Introduction to Statistical Computing: Stata

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Chapter 0: Introduction to Module

0.1 Overview of Module

This is a brief introduction to and overview of the Stata component of the Introduction to Statistical Computing module.

The purpose of these sessions is to introduce you to the statistical package Stata. We will be using Stata version 17, which was released in April 2021. We will assume no prior knowledge of Stata or indeed of any other statistical software. The goal is enable you to use Stata efficiently and to be able to produce datasets that are ready for analysis. This will involve becoming familiar with the Stata windows or working environment, understanding Stata's command syntax, being able to create and manage datasets and to identify and correct errors. We will look at commands for describing and summarising data but more advanced statistical methods will be introduced in other modules. If we have time, we will go through some of the material in the Stata Graphics manual during the last session.

Although no prior experience of using Stata is assumed, anyone who is already familiar with Stata will be able to move ahead more quickly to the more advanced material. However, there is nearly always benefit to be gained from going over the introductory sessions carefully.

Throughout the sessions the key principles of good practice for data management will be emphasised along with the importance of understanding the work-flow of data analysis and of developing a consistent and clear system or convention for data and file management.

Although there is not a formal assessment for this module, many of the other module assignments will require you to use Stata.

0.2 Style

The style of the Stata sessions will be different from most of the other modules on the MSc. Rather than pre-recorded one hour lectures and live practicals, we will be recording short (5-10 mins) screencasts introducing you to the Stata commands to be used in each session. You will be asked to view these in advance of each practical session. We will then have a 1.5 hour practical session where you will be asked to work your own way through the module notes and the accompanying exercises. Tutors will be on hand to answer any questions that you may have. We find that this style works best for this type of module. The best way to learn a new statistical software package is to work your way through the notes whilst sat in front of computer trying out the commands. This style also enables people with different levels of experience of statistical software packages to work along at their own pace.

0.3 Module Files

The data and other files for these sessions can be downloaded from the *U:*/ drive. Copy the "*Med_St_Intro_to_Stata*" folder plus its contents from *U:*/*Download*/*Teach*/ to your own computer. You might want to rename the top folder as Intro to Stata.

0.4 Additional Materials

You are encouraged to expand your learning outside these module materials during the course of your study. This module is intended only as a brief introduction to Stata's capabilities; it will get you started but you will almost certainly run into questions on topics that are not covered here, or you will have some difficulty using Stata with your data. Fortunately you will also almost certainly find that someone has encountered, and publicly queried, the same or similar issues before.

Online:

- The Stata PDF Documentation should be your first port of call. It is a series of e-books containing over 14,000 pages of documentation on Stata's functionality that you can access from within Stata. Click Help -> PDF Documentation from the toolbar and choose the appropriate manual from the hyperlinked bookmarks on the resulting PDF. The manual contains many helpful remarks, including statistical overviews, and examples of how to use commands and interpret their results. You can also find it online here: https://www.stata.com/features/documentation/
- **Statalist**, the official Stata forum run and moderated by Stata users. Questions and their answers date back to 1994, with many useful tips and suggestions on all types of data, statistical and Stata topics. https://www.statalist.org/
- The **Stata YouTube Channel** has been active since 2011 and now contains hundreds of short how-to clips for various data management and analysis tasks. https://www.youtube.com/user/statacorp
- Stata collates and maintains a series of online *third-party resources* that are also extremely helpful. Check out UCLA's Institute for Digital Research and Education, in particular. https://www.stata.com/links/resources-for-learning-stata/

Paper:

- The Workflow of Data Analysis Using Stata (2009); J. Scott Long, Stata Press. "Aimed at anyone who analyses data, this book presents an effective strategy for designing and doing data-analytic projects." Several copies are stocked in the library.
- For those who want to extend beyond introductory topics: *An Introduction to Stata Programming, Second Edition* (2016). Christopher Baum, Stata Press. "Great for anyone who wants to learn Stata programming."

Chapter 1: An Introduction to Stata

Aims & Objectives of Chapter 1

By the end of this chapter you should:

- be aware of Stata's capabilities
- be able to load a Stata dataset
- be familiar with the Stata Windows interface
- know how to change the working directory

The following commands are used in this chapter: use, cd, browse, dir.

1.1 Overview of Capabilities

Stata is an integrated statistical package designed for research professionals. As well as a wide range of *statistical tools*, Stata also provides publication-quality *graphical capabilities* and powerful *data management* features.

Basic <u>STATISTICS</u> tools include summaries, cross-tabulations, correlations, t-tests, chi-square tests and tests of equality of variances plus much more. Tools for the analysis of epidemiological data include epidemiological tables, linear and logistic regression and survival time methods (including life-table, Kaplan-Meier and Cox regression) and much more. See http://www.stata.com/features/ and the *Statistics* drop down menu.

Stata's <u>GRAPH</u> capabilities allow the production of publication-quality distinctly styled graphics. The two-way family of graphs are particularly useful. Stata comes with its own built in Graph Editor with which it is possible to interactively edit Stata graphs. See https://www.stata.com/features/publication-quality-graphics/ and the *Graphics* drop down menu.

Stata has an extensive set of <u>DATA MANAGEMENT</u> commands which can deal with both string and numeric variables. Datasets can be split, combined, reshaped and collapsed. Variables can be transformed, recoded, categorised and combined. There are many commands for dealing with date and time variables. Advanced tools are provided for managing and analysing survival time, time-series, categorical, survey and longitudinal data. See https://www.stata.com/features/data-management/ and the *Data* drop down menu.

Stata is user-friendly; it has a comprehensive on-line help facility and it is possible to access nearly all of its commands through a Graphical User Interface (GUI). Stata comes in different 'flavours' (e.g. SE and IC) which have slightly different specifications regarding the maximum number of variables. With Stata/SE a maximum of 32,767 variables can be stored in a single dataset. With Intercooled Stata (Stata/IC) the maximum number of variables is 2,048. With both flavours the number of observations is limited only by the size of the memory of the computer being used. The current largest computer can hold 2.14 billion observations.

1.2 Loading a Stata Dataset

A Stata dataset can be loaded either by (i) double-clicking on a Stata data file, which automatically launches Stata and loads the dataset, or (ii) by launching Stata through the Start menu or an applications window and then opening the data file from within Stata.

Stata data files have the extension .dta. These are data files that have been created within Stata and have been saved in Stata's own format. Stata data files cannot be opened using any other statistical software. When you double-click on a Stata data file Stata is launched and the data file is loaded into Stata's memory.

Selecting Stata through the Start menu, or via a shortcut icon, will cause Stata to be launched, but without loading any data. The simplest way to load a Stata dataset from within Stata is to use the *File > Open* menu. We will load the *bl_demog.dta* dataset.

1.3 The Stata Windows Interface

On opening Stata you will be faced with 5 windows, a series of drop down menus and a shortcut tool bar (Figure 1.1). The 5 windows are the (i) Variables Window, (ii) Command Window, (iii) History Window, (iv) Results Window and (v) Properties Window. These, along with the drop-down menus and toolbar, are described below.

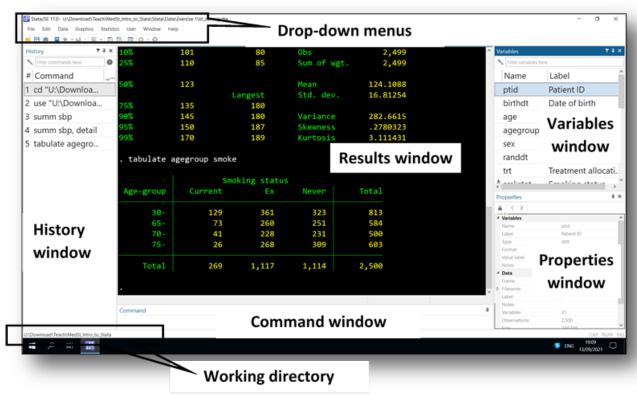


Figure 1.1: The default widescreen Stata windows layout

In Stata 17 the default windows layout is the *widescreen* layout as shown above. You can switch between layouts using the *Edit > Preferences > Load Preference Set >* menu.

(i) Variables Window

When a dataset is loaded in Stata's memory the *Variables Window* displays the name (e.g. smoke) of each variable and its label (e.g. "Smoking status") if a label has been created.

The Variables Window is interactive – variables can be selected into the Command Window (or Graphical User Interface) saving the need to type the variable name. A variable can be selected either by clicking the arrow that appears when the mouse hovers over its name or by double-clicking on the variable name.

A number of options, including choice of font and copying a variable list, can be accessed by right-clicking within the Variables Window. The width of each column can be varied using the cursor by clicking and dragging the vertical line which appears between each column on the bar at the top of the Variables Window.

By default the variables appear in the order in which they are stored in the dataset; the Variables Window can also be sorted alphabetically by variable name or variable label by clicking on the column headers. This does not change the order of the variables in the dataset, but can be useful when trying to locate a variable in a large dataset.

(ii) Command Window

Stata can be used interactively through the *Command Window*. Commands can be typed into the Command Window using the keyboard and submitted using the return (enter) key.

It is possible to scroll back/forwards through any commands that have already been submitted using the page up/down keys. These commands can then be submitted again or can be edited within the Command Window and then resubmitted. Previously submitted commands can similarly be selected from the History Window using the mouse left click.

Variables can be selected into the Command Window from the Variables Window using the mouse. Options such as font size can be changed by right-clicking within the Command Window.

(iii) History Window

The *History Window* keeps a record of all commands that have been submitted through either the Command Window or Graphical User Interface (GUI). (Note this window is called the *Review Window* in Stata 15 and earlier versions). The History Window is interactive so that selecting one of the commands by left clicking on it will cause it to appear in the Command Window. The command can then be edited within the Command Window and resubmitted. Commands that have resulted in an error message are displayed in red in the History Window.

Note that all contents of the History Window are lost when exiting Stata. However, it is possible to send or save all or some of the contents of the History Window to a do-file (more later) or to copy them to the clipboard. This can be done by right-clicking in the History Window and selecting the appropriate options. Commands can also be deleted from the History Window.

There are three column headers; # - the sequence number of the command as submitted in a particular session; Command – the command itself; _rc – contains any error codes. The History Window can be sorted by any of these columns (by clicking the header); this can be useful, for example when wanting to delete all commands containing errors. Once the erroneous commands have been deleted the History Window can then be resorted sequentially by clicking on the # header.

(iv) Results Window

Any command entered either in the command window or via the GUI appear in the *Results Window* along with any output (including error messages) arising from the command. The size of the font and general preferences can be changed by right-clicking within the Results Window.

The Results Window has a limited buffer size. Once the limit has been reached the earliest results from the current session disappear. The size of the Results Window buffer can be increased via the *Edit* drop down menu *Edit* > *Preferences* > *General Preferences* and then select the Results tab, or using the *set scrollbufsize* command. The buffer size can be changed to lie between 10,000 and 2,000,000 bytes. The default is 200,000.

All the contents of the Results Window are lost when exiting Stata. However, it is possible to keep a record of everything that appears in the Results Window in what Stata calls a log-file (more about this later). The status bar along the bottom of the results window indicates whether a log-file is open.

You can also copy-and-paste tables and other text directly from the Results Window into other software such as Microsoft Word or Excel (more later). Using the *File > Print* menu you can print either the whole, or a selection, of the Results Window.

Note that Stata will normally present one full screen of results at a time in the Results Window. If the command you submit requires more than one page of results Stata will pause after the first page and display —more— at the bottom of the Results Window. You can view the next line by pressing the *Enter* key, or scroll to the next page of results by pressing the *Space bar* or by the clicking on —more—. To stop the command press q or the *Break* button at the right hand end of the shortcut toolbar.

(v) Properties Window

The Properties Window shows properties for individual variables (e.g. name, label, type, value label) and for the dataset currently in memory (e.g. name of dataset, pathway, number of variables/observations). By default the properties for the first variable in the dataset are shown; properties for other variables are shown when they are selected in the Variables Window or you can use the arrow in the Properties Window to scroll through the variables.

