------------------------------------------------------------------
package ds1 from http://www.myuni.edu/hande/~aparker
------------------------------------------------------------------------------

TITLE
      ds1.  The base dataset

DESCRIPTION/AUTHOR(S)
      My name and whatever else I wanted to put
      This dataset contains the baseline values for ...
      Distribution-Date: 26sep2024

ANCILLARY FILES                                    (type net get ds1)
      ds1.dta
------------------------------------------------------------------------------


. net get ds1
checking ds1 consistency and verifying not already installed...

copying into current directory...
      copying  ds1.dta
ancillary files successfully copied.

. _
```

See [R] **net**.

Glossary

ASCII. ASCII stands for American Standard Code for Information Interchange. It is a way of representing text and the characters that form text in computers. It can be divided into two sections: plain, or lower, ASCII, which includes numbers, punctuation, plain letters without diacritical marks, whitespace characters such as space and tab, and some control characters such as carriage return; and extended ASCII, which includes letters with diacritical marks as well as other special characters.

Before Stata 14, datasets, do-files, ado-files, and other Stata files were encoded using ASCII.

binary 0. Binary 0, also known as the null character, is traditionally used to indicate the end of a string, such as an ASCII or UTF-8 string.

Binary 0 is obtained by using `char(0)` and is sometimes displayed as `\0`. See **[U] 12.4.10 strL variables and binary strings** for more information.

binary string. A binary string is, technically speaking, any string that does not contain text. In Stata, however, a string is only marked as binary if it contains binary 0, or if it contains the contents of a file read in using the `fileread()` function, or if it is the result of a string expression containing a string that has already been marked as binary.

In Stata, `strL` variables, string scalars, and Mata strings can store binary strings.

See **[U] 12.4.10 strL variables and binary strings** for more information.

BLOB. BLOB is database jargon for binary large object. In Stata, BLOBs can be stored in `strL`s. Thus `strL`s can contain BLOBs such as Word documents, JPEG images, or anything else. See *strL*.

byte. Formally, a byte is eight binary digits (bits), the units used to record computer data. Each byte can also be considered as representing a value from 0 through 255. Do not confuse this with Stata's `byte` variable storage type, which allows values from −127 to 100 to be stored. With regard to strings, all strings are composed of individual characters that are encoded using either one byte or several bytes to represent each character.

For example, in UTF-8, the encoding system used by Stata, byte value 97 encodes "a". Byte values 195 and 161 in sequence encode "á".

characteristics. Characteristics are one form of metadata about a Stata dataset and each of the variables within the dataset. They are typically used in programming situations. For example, the xt commands need to know the name of the panel variable and possibly the time variable. These variable names are stored in characteristics within the dataset. See **[U] 12.8 Characteristics** for an overview and **[P] char** for a technical description.

code pages. A code page maps extended ASCII values to a set of characters, typically for a specific language or set of languages. For example, the most commonly used code page is Windows-1252, which maps extended ASCII values to characters used in Western European languages. Code pages are essentially encodings for extended ASCII characters.

code point. A code point is the numerical value or position that represents a single character in a text system such as ASCII or Unicode. The original ASCII encoding system contains only 128 code points and thus can represent only 128 characters. Historically, the 128 additional bytes of extended ASCII have been encoded in many different and inconsistent ways to provide additional sets of 128 code points. The formal Unicode specification has 1,114,112 possible code points, of which roughly 250,000 have been assigned to actual characters. Stata uses UTF-8 encoding for Unicode. Note that the UTF-8–encoded version of a code point does not have the same numeric value as the code point itself.

disambiguation: characters, and bytes, and display columns. A character is simply the letter or symbol that you want to represent—the letter "a", the punctuation mark ".", or a Chinese logogram. A byte or sequence of bytes is how that character is stored in the computer. And, a display column is the space required to display one typical character in the fixed-width display used by Stata's Results window and Viewer. Some characters are too wide for one display column. Each character is displayed in one or two display columns.