By default the Properties Window is locked so that you cannot edit variable names etc. You can unlock the window by clicking on the small padlock symbol at the top left of the Properties Window. It is then possible to rename variables or add labels interactively.

The Drop Down Menus

Above the main windows interface is the menu bar with eight drop-down menus: File, Edit, Data, Graphics, Statistics, User, Window and Help (Figure 1.2).

Through the *File* menu it is possible among other things to load or save a Stata dataset, open a Stata graph or log-file, execute a do-file, import data saved in non-Stata format (e.g. Excel, delimited text files created by spreadsheets, etc), change the working directory and print the contents of the results, viewer or graph windows.

The *Edit* menu can be used to copy and paste and to change various preferences e.g. general window and graph preferences.

Using the *Data, Graphics* and *Statistics* menus it is possible to access almost all of Stata's commands through the Graphical User Interface (GUI) or dialogue boxes. We will return to these menus and the GUI later.

Through the *Window* menu it is possible to reopen a window (e.g. the review window) if it is closed down during a session. It can also be used to open the data editor, the variables manager, a new or existing do-file or a new viewer.

The *User* menu is for use by programmers, providing a place for additional menu items.

Through the *Help* menu it is possible to search for and view help files for Stata commands, open the PDF documentation that comes with Stata, visit useful pages of the Stata Corp website (e.g. user support and frequently asked questions pages) and check for official updates.

The Shortcut Toolbar

12 shortcut buttons appear on the toolbar.

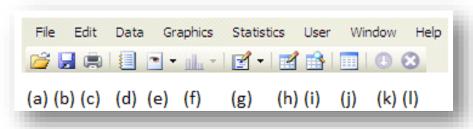


Figure 1.2: Stata drop-down menus and toolbar

From left to right these are: (a) open a Stata dataset, (b) save the current dataset (in Stata format), (c) print (either graph or contents of the viewer), (d) log begin/suspend/close, (e) open/bring to front the Stata viewer, (f) bring to front graph window, (g) open/bring to front do-file editor, (h) open/bring to front data editor, (i) open/bring to front data browser, (j) open/bring to front variables manager, (k) continue following pause, and (l) break, which stops the current action.

The Data Editor and Browser Windows

The data currently in memory can be viewed in either the *Data Editor* (in which the data can be viewed and edited) or in the *Data Browser* (in which the data can be viewed but not edited). The data editor and browser can be opened either via the *Data* drop down menu (*Data > Data Editor*) or through the short cut buttons (Figure 1.2).

The data are presented in a rectangular spreadsheet in which observations are stored in rows and variables in columns (Figure 1.3). Variable names appear at the top of each column.

Stata has a colour system to differentiate between variables of different formats:

Red = string variable

Black = numeric variable

Blue = numeric variable with value labels attached

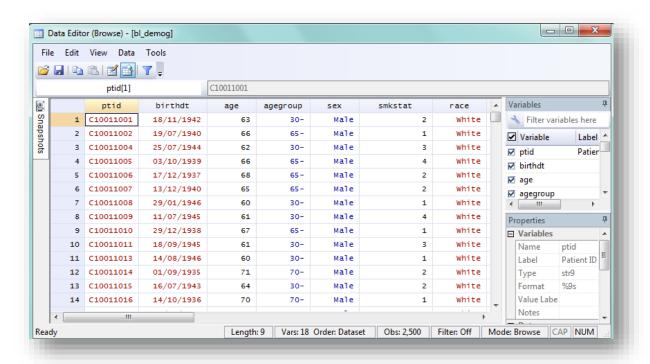


Figure 1.3: Stata's Data Browser Window

The data browser has its own set of menus and shortcut buttons which can be used to filter observations, sort variables, manage different variable properties and take a snapshot of the data currently in memory, which can be restored later if required.

The Data Editor also has a *Variables* and *Properties* window which displays the names and labels (if any exist) of the variables in memory.

The Variables Manager Window

The *Variables Manager* window can be opened using the *Window* menu or by using the Variables Manager button on the shortcut toolbar i.e. (j) in Figure 1.2.

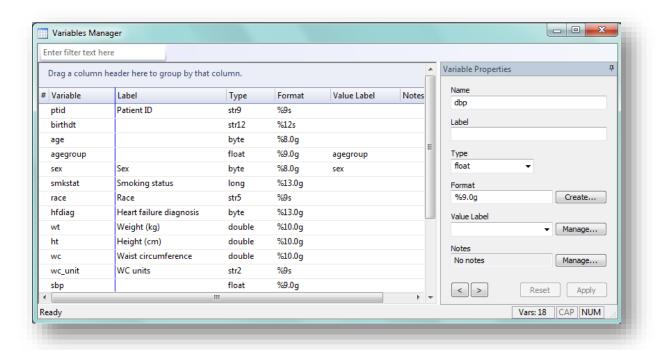


Figure 1.4 The Variables Manager Window

The Variables Manager is an interactive tool for managing the properties of the variables in the dataset in memory. It can be used to rename variables, create variable and value labels, change display formats and more.

When executing a command through the Variables Manager the command is echoed to the Results and History windows.

The list of variables in the Variables Manager Window can be sorted in ascending order by clicking on one of the column headers (a second click sorts in descending order). Clicking on the hash (#) symbol found at the far left of the column header bar will revert to the original ordering.

1.4 The Current Working Directory

It is important to note the *working directory* highlighted in Figure 1.1 above. This is where Stata will look to find files and is where data files, log files and graphs will be saved unless otherwise specified.

Depending on where (e.g. personal laptop, university network) you are using Stata there will be a default working directory e.g. H:/my documents as in Figure 1.1.

If you launch Stata by clicking on a Stata data file the current working directory will be the folder where the data file is located.

The current working directory can be changed either using the *File > Change Working Directory* menu, or on the command line using the **cd** (change directory) command e.g.

```
. cd "C:/Intro to Stata/data"
```

If one of the files or folders in the pathway or directory contains an embedded space or some special characters it is necessary to enclose the whole pathway in double quotes. This happens automatically when using the *File > Change Working Directory* menu.

To see what files are in your current working directory type dir.

1.5 Data Dictionary for the Baseline Data

Dataset name: bl_demog.dta

Description: Stata dataset containing patient id, baseline demographic information plus some

lifestyle, vital signs, anthropometric and laboratory measurements.

Variable name	Variable description	Coding etc.
ptid	Unique patient identifier	String length 9
birthdt	Date of birth	Stata date format
age	Age (years)	Numeric
agegroup	Age categories	0=30-64, 1=65-69, 2=70-74, 3=75+
sex	Sex	String: Female, Male
smkstat	Smoking status (5 levels)	1=Never, 2=Ex-Light, 3=Ex- Heavy, 4=Current-Light, 5=Current-Heavy
smoke	Smoking status (3 levels)	String: Current, Ex, Never
race	Ethnic group	String: Asian, Black, White, Other
hfdiag	Heart failure diagnosis	1=Ischemic, 2=Non-ischemic
wt	Weight (kg)	Numeric
ht	Height (cm)	Numeric
wc	Waist circumference	Numeric
wc_unit	Waist circumference	String: CM, M
sbp	Systolic Blood Pressure (mmHg)	Numeric
dbp	Diastolic Blood Pressure (mmHg)	Numeric
hrate	Heart Rate (bpm)	Numeric
egfr	Estimated Glomerular Filtration Rate (ml/min/1.73m)	Numeric
lvef	Left ventricular ejection fraction (%)	Numeric
diab	Diabetes	0=No, 1=Yes

Chapter 2: Stata Commands and Results

Aims & Objectives of Chapter 2

By the end of this chapter you should:

- know how to submit commands using the Graphical User Interface
- understand the general form of Stata's command syntax
- be able to enter commands in the command window
- be able to use Stata's help and search facilities
- know how to create and use a do-file
- understand good practice for do-files
- be able to save results in a log file
- know how to open and view a saved log file

The following commands are used in this chapter: tabulate, summarize, list, sort, bysort, help, search, net search, log using and log close

2.1 The Graphical User Interface (GUI)

Although throughout this session we will concentrate on learning the command syntax, a brief description of the GUI may be useful. The drop down menus give an idea of the breadth of Stata's statistical, data management and graphical capabilities and can help in learning, or remembering, the syntax for a particular command.

Almost all Stata commands can be accessed in a point-and-click fashion via the three drop-down menus: *Data, Graphics* and *Statistics*. Figure 2.1 shows the options available under the *Statistics* menu.

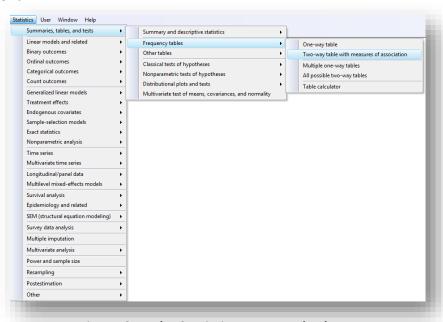


Figure 2.1: The Statistics menu and submenus

Selecting an option via the Statistics menu causes a dialog box for that command to open.

GUI Example 1: A Two-way Table

First we need to launch Stata and load the dataset (bl_demog.dta) from the Exercise 2 folder using the File > Open menu. From the Statistics menu select Summaries, tables and tests > Frequency Tables > Two-way table with measures of association. This should cause the tabulate2 dialog box to open (Figure 2.2).

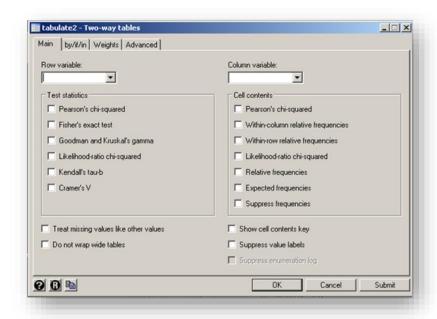
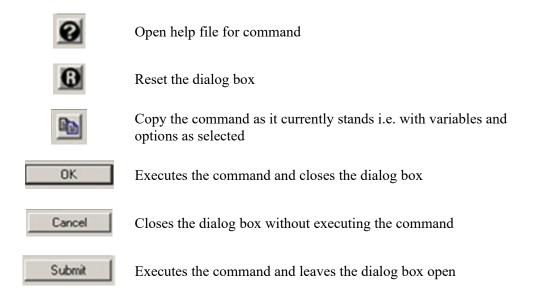


Figure 2.2: The tabulate2 dialog box

The tabulate2 dialog box has 4 tabs; Main, by/if/in, Weights and Advanced. These tabs are used to select the variables to be tabulated and specify different options.

There are also six buttons on the toolbar at the bottom of the dialog box. These are:



The *Main* tab contains the *Variable* fields (Row and Column variable) and a number of 'tick box' options. The variable names can be either typed directly into the row and column fields or selected using the drop-down menu at the right of each field.

Select the variable *agegroup* as the row variable field and the variable *smoke* as the column variable field using the drop-down menus. Click *submit*.

Stata executes the command leaving the dialog box open. The command syntax and the resulting table appear in the Results Window. The command syntax also appears in the History Window. As we did not tick any options we get the default two-way table which contains just the cell and marginal totals along with the variable names (or labels if attached) and the row/column headings.

. tabulate agegroup smoke

Age-group		Smok	ing status		
(years)		Current	Ex	Never	Total
	-+-				
30-		129	361	323	813
65-		73	260	251	584
70-		41	228	231	500
75-		26	268	309	603
	-+-			+	
Total		269	1,117	1,114	2,500

To obtain row percentages select *Within-row relative frequencies* option from the list of Cell contents options on the *Main Tab*. Click the *Submit* button. The results from this are shown below. Make sure you understand the output.

tabulate agegroup smoke , row

+-			-+
	Key		
-			-
	fı	requency	
	row	percentage	
+-			-+

Age-group	Smoking status				
(years)	Current	Ex	Never	Total	
30-	129 15.87	361 44.40	323 39.73	813	
65-	73 12.50	260 44.52	251 42.98		
70-	41 8.20	228 45.60	231 46.20		
75- 	26 4.31	268 44.44	309 51.24		
Total	269 10.76	1,117 44.68	1,114 44.56	2,500 100.00	

GUI example 2: Repeating a command

The *by/if/in* tab allows a command to be repeated over each level of another variable (or combination of variables) or to be limited to a subgroup of the data. For example, we may wish to repeat the two-way tabulation of age-group and smoking status by sex, i.e. for males and females separately.

Select the by/if/in tab, and click the *Repeat command by groups* option and select the variable sex into the *Variables that define groups* box (Figure 2.3).

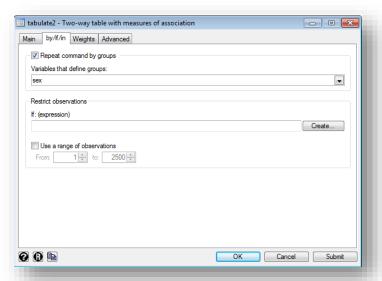


Figure 2.3: Repeating a command over groups

The resulting output is shown below.

Total | 223 998 721 | 1,942

. by sex, sort : tabulate agegroup smoke

Note that the command is now prefixed with by sex, sort:.

GUI example 3: Restricting the observations with if

We may wish to restrict the operation of the command to a subset of the observations in our dataset e.g. to males, those with BMI>30, etc. We can do this via the *by/if/in* tab.

Continuing with the tabulate2 dialog box, in the *by/if/in* tab deselect the *Repeat command by groups* option.

On the same tab we use the If (expression) box. We will restrict the tabulation of agegroup and smoke to just the males (sex = 1) in the study.

In the *if(expression)* box we type *sex*==1. Note the use of the double equals (==) which is Stata's convention when testing if something is equal to something else.

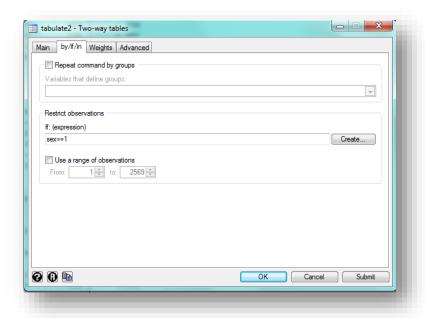


Figure 2.4: Restricting observations for a command

. tabulate agegroup smoke if sex==1

	Smo	oking status		
Age group	Current	Ex	Never	Total
30-	106	322	219	647
65-	61	234	155	450
70-	38	201	153	392
75-	18	241	194	453
Total	223	998	721	1,942

The resulting output is restricted to the 1,942 males in the study.

GUI example 4: Restricting the observations with in

We may wish to restrict the operation of the command to certain rows in our dataset e.g. to the first 10 rows. We will demonstrate this by using the list command. From the drop-down menus select $Data > Describe\ Data > List\ Data$. This will open up the list dialog box. On the main tab enter ptid, birthdt, age and smoke in the variables box.

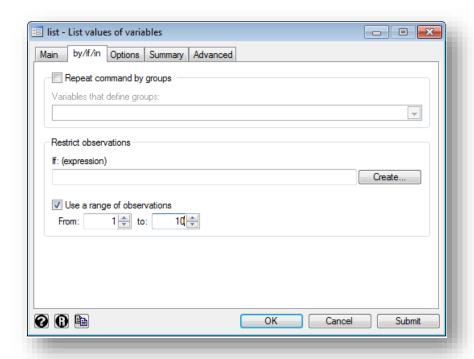


Figure 2.5: Restricting observations using in

list ptid birthdt age smoke in 1/10

					_
	ptid	birthdt	age	smoke	
1. 2. 3. 4.	C10011001 C10011002 C10011004 C10011005 C10011006	18nov1942 19ju11940 25ju11944 03oct1939 17dec1937	63 66 62 66 68	Current Never Current Current Current	1 1 1 1 1
6. 7. 8. 9.	C10011007 C10011008 C10011009 C10011010 C10011011	13dec1940 29jan1946 11ju11945 29dec1938 18sep1945	65 60 61 67 61	Current Never Current Never Current	
	+				+

We now have listed the values for *ptid*, *birthdt*, *age* and *smoke* in the first ten rows of the datatset – as it is currently sorted. We'll see later how to list the last 10 observations in a dataset.

2.2 The command syntax

One of the strengths of Stata is the consistency of its command syntax. Almost all of Stata's commands follow the same general form which makes it much easier to learn to use Stata. The basic form of the command syntax is:

```
[prefix:] command [varlist] [if] [in] [using] [ , options]
```

Square brackets indicate parts of the syntax which may be optional.

Command name

Each Stata command is invoked using the command name e.g. summarize, regress, tabulate, histogram. The command name appears first in the command syntax unless it is being modified by a prefix command.

From the general form of the command syntax above we can see that this is the only part of the command syntax not in square brackets i.e. not optional. Some commands (e.g. summarize, describe, codebook) do not require a variable list – when no variable list is specified Stata interprets this as meaning all variables in the dataset. For example;

summarize

Variable	Obs	Mean	Std. Dev.	Min	Max
ptid dob age sex	0 2500 2500 2500	-7653.395 68.6632 1.2232	2867.442 7.675033 .4164747	-17807 43 1	1890 95 2
[some output	omitted]				
creat hb pot sodium	2500 2500 2500 2500	211.9553 425.1898 108.2695 483.181	1042.164 1984.981 1014.15 1807.237	15.912 8.8 2.2 106.9	9999 9999 9999 9999
totbil	2500	636.6483	2415.778	0	9999

Using the GUI we created a two-way table. The syntax began with the command name which was tabulate:

tabulate agegroup smoke

Age-group	Si	moking stat	us	
(years)	Current	Ex	Never	Total
	+			+
30-	129	361	323	813
65-	73	260	251	584
70-	41	228	231	500
75-	26	268	309	603
Total	+ 269	1,117	1,114	2,500

Command names can be abbreviated. The minimum abbreviation accepted is underlined in the help file for each command (see help with Stata commands later). For example, the command summarize can be abbreviated to summ.

Stata is case-sensitive with command names - all of Stata's commands are lower case. If you use the wrong case or misspell a command then Stata will return an error message (in red) reporting that the command has not been recognized.

```
sumarize sbp dbp
unrecognized command: sumarize
r(199);
```

Such an error message tells you that the mistake is right at the start of the syntax.

Variable list

Following command in the command syntax is [varlist] the variable list. This is a list of one or more variable names that identify which variables that are to be used in the command. The number and order of the variable names may or may not be important.

As we saw above, for some commands, e.g. summarize the variable list is optional; Stata interprets no variables to mean all the variables in the dataset. By adding a variable name or names we restrict the operation of the command to those variables specified. For example, to obtain summary statistics for the variables *sbp* and *dbp*,

. summ sbp dbp

Variable	Ok	s Mean	Std. Dev	. Min	Max
sbp	1 249	9 124.1012	16.81271	72	189
dbp		74.58944		· -	117

Here the order of the variable list is only important in that it affects the order in which the results are presented.

Sometimes the number and order are important. For example, tabulate requires a minimum of one variable (for a one-way tabulation) and a maximum of two variables. When two variables are specified with tabulate the order is important - the first variable is the row variable and the second the column variable.

tabulate agegroup smoke

	5	Smoking stat	tus	
agegr	Current	Ex	Never	Total
	+			-+
30-	129	361	323	813
65-	73	260	251	584
70-	41	228	231	500
75-	26	268	309	603
	+			-+
Total	269	1,117	1,114	2,500

. tabulate smoke agegroup

Smoking		ag	egroup		
status	30-	65-	70-	75-	Total
	+				-+
Current	129	73	41	26	269
Ex	361	260	228	268	1,117
Never	323	251	231	309	1,114
	+				+
Total	813	584	500	603	2,500

Specifying either none or more than two variables after tabulate would result in an error message as shown below.

```
. tabulate
varlist required
```

. tabulate sex agegroup race too many variables specified

With statistical modelling commands like regress (linear regression) and logistic (logistic regression) the order of the variables is very important. With such commands the first variable in the list is the dependent or response variable and any subsequent variables are explanatory variables.

As with command names, variable names can be abbreviated providing they are not ambiguous. Stata is case-sensitive with variable names; it is good practice to keep all variable names in lower case.

If you use the wrong case or incorrectly spell a variable name Stata will return an error message saying that the variable could not be found. For example:

```
. summarize spb
variable spb not found
```

This should immediately alert you that there is an error in the variable list, most probably an error in spelling or perhaps the wrong dataset has been loaded.

If and In

We saw above in *GUI example 3* that we can restrict the operation of a command to a subset of the data using an if expression. We can also use in to restrict a command to certain rows in the dataset. If neither if nor in are used then all observations in the dataset will be used (or at least all non-missing observations).

By using the if qualifier followed by some *expression* we restrict the operation of the command to the observations in the dataset for which the *expression* is true. For example, to obtain summary descriptive statistics of *sbp* for subjects where *weight* is less than 90 kg:

. summ sbp if wt<90

Variable	Obs	Mean	Std. Dev.	Min	Max
sbp	1890	123.3648	17.00194	 72	189

When using if to restrict to observations *equal* to some value (number or string) then Stata's convention is to use a *double equals*.

For example, for a summary of *sbp* for observations where *agegroup* equals 1:

summarize sbp if agegroup==1

Variable	C	bs	Mean	Std.	Dev.	Min	Max
	+						
sbp	1 5		2089	16.98	261	85	180

For observations where *race* is recorded as White (note that we enclose the string in quotes):

summarize sbp if race=="White"

Variable	Obs	Mean	Std. Dev.	Min	Max
sbp	2066	124.5714	16.50045	74	189

If you use a single equals rather than a double equals you will get an error message saying invalid syntax. This is not the most helpful error message as it does not tell you where in the syntax the error is found. However, if you do get such an error message when you have an if expression in the syntax it usually means that you have used a single rather than a double equals.

The if expression can involve more than one condition but only one if is required. For example, to get a summary of *sbp* for observations where *weight <90* and *race* is "White":

. summarize sbp if wt<90 & race=="White"

Variable	Obs	Mean	Std. Dev.	Min	Max
	+				
sbp	1498	123.8959	16.73348	80	189

Note that if only appears once and "&" is used to join the two conditions.

If expressions can contain the following symbols

Symbol	Meaning
>	greater than
<	less than
>=	greater than or equal to
<=	less than or equal to
==	equal to
!=	not equal to
~=	not equal to (alternative to above)
&	and
1	or

Note: the symbol | meaning "or" is found on the backslash key

Note that care needs to be taken when using if with > when there are missing data. We will return to this point later.

The in range qualifier is used to restrict the operation of the command to a specified range of rows (observations) in the dataset as currently sorted. For example, to list *ptid* and *age* for the first 5 observations in the dataset:

. list ptid age in 1/5

+-----
| ptid age |

|------|

1. | C10011001 63 |

2. | C10011002 66 |

3. | C10011004 62 |

4. | C10011005 66 |

5. | C10011006 68 |

The range 1/5 refers to rows 1 to 5 in the dataset. The range can be specified as either a single number e.g. in 1 or as range between two numbers as in the example above.

Using

Some Stata commands require a filepath/filename to be specified. For example, in GUI example 6 when beginning a log-file we specified the location and name of the log-file with using.

. log using "H:\Stats Computing/Stata/logfiles\example1.log"

When importing data from non-Stata formats we will sometimes have to use using to tell Stata where the data are and the name of the file.

Options

Nearly all Stata commands allow a number of options which modify what the command does. These must be separated from the main command syntax by a comma. For example, the summarize command will, by default, display the number of observations, the mean, standard deviation and the minimum and maximum values.