For plain ASCII characters, the number of characters always equals the number of bytes and equals the number of display columns.

For UTF-8 characters that are not plain ASCII, there are usually two bytes per character but there are sometimes three or even four bytes per character, such as for Chinese, Japanese, and Korean (CJK) characters. Characters that are too wide to fit in one display column (such as CJK characters) are displayed in two display columns.

In general, for Unicode characters, the relationship between the number of characters and the number of bytes and the relationship between the number of characters and the number of display columns is more ambiguous. All characters can be stored in four or fewer bytes and are displayed in Stata using two or fewer display columns.

See **[U] 12.4.2.1 Unicode string functions** and **[U] 12.4.2.2 Displaying Unicode characters** to learn how to deal with the distinction between characters, bytes, and display columns in your code.

display column. A display column is the space required to display one typical character in the fixed-width display used by Stata's Results window and Viewer. Some characters are too wide for one display column. Each character is displayed in one or two display columns.

All plain ASCII characters (for example, "M" and "9") and many UTF-8 characters that are not plain ASCII (for example, "é") require the same space when using a fixed-width font. That is to say, they all require a single display column.

Characters from non-Latin alphabets, such as Chinese, Cyrillic, Japanese, and Korean, may require two display columns.

See **[U] 12.4.2.2 Displaying Unicode characters** for more information.

display format. The display format for a variable specifies how the variable will be displayed by Stata. For numeric variables, the display format would indicate to Stata how many digits to display, how many decimal places to display, whether to include commas, and whether to display in exponential format. Numeric variables can also be formatted as dates. For strings, the display format indicates whether the variable should be left-aligned or right-aligned in displays and how many characters to display. Display formats may be specified by the `format` command. Display formats may also be used with individual numeric or string values to control how they are displayed. Distinguish display formats from storage types.

encodings. An encoding is a way of representing a character as a byte or series of bytes. Examples of encoding systems are ASCII and UTF-8. Stata uses UTF-8 encoding.

For more information, see **[U] 12.4.2.3 Encodings**.

extended ASCII. Extended ASCII, also known as higher ASCII, is the byte values 128 to 255, which were not defined as part of the original ASCII specification. Various code pages have been defined over the years to map the extended ASCII byte values to many characters not supported in the original ASCII specification, such as Latin letters with diacritical marks, such as "á" and "Á"; non-Latin alphabets, such as Chinese, Cyrillic, Japanese, and Korean; punctuation marks used in non-English languages, such as "<", complex mathematical symbols such as "±", and more.

Although extended ASCII characters are stored in a single byte in ASCII encoding, UTF-8 stores the same characters in two to four bytes. Because each code page maps the extended ASCII values differently, another distinguishing feature of extended ASCII characters is that their meaning can change across fonts and operating systems.

frames. Frames, also known as data frames, are in-memory areas where datasets are analyzed. Stata can hold multiple datasets in memory, and each dataset is held in a memory area called a frame. A variety of commands exist to manage frames and manipulate the data in them. See [D] **frames**.

higher ASCII. See *extended ASCII*.

immediate command. An immediate command is a command that obtains data not from the data stored in memory but from numbers typed as arguments. Immediate commands never disturb the data in memory. See **[U] 19 Immediate commands** for an overview.

locale. A locale is a code that identifies a community with a certain set of rules for how their language should be written. A locale can refer to something as general as an entire language (for example, "en" for English) or something as specific as a language in a particular country (for example, "en_HK" for English in Hong Kong).

A locale specifies a set of rules that govern how the language should be written. Stata uses locales to determine how certain language-specific operations are carried out. For more information, see **[U] 12.4.2.4 Locales in Unicode**.

lower ASCII. See *plain ASCII*.

null-terminator. See *binary 0*.