. summarize age

Variable	Obs	Mean	Std. Dev.	Min	Max
	+				
age	2500	68.6632	7.675033	43	95

Summarize has the option **detail** which requests a more detailed output of summary statistics. For example, compare the following with the output above.

. summarize age , detail

Age (years)						
	Percentiles	Smallest				
1%	55	43				
5%	57	49				
10%	59	50	Obs	2500		
25%	63	51	Sum of Wgt.	2500		
50%	68		Mean	68.6632		
		Largest	Std. Dev.	7.675033		
75%	74	91				
90%	79	92	Variance	58.90613		
95%	82	94	Skewness	.2433231		
99%	86	95	Kurtosis	2.473595		

When more than one option is specified the order is not important. However, they should be separated from the main command syntax by a single comma i.e. you do not need multiple commas for multiple options. For example, you will find that the commands,

```
tabulate agegroup smoke , chi row tabulate agegroup smoke , row chi
```

produce the same output. A common mistake made with options is to omit the comma; generally this will result in an error message saying variable "xxx" not found, e.g.

```
tabulate agegroup smoke chi
variable chi not found
r(111);
```

Type help commandname to find what options are available with each command.

Prefix commands

Most Stata commands may be preceded by a prefix command. The most commonly used prefix commands is by <code>varlist</code>: or <code>bysort varlist</code>: which causes the main command to be repeated over the groups defined in <code>varlist</code>.

We saw the use of the by prefix in *GUI example 2* where we obtained a two-way tabulation of age-group and smoking status by sex. In order to execute a command by levels of a variable or variables the dataset has to be sorted by that variable (or variables).

```
. sort sex
. by sex:tabulate agegroup smoke
```

This can be done in a single step either as

```
by sex , sort: tabulate agegroup smokeorbysort sex: tabulate agegroup smoke
```

The second is the simplest to remember.

2.3 Getting help in Stata

Stata has an extensive built-in and on-line help system providing a wealth of information to help you learn and use Stata.

The options under the *Help* menu (see Figure 2.6) include links to the PDF documentation, Advice, Contents, Search and Stata Command. These are described briefly below.



Figure 2.6: Stata's Help menu

Help > PDF documentation

Version 17 comes with complete PDF documentation, including *Getting Started with Stata, Base Reference Manual, User's Guide, Data-Management Reference Manual, Graphics Reference Manual,* and all the programming and specialized statistics manuals. The PDF documentation is linked into the existing interactive help file system.

Help > Advice

Advice provides a useful description of Stata's extensive help facilities as well as guidance on how to make best use of them.

Help > Contents

This provides help in the form of a category listing, which includes: Basics (language syntax, functions, etc.); Data management (inputting data, creating new variables, etc.); Statistics (tables, estimation commands, etc.); Graphics (scatter plots, bar charts, etc.) and Programming and matrices (do-files, matrices, etc.).

Help > Search

This enables the user to search for *keywords* in official help-files, Stata manuals, FAQs, the Stata Journal and Stata Technical Bulletin. There are also a number of trusted academic net resources that can be searched, including sites at UCLA, Boston College, Imperial College and UCL.

Searches can be carried out directly from within the Command window with the command search or net search. For example, to search for help on the keyword *meta* within the Stata documentation and FAQs;

. search meta

To search the net resources type;

. net search meta

You can find advice on how to carry out searches under *Help > Advice*.

Help > Stata Command

This provides help for specific Stata commands. Stata's help files provide information on the command syntax, a brief description of what the command does, a summary of the options available, links to the related dialog box and the PDF documentation, examples of the command syntax and links to related commands. Help files can be viewed either in a Stata viewer or in the Results window.

For example, to open the help file for summarize from within the Command window and view it in the Stata viewer;

. help summarize

Also try out the Stata YouTube channel.

2.4 Creating and Using Do-files

It may at first seem preferable to access Stata's commands through the Graphical User Interface. Why go to the trouble of learning the command syntax if you can produce exactly the same results by point-and-click? The reason why is the 'do-file'.

Whilst it is possible to use Stata interactively, i.e. to use the GUI or to submit commands in the command window, a far better alternative for serious research projects is use a do-file. A do-file is a text file containing a series of commands. The commands in the do-file can then be submitted, either in part or whole, as a sequence of commands. Stata has its own built-in file editor called the *Do-file Editor* and files created using Stata's editor are saved with the extension .do. It is also possible to use other text file editors to create do-files.

There are many advantages to using do-files. In particular, time is saved if it is necessary to repeat analyses e.g. routine reports during an ongoing study, or if an error is found in the data. In this case, the data are updated and the do-file is rerun.

Also very importantly the do-file serves as a record of how the data were managed, processed and analysed. A great importance is placed on audit trails in medical research and the do-file is an excellent starting point.

Creating a New Do-file

Do-files can be created in a number of ways.

In chapter 1 we saw how to save the contents of the History window at the end of a Stata session. It is also possible to send some or all of the commands in the History window to a new do-file, at the end of, or during, an interactive session. This is done by selecting some or all the commands, right-clicking in the History window and selecting 'Send to Do-file editor'.

However, remember that the History window contains a complete history of all commands submitted in the Command window, including those with errors, typos, etc. So creating a dofile in this way will require some discernment and editing.

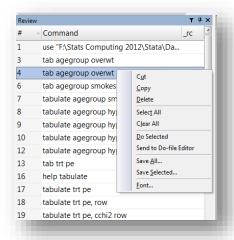


Figure 2.7 Creating a do-file from the History window contents

Using the Save All or Save Selected option will open the Save Review Contents dialog box. With this dialog box you can specify the location (Save in) and the name of the do-file. The default extension is .do but the files can be saved with other extensions, for example, .txt.

Using the *Send to Do-file Editor* option will automatically open the built in Do-file editor and dump the selected commands from the History window into a new do-file. This will initially be named *Untitled1.do* or something similar. The name appears on a tab just below the Do-file window menu bar. You will note that there is an asterisk next to the name, indicating that the file has changed since it was last saved - in fact the file has not yet been saved at all. We need to save the file to disk using the *File > Save as* menu within the Do-file Editor window.

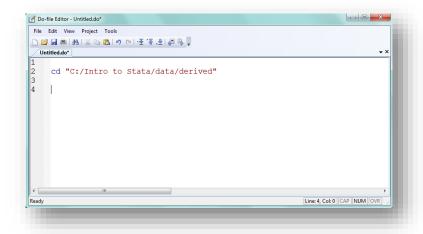


Figure 2.8: Stata's Do-file Editor window

Perhaps the best way to create a do-file for a new research project is to start from scratch using Stata's built in *Do-file editor*. The Do-file editor can be opened either through the *Window > Do-file editor* menu or the *Do-file editor short cut button*.

Commands are then typed directly into the do-file editor. The do-file can then be saved to disc using the *File > Save* menu from within Stata's Do-file editor. If building up a do-file in this way it is very important to save the file regularly as this is where most of your time is being invested.

Opening a previously created do-file

Previously created do-files are best opened from within Stata. This is done by opening the do-file editor (as described above) and using the *File > Open* menu within the do-file window.

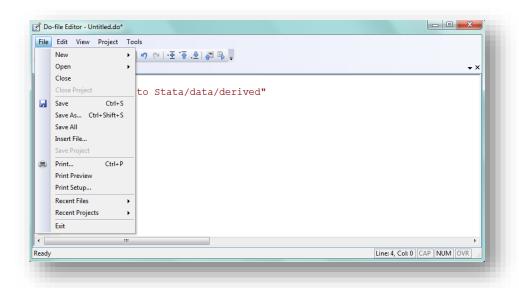


Figure 2.9: File menu in the Do-file editor window

It is possible to have several do-files opened within one Do-file Editor window – the names are displayed in tabs below the menu bar, as well as to have several Do-file Editors opened. *Executing Commands Saved in a Do-file*

Commands saved within a do-file can be executed using the execute/do button on the toolbar.



To submit part of the do-file highlight the required section using the mouse and then click the do button. To execute all the commands contained in the do-file in sequence click the execute button without any of the commands or comments being highlighted.

Note that when commands are executed from within a do-file the History Window records only the do command (a single command) and not the individual commands executed within the file. However, both the commands and the output appears in the Results window and the log-file (if opened) if executed using the do command/button.

Note that when Stata encounters an error in a do-file, the error is reported and the do-file is stopped at the point of the error. This means that all the commands up to the point of the error will have been executed, but not commands after the point of error.

Adding Comments to Do-files

It is good practice to add comments to your do-files. For example, the first few lines of a do-file may contain information about the purpose of the do-file, the project name, the author, the date of creation and the date last edited.

It is possible to 'comment out' a single line in a do-file using an asterisk (*). E.g.,

```
* INTRODUCTION TO STATA: October 2022
```

If the asterisk was omitted from the first line above Stata would look for a command called INTRODUCTION and since no such command exists give an error message.

Comments can also be added at the end of a line using two forward slashes. E.g.,

```
tabulate agegroup diab , row // diab = diabetes 0=No 1=Yes
```

To comment out a series of lines in a do-file use a forward slash asterisk (/*) at the beginning of the section and an asterisk forward slash (*/) at the end of the section. E.g.

```
/*
The following errors were discovered:
Some heights were measured in metres
One case of date of birth & date of screening have been transposed
*/
```

Dealing with Long Commands in Do-files

Stata views a command as being submitted at the carriage return character. Sometimes, particularly with graphic commands, a command line may exceed the width of the visible page making it awkward to view and edit. In this case it may be wished to have the command run over several lines in the do-file.

A simple way of dealing with a moderately long command line is to place a triple forward slash at the end of an unfinished line. E.g.

```
summarize sbp dbp hrate qrsint gfrate ///
age wc if sex==2
```

2.5 Saving Results in Log Files

Stata has the ability to send a copy of everything that appears in the *Results window* to a file, called a log file. The log file is a record of everything that appears in the Results window, including commands, output, error messages, comments, etc. Results that appear in other windows, such as the Graph window, need to be saved separately.

Starting a Log File

Before a log file is started any output appearing in the Results window will not be captured. It is good practice to start a log file whenever you begin any serious work in Stata, particularly if you are working without a do file. Log files serve as a record or audit trail of all your work carried out during a Stata session. Once a log file is opened all subsequent results are immediately written to the file meaning that they can protect you from disasters such as sudden power failures. Log files can be started using either the *File > Log > Begin* menu or the log using command.

Log files can be created in two different formats. The default format for log files is *SMCL* (Stata Markup & Control Language). Log files in SMCL format preserve all the formatting and links from the Results window. These can be opened and viewed using the Stata Viewer but cannot be easily edited or copied and pasted into different software packages. Alternatively, it is possible to save the log file as a plain-text file; for keeping a record of your results that you can edit and then print, it is best to save your results as a text file. It is possible to translate a *.smcl* log file into a text file using the *File > Log > Translate* menu.

The command syntax to open a log file called *mylog* in the current working directory in text format is:

```
log using mylog.logorlog using mylog , text
```

Unless you specify the directory, the log file will be saved in the current working directory. The .log extension and the option text are alternative ways of specifying text format rather than SMCL.

When using the File menu to begin a log file you will find the Save as type drop down menu at the bottom of the dialog box. The default is Formatted Log (*.smcl) with Log (*.log) as the alternative.

Stata puts a header at the beginning of the log file that records the name of the log file (not the same as the filename), the pathway and filename, the log type, and a date-stamp showing the date and time the log file was opened.

```
name: <unnamed>
        log: h:\intro to stata\mylog.log
   log type: text
   opened on: 2 Sep 2022, 10:55:35
```

When a log file has been started the Results window status bar (at the bottom of the Results window) indicates that the log file is on as well as what format (smcl or text). You can tell Stata to start logging at any point during a Stata session, but remember that only the output that appears on the screen *after* opening the log file will be captured.

It is possible to have multiple log files open. This requires using the name (logname) option. See help log for more details.

Closing a Log File

Stata will continue to save output to the log file until you close the log file with the *log close* command or exit Stata (when Stata automatically closes the file).

Note that you do not need to save the log file.

When you close the log file Stata adds a footer to the end of the file recording the name of the log file, the pathway and filename, the log type, and a date-stamp showing the date and time the log file was closed.

```
name: <unnamed>
    log: h:\intro to stata\mylog.log
log type: text
closed on: 2 Sep 2021, 11:22:59
```

Replacing and Appending Log Files

If the file *mylog* already exists, and you would like to overwrite it, use the replace option, i.e. submit the command,

```
. log using mylog , replace
```

If the file already exists and you would like to add more output to the end of it, use the append option, i.e. submit the command,

```
. log using mylog , append
```

Viewing and Printing a Log File

SMCL log files are best viewed using the Stata viewer. This can be accessed using the *File > Log > View* menu. The viewer has a print option.

Text format log files can be opened and viewed in text file editor or word processor such as Notepad or Word. Once in Word, the font may need to be changed to a non-proportional or monospaced font such as Courier New — tables and other output will not be aligned if you don't do this. Page breaks can also be put in appropriate places. It is good practice to edit the log file to remove any unwanted output before printing.

Adding Comments to Log Files

It is often helpful to add comments to your output during a session. Stata will treat any line starting with a '*' as a comment and will ignore it. For example, if you wanted to add the comment 'Stata session 1' to your output you would enter the line

* Stata session 1

Stata will ignore the comment, but the comment will appear in your log file.

Summary of Log File commands

Syntax	Purpose	Example
log using filename	Open a SMCL log file in the current directory	log using log1
log using "pathway/filename"	Open a SMCL log file in a specified location	log using "c:/temp/log2"
log using <i>filename</i> , text log using <i>filename</i> .log log close	Open a plain text log file Same as above Close the log file	log using log3, text log using log4.log log close
log off	Temporarily stop sending results to the log file (without closing log file)	log off
log on	Resume sending results to the log file	log on
set logtype {text smcl }	Sets the default log type to text or SMCL	set logtype text

Chapter 3: Inspecting Data

Aims and Objectives of Chapter 3

By the end of this chapter you should:

- know how to obtain a description of the data in memory
- be able to sort and view the data in the Data Browser and Results Window
- be able to obtain summaries of variables
- be able to check for errors and identify outlying or unusual values
- be able to check for duplicated values

The following commands are used in this chapter: describe, browse, sort, gsort, list, summarize, tabulate, codebook, histogram, twoway scatter, duplicates report.

3.1 Inspecting Data

Having loaded a dataset into memory it is very tempting to rush straight into the statistical analysis to get out the odds-ratio or p-value you are interested in. However, and this is really important, before you start any analysis you should take time to inspect your data.

Inspecting the data has two main purposes.

Firstly, and most importantly, the goal is to identify any errors or spurious values. You may have loaded your data successfully, carried out the appropriate statistical tests and used the appropriate statistical model, but, if there are serious errors in your data, the results may be completely invalid. Once identified the errors should be corrected where possible or dealt with in some other way if not. This is not always very exciting work but it is essential work.

The second goal in inspecting the data is to familiarise yourself with what data you have. What variables do you have? How many observations are there? Are there any missing values? How are the variables distributed? These are all key questions you should address at the beginning of any analyses.

In this chapter we will visit a number of commands that Stata has for looking at data, checking distributions of continuous and categorical variables, searching for spurious values or inconsistencies in the data and checking for duplicated values.

3.2 Describing a Dataset

The describe command gives a general summary of the dataset in memory or of a Stata data file saved on disk. It displays the filename and directory, the number of observations and

variables, the date/time that the data file was created, the names of the variables and details of storage type, the display format, and details of any value and variable labels. For example, if we have loaded *bl_demog.dta* to obtain a description of the entire set the command syntax is:

describe

Contains data from H:\Stats Computing\Stata\Exercise 3\bl demog.dta

obs:	2,500			
vars:	21	14 Sej	2015	16:09
size:	250 , 000			

variable name	_	display format	variable label
randdt trt smkstat smoke race	byte float byte float str7	%d %8.0g %9.0g %8.0g %d %9s %13.0g %9s %9s %10.0g %10.0g %10.0g %9.0g %9.0g %9.0g %9.0g %9.0g %9.0g %10.0g %10.0g	Patient ID Date of birth Age (years) Age-group Sex Date randomized Treatment allocation Smoking status Smoking status Race Heart failure diagnosis Weight (kg) Height (cm) Waist circumference WC units eGFR (ml/min/1.73msq) LVEF (%)

Sorted by: ptid

As we have not specified a variable list following the command name Stata's default is to describe all variables. Typing describe followed by a list of variable names describes only those variables in the list. For example,

```
describe ptid age sex
```

When starting out on a set of analyses for a new research project it can be very useful to have a hard copy of the output from the describe command for each of the data files. These can be kept in a folder for easy reference and annotated as necessary.

It is also possible to obtain a description of a Stata data file saved on disk without loading the data. For example, to obtain a description of the Stata data file *fup_vitals1.dta*,

```
describe using fup vitals1.dta
```

The command can also be accessed using the *Data > Describe data > Describe data in memory* menu. See help describe for a description of the options available.

3.3 Viewing the Data

One of the first things to do having loaded a dataset into memory is to actually look at the data. Do not underrate the value of looking at the data with your eyes! You can pick up many issues by simply 'eyeballing' the data.

Data can be viewed either in the *Data Editor* using the browse command or in the *Results window* using the list command. We will consider both these commands along with the sort command which enables us to view the ends of distributions.

The Data Editor Window

The *Data Editor* window can be opened in either *Browse* or *Edit* mode and provides a live view of the data. In *Browse* mode the data can be viewed but not altered, whereas in *Edit* mode the data can be edited. So, if you are simply interested in looking at the data it is best to open the Data Editor in *Browse* mode. We can do this either using the *Data Editor > Data Editor (Browse)* menu or the browse command or the *Data Editor (Browse)* shortcut button, shown in Figure 3.1. Note that the shortcut buttons for Edit and Browse mode are next to each other, with the Browse button on the right.

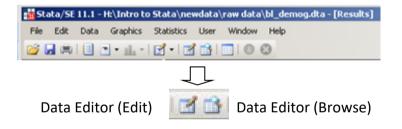


Figure 3.1 Data Editor Shortcut buttons

The syntax for the browse command is:

```
browse [variable list] [if] [in]
```

If no variable list is specified then the entire dataset is viewed.

A very useful feature of the browse command is that we can view a selection of variables. For example, we can view two variables next to each other in the Data Editor that may be some distance apart in the dataset. This saves scrolling back and forth along the spreadsheet or having to hide columns. If a variable list is specified then only these variables will be shown in the *Data Editor*. Note that the variables will appear in the order they are found in the dataset and not in the order in the variable list.

Clicking on the *Data Editor (Browse)* shortcut button will open the Data Editor window in browse mode and display all the variables in the dataset. The data are viewed in a rectangular matrix with observations appearing in rows and variables in columns.

The Data Editor window has its own drop down menus and toolbar (see Figure 3.2). From within this window we can limit the data being viewed. The number of observations (rows) can be reduced using the *Filter observations* and the number of variables can be reduced using the *Hide/Show Variables* buttons on the data browser shortcut toolbar (see Figures 3.2 and 3.3).

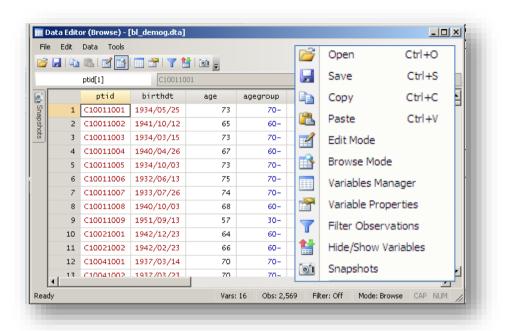


Figure 3.2: The Data Editor (Browse mode)

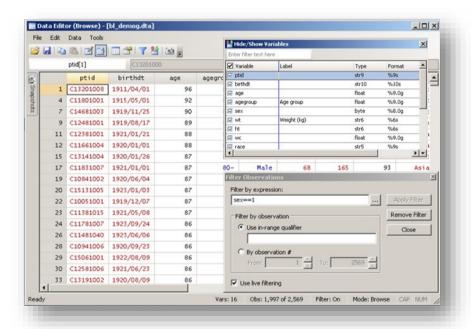


Figure 3.3: Filtering observations and Hiding variables in the Data Editor

Note that neither hiding variables nor filtering observations makes any changes to the dataset in memory. They simply change our view of the data.

Sorting data in the browser

When we open the *Data Editor* we get a live view of the data i.e. we view in the order in which the dataset is currently sorted. For example, the data may be sorted by a subject id number. When checking for errors it can be very useful to view the data sorted by another variable, say by date of birth or age. Note that when we sort the data all the observations for each subject stay together.

We can sort within the *Data Editor* by using the *Data > Sort* menu which opens the sort dialogue box (Figure 3.4). We can select *Standard* (ascending sort only) or *Advanced* (mixed ascending/descending sort). In Figure 3.4 we have selected the *Standard sort* option and sorted on the variable *age*. We can see that the youngest patient in the dataset is 43 years old.

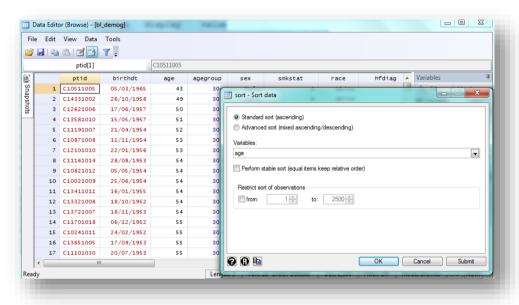


Figure 3.4: Sorting in the Data Editor

Under the Ascending and descending sort option we can specify a descending sort by inserting a minus sign (-) before the variable name. A plus sign (+) specifies an ascending sort. We can sort by more than one variable and include both ascending and descending sorts.

If you look at the commands echoed to the *History Window* following the *Standard* and *Advanced* sort you will see that there are two different commands names; the command sort relates to the *Standard sort* and gsort to the *Advanced sort*.

Sort by variable age in ascending order:

. sort age

Sort by agegroup in ascending order and sbp in descending order:

```
. gsort + agegroup - sbp
```

As mentioned above, when sorting by one or more variables the order of all other variables will be changed accordingly i.e. the whole dataset is sorted not just the variables specified.

Listing Data in the Results Window

The Data Editor provides us with a live view of the data. The list command provides a data listing *in the Results window*. This means that we can capture a record of the observations in a log file, if one is open. The syntax for the command is:

```
. list [varlist] [if] [in]
```

Typing list without any subsequent variable list will result in a listing of the entire dataset as it is currently ordered; it's not often that you will want to do that. Typing list followed by a list of variable names results in a listing of all observations on those variables specified.

More often it may be desired to list only a limited number of observations on a restricted set of variables. For example, to list the first 5 observations in the dataset for variables *ptid*, *birthdt* and *wc*:

. list ptid birthdt wc in 1/5

	+			+
		ptid	birthdt	WC
	- 1			
1.		C10011001	18/Nov/1942	116
2.		C10011002	19/Jul/1940	107
3.		C10011004	25/Jul/1944	112
4.		C10011005	3/Oct/1939	70
5.		C10011006	17/Dec/1937	118
	+			+

To list the *last 5 observations* in the dataset we specify *negative* numbers which Stata treats as counting 'from the last row' of the dataset.

. list ptid birthdt wc in -5/-1

	+.			+
	į	ptid	birthdt	WC
	-			
2496.		C20021033	13/Feb/1935	112
2497.		C20021035	3/May/1948	134
2498.		C20021036	10/Jul/1930	103
2499.		C20051001	19/Aug/1934	82
2500.		C20051002	30/Sep/1946	77
	+-			+

Note that the -5/-1 essentially means 1/5 counting from the last row of the dataset – as it is currently sorted.