numlist. A numlist is a list of numbers. That list can be one or more arbitrary numbers or can use certain shorthands to indicate ranges, such as `5/9` to indicate integers 5, 6, 7, 8, and 9. Ranges can be ascending or descending and can include an optional increment or decrement amount, such as `10.5(-2)4.5` to indicate 10.5, 8.5, 6.5, and 4.5. See **[U] 11.1.8 numlist** for a list of shorthands to indicate ranges.

option. A Stata option is a modifier to a Stata command that indicates additional specifications for the command. For example, the `detail` option of `summarize` asks Stata to specify additional statistics. An option is always specified following a comma after the Stata command. See **[U] 11.1.7 options**.

plain ASCII. We use plain ASCII as a nontechnical term to refer to what computer programmers call lower ASCII. These are the plain Latin letters "a" to "z" and "A" to "Z"; numbers "0" through "9"; many punctuation marks, such as "!"; simple mathematical symbols, such as "+"; and whitespace and control characters such as space (" "), tab, and carriage return.

Each plain ASCII character is stored as a single byte with a value between 0 and 127. Another distinguishing feature is that the byte values used to encode plain ASCII characters are the same across different operating systems and are common between ASCII and UTF-8.

Also see *ASCII* and *encodings*.

prefix command. A prefix command is a command in Stata that prefixes other Stata commands. For example, `by` *varlist*`:`. The command `by region: summarize marriage_rate divorce_rate` would summarize `marriage_rate` and `divorce_rate` for each region separately. See **[U] 11.1.10 Prefix commands**.

storage types. A storage type is how Stata stores a variable. The numeric storage types in Stata are `byte`, `int`, `long`, `float`, and `double`. There is also a `string` storage type. The storage type is specified before the variable name when a variable is created. See **[U] 12.2.2 Numeric storage types**, **[U] 12.4 Strings**, and [D] **Data types**. Distinguish storage types from display formats.

str1, **str2**, …, **str2045**. See *strL*.

strL. `strL` is a storage type for string variables. The full list of string storage types is `str1`, `str2`, …, `str2045`, and `strL`.

`str1`, `str2`, …, `str2045` are fixed-length storage types. If variable `mystr` is `str8`, then 8 bytes are allocated in each observation to store `mystr`'s value. If you have 2,000 observations, then 16,000 bytes in total are allocated.

Distinguish between storage length and string length. If `myvar` is `str8`, that does not mean the strings are 8 characters long in every observation. The maximum length of strings is 8 characters. Individual observations may have strings of length 0, 1, …, 8. Even so, every string requires 8 bytes of storage.

You need not concern yourself with the storage length because string variables are automatically promoted. If `myvar` is `str8`, and you changed the contents of `myvar` in the third observation to "Longer than 8", then `myvar` would automatically become `str13`.

If you changed the contents of `myvar` in the third observation to a string longer than 2,045 characters, `myvar` would become `strL`.

`strL` variables are not necessarily longer than 2,045 characters; they can be longer or shorter than 2,045 characters. The real difference is that `strL` variables are stored as varying length. Pretend that `myothervar` is a `strL` and its third observation contains "this". The total memory consumed by the observation would be $64 + 4 + 1 = 69$ bytes. There would be 64 bytes of tracking information, 4 bytes for the contents (there are 4 characters), and 1 more byte to terminate the string. If the fifth observation contained a 2,000,000-character string, then $64 + 2{,}000{,}000 + 1 = 2{,}000{,}069$ bytes would be used to store it.

Another difference between `str1`, `str2`, …, `str2045`, and `strL`s is that the `str#` storage types can store only ASCII strings. `strL` can store ASCII or binary strings. Thus a `strL` variable could contain, for instance, the contents of a Word document or a JPEG image or anything else.

`strL` is pronounce *sturl*.

titlecase, **title-cased string**, and **Unicode title-cased string**. In grammar, titlecase refers to the capitalization of the key words in a phrase. In Stata, titlecase refers to (a) the capitalization of the first letter of each word in a string and (b) the capitalization of each letter after a nonletter character. There is no judgment of the word's importance in the string or whether the letter after a nonletter character is part of the same word. For example, "it's" in titlecase is "It'S".