3.4 Commands for summarising distributions and checking for errors

Codebook

The single most useful command for checking data is <code>codebook</code>. This is particularly useful in that it produces a summary for each variable that takes into account the format of the data e.g. numeric, categorical, string etc.

For numeric variables codebook produces a summary consisting of the range, number of unique values, units, mean and SD and the number of missing values. The range immediately identifies spurious values lying outside the expected range. The number of unique values can help identify problems with unique identifiers.

If the variable is categorical the same summary is produced, but with a frequency tabulation rather than a mean and SD (the default maximum number of unique values for Stata to regard a variable as categorical rather than continuous is 9).

For string variables Stata presents the number of missing values, number of unique values and examples of the various strings. For date variables (numbers stored as elapsed dates) then the summary will include the range, the median date and other percentiles. Note that in the output from codebook shown below we can see that the date is stored as a string and not as an elapsed date – more about dates later. The syntax for the command is:

```
. codebook [varlist] [if] [in] [ , options]
```

As with a few other Stata commands if no variable list is specified then the command is executed on all the variables in the dataset in memory. Below we have executed the command on one variable at a time:

```
. codebook ptid

-----
ptid

Patient ID
```

```
type: string (str9)
```

unique values: 2500 missing "": 0/2500

examples: "C10951001"
"C11861013"
"C12501006"
"C13491008"

The variable *ptid* (patient identifier) is the variable that uniquely identifies each patient in our trial and which links most of the data files for this project. The output from codebook shows us that it is a string variable consisting of 9 characters. Importantly we see that there are 2500 unique values and no missing values. If there were less than 2500 unique values this would indicate that there are duplicated patient ids.4 example strings are presented.

. codebook age

age Age (years)

type: numeric (byte)

range: [43,95] units: 1

unique values: 47 missing .: 0/2500

mean: 68.6632 std. dev: 7.67503

percentiles: 10% 25% 50% 75% 90% 59 63 68 74 79

As the variable is a numeric variable, with more than 9 unique values, <code>codebook</code> presents the range, mean, standard deviation and a selection of percentiles including the median (50%). The ages of the patients in our dataset range from 43 to 95 (years) with a mean age of 68.7 and median age of 68 years. The variable is labelled and there are no missing values.

. codebook sex

/....1 - 1 - 1 - 1 - 1 - 1

------ (unitabetea

type: numeric (byte)

label: sex

range: [1,2] units: 1

unique values: 2 missing .: 0/2569

tabulation: Freq. Numeric Label
1997 1 Male
572 2 Female

The variable sex is a numeric variable stored as a byte. As it only takes two unique values (1 or 2) codebook deals with this as a categorical variable and presents a frequency tabulation rather than mean, standard deviation as above with age. The table shows the numeric values and the label attached to each value. These are called value labels (more later).

See help codebook for more details.

Histogram

Another good way of checking for outlying values for a continuous variable, and examining the shape and spread of the distribution, is to plot a histogram. We can do this using the histogram command. For example to plot a histogram of waist circumferences:

. histogram wc , normal freq
(bin=34, start=.70999998, width=5.3320588)

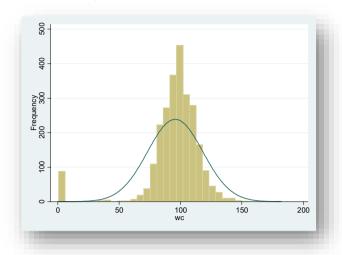


Figure 3.5 Histogram of waist circumference

The options specified in the command above are:

normal requests a normal curve to be superimposed freq requests y-axis to show frequency rather than density.

The histogram shows that the variable wc is quite normally distributed, but that there is a blob of patients near to zero.

How could you plot a histogram for the group near zero?

Tabulate

Distributions of categorical variables can be checked with the tabulate command. By default tabulate ignores missing values but if we specify the option missing then tabulate presents a separate row for any missing values. For example,

. tabulate race , missing

Race	Freq.	Percent	Cum.
Asian	295	11.80	11.80
Black	60	2.40	14.20
Other	79	3.16	17.36
White	2,066	82.64	100.00
Total	2 , 500	100.00	

In this case there are no missing values and no strange values.

Two-way cross-tabulations of categorical variables might help identify inconsistencies in the data. For example, if we had smoking status (*smoke*) and years since stopped smoking (*smkstop*) we would expect *smkstop* to be missing for any *Never* smokers or any *Current* smokers.

Scatter Plots

Other graphs that might be useful for checking for errors include twoway scatter plots. These might be used to check for unusual combinations of values. For example if you have two variables that you expect to be strongly correlated (e.g. sbp and dbp) then a twoway scatter plot might help identify strange values. For example,

. twoway scatter sbp dbp , ms(oh)

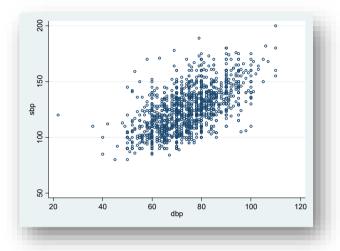


Figure 3.6: Scatter plot of sbp and dbp

In this case there are no obvious problems although there is one obvious outlier in terms of dbp. The option in the scatter plot command ms (oh) means use a hollow small circle for the marker symbol.

Summarize

For continuous numeric variables the command summarize with the option detail provides some additional descriptive statistics. For example,

sum	wc , d			
		WC		
	Percentiles	Smallest		
1%	.82	.69		
5%	.95	.71		
10%	1.09	.73	Obs	2369
25%	85	.73	Sum of Wgt.	2369
50%	96		Mean	85.88955
		Largest	Std. Dev.	35.65602
75%	106	143		
90%	114	146	Variance	1271.351
95%	120	147	Skewness	-1.633495
99%	132	165	Kurtosis	4.513849

3.5 Checking for Duplicates

Above we saw that the command <code>codebook</code> can be helpful in identifying duplicated observations, i.e. check whether the number of unique values is the same as the number of observations. E.g.

ptid Patient ID

type: string (str9)

unique values: 2500 missing "": 0/2500

examples: "C10951001"
"C11861013"
"C12501006"
"C13491008"

However, if there are missing values or if there is more than one variable by which we identify unique observations (e.g. patient id and centre id) then we need something more than codebook.

The duplicates set of commands enables us to investigate whether we have any duplicated observations in our dataset across any number of variables. It also helps to identify which are the duplicated records and can also be used to delete if appropriate.

The syntax for duplicates is similar to the label commands (label variable, label define, label attach) in that it has a series of subcommands. The syntax is:

. duplicates subcommand [varlist]

If no variable list is specified then Stata checks for duplicates across all the variables in the dataset. The subcommands include report, list, tag and drop

Duplicates Report

The command duplicates report produces a table showing observations that occur as one or more copies and indicating how many observations are *surplus* in the sense that they are the second, third, etc. copies of the first of each group of duplicates.

Example 1: Check whether there are any duplicate patient ids in the *bl_demog* data file:

. duplicates report ptid

Duplicates in terms of ptid

copies	 	observations	surplus
1	'	2500	0

Here we see that there is only one copy of each value of the variable ptid i.e. there are 2500 unique patient ids out of 2500 observations (patients) in our dataset.

Example 2: Now load *fup_egfr.dta* and check for duplicate patient ids.

- . use fup egfr
- . duplicates report ptid

Duplicates in terms of ptid

copies	observations	surplus
+		
1	339	0
2	948	474
3	1344	896
4	1712	1284
5	4040	3232

Here we find that we have only 339 observations where there is 1 unique value of *ptid*, 948 values of *ptid* where there are 2 copies (so 474 duplicated twice), 1344 values of ptid of which there are 3 copies (so 448 appearing three times each) etc.

Why are there so many duplicated values? If you look at the dataset you will see that there are multiple rows per patient because each visit for each patient is recorded on a separate row.

Repeat the command adding visit to the variable list.

```
. duplicates report ptid visit

Duplicates in terms of ptid visit

copies | observations surplus

1 | 8383 0
```

We now see that there is only one copy of each combination of ptid and visit.

Other subcommands

If we discover that there are some genuinely duplicated observations we can use duplicates tag to generate a new variable to identify the duplicate observations. The syntax requires us to specify a name for the new variable using the gen (varname) option. For example to generate a new variable called duplicates, which identifies duplicates in terms of ptid and visit, the syntax would be:

. duplicates tag ptid visit , gen(duplicates)

This new variable called duplicates will take the value 0 for all unique observations, the value 1 for all observations for which there is 1 extra copy, 2 if 2 extra copies, 3 if 3 extra copies, etc.

The command duplicates drop drops all but the first occurrence of each group of duplicated observations. This should be used with CAUTION.

Chapter 4: Creating and Combining Stata Datasets

Aims and Objectives of Chapter 4

By the end of this chapter you should:

- know how to enter data using the Data Editor or input command
- know how to import data into Stata from an Excel spreadsheet
- know how to save a Stata dataset
- be able to import data from tab or comma delimited text files
- be able to load data from a free format or fixed format text file
- know how Stata deals with data in memory and on disk
- know how to combine Stata datasets using append and merge

The following commands are used in this chapter: input, save, import excel, import delimited, infile and infix, list, type, append, merge, drop.

4.1 Entering Data using the Data Editor

Data can be entered interactively using the Data Editor.

Submitting the command edit or clicking on the *Data Editor* button opens up the data editor which looks like a standard spreadsheet. Data can be entered into the spreadsheet using the keyboard. Using the mouse select the cell into which the data is to be entered, type the data and press the *Enter* key (¬). The cursor keys or mouse are used to move up/down columns and across rows. Variable are stored in columns and records are stored in rows.

The storage type for each variable is determined automatically: if you type a number for the first entry, the new variable will be numeric; if the first entry is a string, the variable will be a string. By default the first variable will be called var1. We can rename the variable using the *Variable Properties* window which is on the right of the Data Editor window (see Figure 4.1).

Example: Here we will enter data from a published trial. Here is some text from the results section of the paper.

"The primary prespecified outcome at 1 year was observed in 28 of the 205 patients who received active treatment compared to 43 of the 197 patients who received placebo (p=0.03)."

We can use Stata as a calculator to work out the number of patients who did not have an event.

```
. display 205-28
177
. display 197-43
154
```

So in the active treatment group there were 28 patients with and 177 patients without the event; in the placebo group there were 43 with and 154 without the event.

This equates to the following two-by-two table.

Carre	Outcome			
Group	No (0)	Yes (1)		
Placebo (0)	154	43		
Active (1)	177	28		

We will need to create a dataset with three variables (one to indicate the treatment group, a second for the outcome and a third for the number of patients in each category) and four rows (one for each combination of treatment group and outcome). For treatment group (trt) we can use the values 0 and 1 for placebo and treatment respectively; for outcome (out) we can use the values 0 and 1 to indicate no event and the event respectively. We can name the third variable *freq* and put in the actual number of patients.

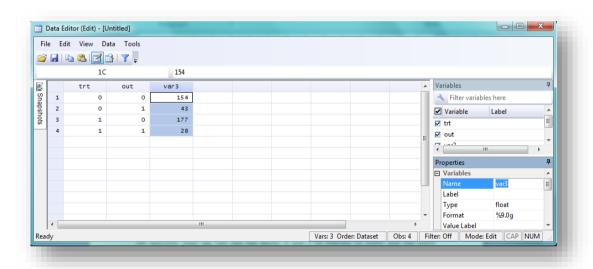


Figure 4.1 Entering data into the Data Editor

Clicking on a particular variable will cause the properties for that variable to appear in the *Variables Properties* window. We can type in a new name and press the Enter key.

We can now use Stata's frequency weight option to do some simple analyses of the data.

•	tab	trt	outcome	[fw=fre	q] ,	chi	row
		trt	 -	outcome 0		1	Total
		0	3 78	154 .17	4: 21.8:	- 1	197 100.00
		1	-+ :	 177	2	+ 8	205

86.34 13.66 | 100.00 71 | Total | 331 402

82.34

Pearson chi2(1) = 4.6098 Pr = 0.032

17.66 |

Note that [fw=freq] is not an option and comes before the comma. The fw means frequency weights and we use =freq to tell Stata the name of the variable containing the weights.

100.00

Having created the dataset in memory we can then save this to disk as a Stata dataset using the save command. E.g. save dataset1.

4.2 Entering Data using the input command

We could have entered the same data using the input command. This can be done either in the command window or more usually within a do-file (Figure 4.2).

The variable names are specified on the same line as the input command. This is then followed by the rows of data, each on a separate line. The command end tells Stata when the data entry is complete. The first observation in each row corresponds to the first variable named on the input command line.

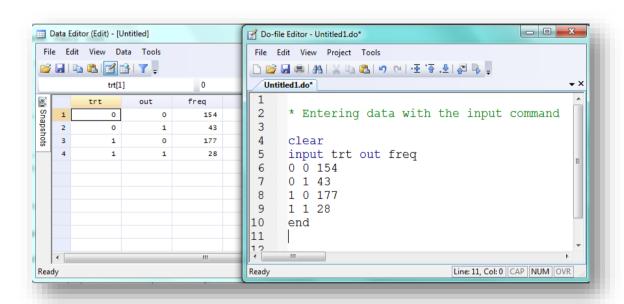


Figure 4.2 Entering data with the input command

4.3 Importing Data from Excel

We can import data directly into Stata from an Excel spreadsheet either through the menus using File > Import > Excel Spreadsheet (Figure 4.3) or with the import excel command.

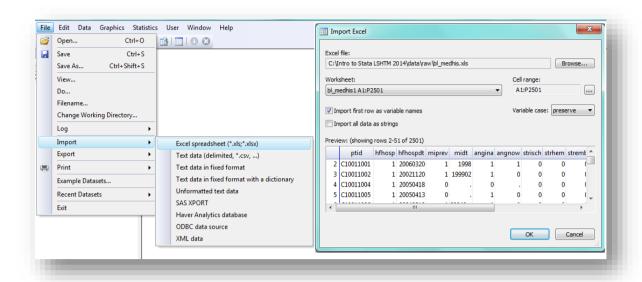


Figure 4.3 Importing Data from Excel

Note in Figure 4.3 that we specified the directory and Excel filename, we ticked the *Import first row as variable names* box and that the worksheet to be imported is *bl medhis1*.

The equivalent Stata command to do this (assuming that this file is the current directory) is:

```
. import excel using bl medhis.xls, firstrow sheet(bl medhis1)
```

The Excel file is specified with using along with the appropriate file extension (either .xls or .xlsx).

The firstrow option tells Stata that the first row of the Excel file should be treated as variable names rather than data. If this option is not specified then the first row will be imported as data.

Data can only be imported from one sheet at a time. The option <code>sheet("sheetname")</code> indicates which sheet to import. If the <code>sheet()</code> option is not specified the default is to import the first worksheet.

Data can only be imported if there is no data in memory, or if the option clear is specified.

See help import excel for more details.

Saving a Stata Data File

Having imported the data from Excel into Stata we now need to save to disk as a Stata dataset. We can do this either through the *File > Save as* menu or the save command. E.g.

```
. save bl medhis1
```

If the data file *bl_medhis1.dta* already exists on disk then if you are using the *File > Save as* menu Stata will give you the option of replacing the data file on disk with the file currently in memory or cancelling the save. If you are using the save command then Stata will return an error message saying:

```
. save bl_medhis1
file bl medhis1 already exists
```

The save command has the option replace which forces Stata to overwrite the data file. When working within a do-file it is generally ok to add the option replace to any save command. This will stop the do-file breaking down. Remember it is important to keep at least one copy of the original 'raw' data.

```
. save bl medhis1, replace
```

Once the Stata dataset has been created it can be loaded either through the *File > Open >* menu or with the use command. You can also double-click on a Stata data file, which automatically launches Stata and loads the dataset.

Data in Memory and Data on Disk

It is very important to be aware of how Stata works with data. Above we loaded data that existed on disk as an Excel file. As we do this Stata loads a copy of the data contained in those files into its memory (RAM). Any work carried out on the dataset currently in memory e.g. adding labels, generating new variables, etc. affects only the data in memory. The file from which the data was loaded is completely unaffected and remains in its original state. It is good practice to always keep (at least) one copy of the 'raw' data.

The process carried out above for the Medical History data is explained below.

Step 1: We started with the single Excel file (*bl_medhis.xls*) containing two worksheets saved on disk; this remains unchanged at the end of the process and can be regarded as our original or raw data. Keep this safe.

Step 2: We then loaded the first worksheet into Stata's memory. This only existed in Stata's memory i.e. it was not saved on disk.

Step 3: We then saved this file to disk (using save command) as a Stata data file. This file contains exactly the same information as the Excel file, but in a different format.

4.4 Importing Delimited Text Files

The import command can also be used to import data from other formats including tab delimited or comma delimited text files — often called CSV files. These are files that have been created by a spreadsheet style package.

We will demonstrate here using two files: *bl_labs1.txt* (a tab-delimited text file) and *bl_rand.txt* (a comma delimited text file).

Firstly we will view both files. We can do this either in a text editor e.g. notepad or alternatively within the *Results Window* by using the type command. E.g.

```
. type bl labs1.txt, lines(5)
      regid creat hb
ptid
                           pot
                                 sodium totbil
                                 4 140
             1
"C10161001"
                    71
                           12.6
                                               15.4
"C10161002"
                          17.4
                    150
                                               12
"C10161003"
                                               23.9
            1
                    115
                          11.7
                                 4.7
                                        132
"C10161004"
            1
                    115
                           9.5
                                 3.5
                                        140
                                               15.4
```

We have used the option lines (#) to restrict to the first few lines of the dataset. If we use the showtabs option we will see that the gaps between the variable names and the observations are tabs rather than multiple spaces.

```
. type bl_labs1.txt, lines(5) showtabs
ptid<T>regid<T>creat<T>hb<T>pot<T>sodium<T>totbil
"C10161001"<T>1<T>71<T>12.6<T>4<T>140<T>15.4
"C10161002"<T>1<T>150<T>17.4<T>3.3<T>142<T>12
"C10161003"<T>1<T>115<T>11.7<T>4.7<T>132<T>23.9
"C10161004"<T>1<T>115<T>9.5<T>3.5<T>140<T>15.4
```

For the bl_rand.txt file you should see that the first line or row contains the variable names and that names and values are separated (or delimited) by commas.

```
. type bl_rand.txt, lines(5)
rcode,indx_day,indx_mon,indx_year,consdt,randdt
2073,2,7,2006,"07-20-06","20060721"
2074,22,5,2006,"07-21-06","20060721"
2076,21,8,2006,"08-21-06","20060822"
2077,21,8,2006,"08-22-06","20060822"
```

Note in both these datasets that the first row contains the variable names and that each record is on a single separate line.

Importing a tab-delimited text file

To import the first of these files into Stata (assuming that the file is in the current working directory):

```
. import delimited using bl_labs1.txt, varnames(1)
(7 vars, 347 obs)
```

Stata reports that 7 variables and 347 observations have been imported.

Note that as before the syntax includes a command (import) and a subcommand (delimited) and again use using to specify the filename and extension. This time we use the option varnames(#) to specify which row (if any) contains the variable names. See what happens if you omit this option.

It is good practice to look at the data once it has been imported. We can do this using browse or list.

. list in 1/5

+ 	ptid	regid	creat	hb	pot	sodium	+ totbil
	0161001	1	71 150	12.6 17.4	4	140 142	15.4 12
3. C1	.0161003	1	115	11.7	4.7	132 140	23.9
	0161005	1	97	13.6	4.9	140	6.8

It appears that the data have been imported correctly.

Importing a comma-delimited text file

To import the second file above i.e. the *bl_rand.txt* comma delimited text file we again use the import delimited command.

```
. import delimited using bl_rand.txt, varnames(1) delimiter(",")
(6 vars, 2500 obs)
```

With import delimited Stata expects that the delimiter will either be a comma or a tab so we don't really need to specify the delimiter (",") option. However, we include this option to demonstrate how other delimiters could be specified if required.

As before we should now look at the file and then save as a Stata file.

. list in 1/5

	rcode	indx_day	indx_mon	indx_y~r	consdt	randdt
1.	2073	2	7	2006	07-20-06	20060721
2.	2074	22	5	2006	07-21-06	20060721
3.	2076	21	8	2006	08-21-06	20060822
4.	2077	21	8	2006	08-22-06	20060822
5.	2078	28	8	2006	08-29-06	20060829

```
. save bl_rand
file bl rand.dta saved
```

4.5 Loading Free-Format Text Files

Free format text files are quite different to delimited text files. In the above two examples all the observations for a particular subject were found on a single line and the observations were separated by a distinct character (e.g. a comma or tab).

In free format files observations for a particular subject can go over many lines or indeed the observations for more than one subject can appear on a single line. Observations can be separated by single or multiple spaces. String variables must be enclosed in quotes, particularly if the strings contain spaces.

We will use the datafile bl_meds.txt to illustrate. As before the first thing we should do is to look at the file in a text editor or using the type command.

```
. type bl meds.txt, lines(30)
"C10011001" "Paroxetine"
"Aspirin"
"Enalapril"
"Risperidona"
"Furosemide"
"Carvedilol"
"Valsartan"
11 11
11 11
"C10011002" "Losartan"
"Aspirin"
"Carvedilol"
"Digoxine"
"Rosiglitazone"
"Furosemide"
** **
** **
"C10011003" "Losartan"
"Insuline"
"Aspirin"
"Furosemide"
"Salbutamol"
"Valsartan"
"Simvastatin"
"Amlodipine"
"Carvedilol"
"Clopidogrel"
```

The first thing we notice is that the data for each subject runs over several lines. All the observations here are strings and are contained in quotation marks including any missing or empty values. We can also see that there are no variable names.

At present the import command cannot deal with such data. The appropriate command for this type of dataset is infile.

With the infile command we will need to specify the names of the variables. Additionally we will need to indicate if any of the variables are strings and the length of the string. Finally we will need to specify the name of the file we are loading including its file extension.

We will load the bl_meds.txt dataset. The first variable is the patient identifier which we will call ptid. This variable is a string of 9 characters in length. The remaining 10 variables are also string variables. The length of the strings varies — it is not obvious what the longest string length for each of these variables so the best option is to specify a large number of characters and then compress afterwards. If we specify too short a length then the observations will be truncated.

```
infile str9 ptid str90 (med1 med2 med3 med4 med5 med6 med7 med8
med9 med10) using bl meds.txt , clear
```

Note that *str9* is a string format meaning that the following variable is a string variable of maximum 9 characters. This comes immediately before the name of the variable *ptid* which it is being applied to. Rather than specifying a separate string format for each of the variables med1 to med10 we can specify a single string format (*str90*) and then apply this to all the following variables within the brackets. We chose a relatively large number 90 as the maximum length of the string to make sure none were truncated. We checked this was sufficient by using the compress command. As all the variables were then compressed to fewer than 90 characters we can be confident that no observations were truncated.

```
. compress
  med1 was str90 now str47
  med2 was str90 now str60
  med3 was str90 now str59
  med4 was str90 now str60
  med5 was str90 now str45
  med6 was str90 now str45
  med7 was str90 now str45
  med8 was str90 now str51
  med9 was str90 now str45
  med10 was str90 now str45
  med10 was str90 now str45
  (559,563 bytes saved)
```

Don't forget to look at the data.

. list ptid-med4 in 1/5

	+					+
	1	ptid	med1	med2	med3	med4
1.	C10	011001	Paroxetine	Aspirin	Enalapril	Risperidona
2.	C10	011002	Losartan	Aspirin	Carvedilol	Digoxine
3.	C10	011003	Losartan	Insuline	Aspirin	Furosemide
4.	C10	011004	Enalapril	Amiodarone	Thiazides	Acenocumarol
5.	C10	011005	Carvedilol	Enalapril	Amiodarone	Lanoxin Digoxina
	+					+

This command can also be accessed through the File > Import > Unformatted Text Data menu. Also see help infile.