A title-cased string is any string to which the above rules have been applied. For example, if we used the `strproper()` function with the book title *Zen and the Art of Motorcycle Maintenance*, Stata would return the title-cased string `Zen And The Art Of Motorcycle Maintenance`.

A Unicode title-cased string is a string that has had Unicode title-casing rules applied to Unicode words. This is almost, but not exactly, like capitalizing the first letter of each Unicode word. Like capitalization, title-casing letters is locale-dependent, which means that the same letter might have different titlecase forms in different locales. For example, in some locales, capital letters at the beginning of words are not supposed to have accents on them, even if that capital letter by itself would have an accent.

If you do not have characters beyond plain ASCII and your locale is English, there is no distinction in results. For example, `ustrtitle()` with an English locale locale also would return the title-cased string `Zen And The Art Of Motorcycle Maintenance`.

Use the `ustrtitle()` function to apply the appropriate capitalization rules for your language (locale).

Unicode. Unicode is a standard for encoding and dealing with text written in almost any conceivable living or dead language. Unicode specifies a set of encoding systems that are designed to hold (and, unlike extended ASCII, to keep separate) characters used in different languages. The Unicode standard defines not only the characters and encodings for them, but also rules on how to perform various operations on words in a given language (locale), such as capitalization and ordering. The most common Unicode encodings are mUTF-8, UTF-16, and UTF-32. Stata uses UTF-8.

Unicode character. Technically, a Unicode character is any character with a Unicode encoding. Colloquially, we use the term to refer to any character other than the plain ASCII characters.

Unicode normalization. Unicode normalization allows us to use a common representation and therefore compare Unicode strings that appear the same when displayed but could have more than one way of being encoded. This rarely arises in practice, but because it is possible in theory, Stata provides the `ustrnormalize()` function for converting between different normalized forms of the same string.

For example, suppose we wish to search for "ñ" (the lowercase n with a tilde over it from the Spanish alphabet). This letter may have been encoded with the single code point U+00F1. However, the sequence U+006E (the Latin lowercase "n") followed by U+0303 (the tilde) is defined by Unicode to be equivalent to U+00F1. This type of visual identicalness is called canonical equivalence. The one-code-point form is known as the canonical composited form, and the multiple-code-point form is known as the canonical decomposed form. Normalization modifies one or the other string to the opposite canonical equivalent form so that the underlying byte sequences match. If we had strings in a mixture of forms, we would want to use this normalization when sorting or when searching for strings or substrings.

Another form of Unicode normalization allows characters that appear somewhat different to be given the same meaning or interpretation. For example, when sorting or indexing, we may want the code point U+FB00 (the typographic ligature "ff") to match the sequence of two Latin "f" letters encoded as U+0066 U+0066. This is called compatible equivalence.

Unicode title-cased string. See *titlecase, title-cased string, and Unicode title-cased string*.

UTF-8. UTF-8 stands for Universal character set + Transformation Format—8-bit. It is a type of Unicode encoding system that was designed for backward compatibility with ASCII and is used by Stata 14.

value label. A value label defines a mapping between numeric data and the words used to describe what those numeric values represent. So, the variable disease might have a value label status associated with it that maps 1 to positive and 0 to negative. See **[U] 12.6.3 Value labels**.

varlist. A varlist is a list of variables that observe certain conventions: variable names may be abbreviated; the asterisk notation can be used as a shortcut to refer to groups of variables, such as `income*` or `*1995` to refer to all variable names beginning with `income` or all variable names ending in `1995`, respectively; and a dash may be used to indicate all variables stored between the two listed variables, for example, `mpg-weight`. See **[U] 11.4 varname and varlists**.

Subject and author index

See the combined subject index and the combined author index in the *Stata Index*.