4.6 Loading Fixed-Format Text Files

The final type of data we will consider is fixed format text files. These are rarely encountered but are dealt with here in case you should come across such a file.

For this example we will use the trtcodes.txt file. This contains the randomisation code, the randomisation date and the treatment group.

```
. type trtcodes.txt , lines(5)
2073200607211
2074200607212
2076200608221
2077200608221
2078200608291
```

The randomisation code is 4 characters in length and occupies the first 4 columns of the dataset. The randomisation date is 8 characters in length and occupies columns 5 to 12 of the dataset. The treatment group is just a single character (1 or 2) and occupies column 13.

Note that for each variable the observations are the same length and therefore occupy the same columns in the dataset. Note also that there are no separating characters and that the dataset does not contain any variable names.

As with the infile command we will need to specify the names of the variables, the format type if required (compulsory for strings) and to specify the data file to be loaded. Additionally we will need to specify the columns that each variable occupies.

```
infix rcode 1-4 str randdate 5-12 trtcode 13 using trtcodes.txt, clear (2500 observations read)
```

Unlike the infile command we do not need to specify the length of the string since this is implicit from the column numbers that are specified.

. list in 1/5

		rcode	randdate	trtcode
1. 2. 3. 4. 5.	-	2073 2074 2076 2077 2078	20060721 20060721 20060822 20060822 20060829	1 2 1 1 1
	+-			

Note that if we had decided to import the randomisation date as a number rather than a string it would be best to specify the type as long format because of the size of that number. E.g.

infix rcode 1-4 long randdate 5-12 trtcode 13 using trtcodes.txt, clear (2500 observations read)

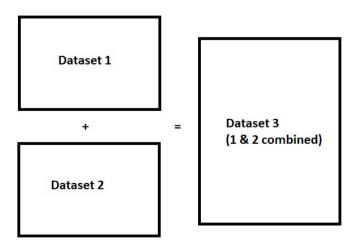
As we finish this section on creating datasets it is very important to again recall how Stata works with data. Above we loaded data that existed on disk as delimited files. As we do this Stata loads a copy of the data contained in those files into its memory (RAM). Any work carried out on the dataset currently in memory e.g. adding labels, generating new variables, etc. affects only the data in memory. The file from which the data was loaded is completely unaffected and remains in its original state. It is good practice to always keep (at least) one copy of the 'raw' data.

4.7 Appending Datasets

It is often the case in large clinical trials or studies involving a long period of follow-up that data will be stored in more than one file. For example, data on baseline demographics may be recorded and saved in one dataset, baseline blood measurements in another and follow-up measurements in yet more. It is then often necessary to combine these data files in to one large dataset in order to carry out a full analysis.

Stata has two main commands for combining datasets (append and merge). Which to use depends on whether you are adding more observations (making the dataset longer) or adding more variables (making the dataset wider). We start here with appending.

With the append command we are combining data files by stacking them one beneath the other. This means that the combined dataset will be longer (i.e. more observations) but will usually be the same width (i.e. same number of variables) as the individual data files as shown in the figure below.



The datasets being combined will generally contain the same variables (though some datasets may contain additional variables) but measured either at different time-points or at different centres.

For example, in a single trial we may have data files created at different centres, collecting information on the same variables (say age, sex, height, etc.) but for subjects recruited at each centre. The variables being collected are the same, but the subjects are different. Providing that the variable names are the same, e.g. age is called age in all datasets, we can combine these files by stacking or appending them one under the other.

For example, if we look at the first 5 observations in each of *bl_labs1.dta*, *bl_labs2.dta*, *bl_labs3.dta* and *bl_labs4.dta* we find that they contain the same 7 variables, but on different patients i.e. from different regions.

- . use bl labs1, clear
- . list in 1/5, nolab

ptid regid	creat	hb	pot	sodium	totbil
1. C10161001	70.72	12.6	4	140	15.39
	150.28	17.4	3.3	142	11.97
	114.92	11.7	4.7	132	23.94
	114.92	9.5	3.5	140	15.39
	97.24	13.6	4.9	140	6.84

- . use bl labs2, clear
- . list in 1/5, nolab

+ ptid	l regid	creat	hb	pot	sodium	totbil
1. C10011001 2. C10011002 3. C10011004 4. C10011005 5. C10011006	2 2 2	129 105 98 122 98	12.5 14.8 13.5 13.9 13.8	4.9 3.9 4.7 4.9	148 147 144 137 145	10 10 10 16 23 4

- . use bl labs3, clear
- . list in 1/5, nolab

	+						+
	ptid	regid	creat	hb	pot	sodium	totbil
1.	C10371001	3	97.24	12.5	4.6	142	6.84
2.	C10371002	3	123.76	13.9	4.49	137.4	23.94
3.	C10371003	3	123.76	15.3	4.4	142.3	30.267
4.	C10371004	3	106.08	11.7	4.5	138	21.033
5.	C10371005	3	114.92	10.9	4.42	136.4	13.167
	+						

- . use bl labs4
- . list $\overline{\text{in}}$ 1/5, nolab

	ptid	regid	creat	hb	pot	sodium	totbil
2. 3.	C10321001 C10321002 C10331001 C10331002 C10331003	4 4 4 4 4	67 153 71 101 123	15.3 10.4 13.4 15.4 13.1	4.5 4.6 4.5 4 4.6	142 137 141 138 142	8 9 6 22 16

Note that the variable names in each dataset are identical: *ptid*, *regid*, *creat*, *hb*, *pot*, *sodium* and *totbil*.

Hopefully it should be clear that we want to stack these 4 datasets to produce a longer dataset with the total number of variables still being 7 and the total number of observations equal to the sum of the observations in the 4 datasets.

To combine these datasets we can load one dataset into memory and then append the other datasets e.g.

```
. use bl_labs1 , clear
. append using bl_labs2 bl_labs3 bl_labs4
```

Alternatively we can clear any data from memory and then specify all the datasets to be appended on the append command, e.g.

```
. clear
. append using bl labs1 bl labs2 bl labs3 bl labs4
```

If required we can generate a variable that indicates which dataset the observation came from we can use the gen (newvarname) option, e.g.

```
. append using bl labs1 bl labs2 bl labs3 bl labs4, gen(datasetid)
```

This will generate a new variable called datasetid in the combined dataset which will take values 1 for all observations from the first dataset in our list (bl_labs1), 2 for all observations from the second dataset in the list (bl_labs2) and so on.

In our example above this is not necessary as there is already a variable, *regid*, that identifies which dataset the observation comes from.

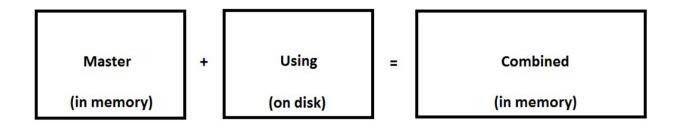
Having done used the append command we should check that things have worked out as we expected (e.g. browse the dataset and do a tabulation of regid) and then, if it has worked, save the new dataset with an appropriate name, e.g.

```
. save bl labsall
```

The append command can also be accessed via the Data > Combine datasets menu.

4.8 Merging Stata Datasets

With the merge command we are able to add to the dataset in memory (called the master dataset) a second dataset (called the using dataset) which contains additional variables. When combining datasets in this way we do not want to stack them but rather add them on to the 'right-hand side' of the 'master' dataset. This time we end up with a wider dataset containing more variables as shown in the figure below (for one-to-one merges).



The number of observations in the merged dataset may be different if the master and using datasets are not perfectly matched or if we are not doing a one-to-one merge (more later).

Example of a one-to-one merge

Below we have listed the values for some variables in the first five rows of *bl_demog.dta* and for the first five rows of *fup_endpoints.dta* (follow-up dataset for the primary endpoint).

- . use bl demog
- . list ptid age sex in 1/5

	+			+
	ptid	age	sex	
1.	C10011001	63	Male	
2.	C10011002	66	Male	
3.	C10011004	62	Male	
4.	C10011005	66	Male	
5.	C10011006	68	Male	
	+			+

- . use fup_endpoints
- . list in 1/5

	ptid	rcode	pep	pep_dt	acdeath	acdth_dt	+ -
1. 2. 3.	C10011001 C10011002 C10011004	2073 2074 2076	1 1 0	26nov2007 23mar2009 02sep2010	0	15jan2009 08sep2010 02sep2010	
4. 5.	C10011005 C10011006	2077 2077 2078	1 0	06apr2010 13sep2010	0 0	09aug2010 13sep2010	

When merging datasets it is important that we have an identification variable (or variables) which link the observations in each dataset. We can see above that the variable *ptid* appears in both datasets. This is the patient identifier which we will use to link the records in the two datasets. Other than *ptid* the two datasets contain different variables. The linking variable name should be identical in each dataset. It cannot be *ptid* in one and *patid* in another. To merge the two data files we first load one of them into Stata - this is called the **master** dataset in Stata terminology. In this case it makes sense to start with the baseline data file. We then use the merge command to add on or merge the second data file – called the **using** dataset in Stata terminology.

On the command line, following the command name, we need to specify the type of merge. In this case we are carrying out a one-to-one merge i.e. there is one unique record for each subject in both the master and using data files. We indicate a one-to-one merge by 1:1. Next on the command line we specify the linking variable (or sometimes variables). In our case the variable ptid uniquely identifies the records that are to be linked.

Finally we indicate where the file to be merged is located with using filename which might just be the filename if it is located in the current working directory or the directory and filename if located elsewhere.

So to merge *bl_demog.dta* and *fup_endpoints.dta* the syntax would be:

- . use bl demog , clear
- . merge 1:1 ptid using fup endpoints

```
Result # of obs.
-----
not matched 0
matched 2,500 (_merge==3)
```

Each time two files are merged Stata automatically creates a new variable which is named $_merge$. This variable can take values 1, 2 or 3, indicating 1 – the observation was in the master dataset but was not found in the using data; 2 – the observation was found in the using data but was not found in the master data; 3 – the observation was found in both master

and using data. It is possible to carry out more advanced merges involving updating variables, in which case *merge* can take values 4 or 5.

Immediately after the merge command Stata presents a tabulation of _merge (see output above) so we can see how well the matching has gone. In our example above we see that we have complete matching for all 2500 observations. The _merge variable remains in the dataset which means that it can be tabulated later. We have to rename or drop the variable before carrying any more merges. If we don't we will get an error message saying that _merge is already defined.

Alternatively we can use the gen (varname) option with the merge command by which we provide the name for the *merge* variable e.g.

```
. merge 1:1 ptid using fup endpoints , gen(pe merge)
```

This will generate a new variable called *pe_merge* instead of *merge*.

As the matching was complete we could simply drop the _merge variable from our dataset using the drop command:

```
. drop merge
```

Or if would prefer to keep but rename the variable we can use the rename command. The command syntax is rename *oldvarname* newvarname. E.g.

```
. rename merge pe merge
```

Note that following the merge command we now have the two files *bl_demog.dta* and *fup_pe.dta* exactly as they were on disk and the combined file in memory. We can save the dataset in memory under a new name or continue adding more data files.

Non-Unique Merges

Here we will look at merging where the linking variable is not unique, either in the master or using datasets or both. Recall that when carrying out a merge the dataset currently in memory is called the master dataset and the dataset being merged on to the dataset in memory is called the using dataset.

There are 3 possible scenarios:

- (i) The linking id variable(s) is unique in the master dataset but not in the using dataset. This is called a *one-to-many* (1:m) merge,
- (ii) The linking id variable is duplicated in the master dataset but is unique in the using dataset. This is called a *many-to-one* (m:1) merge,
- (iii) Or the linking id variable is duplicated in both variables. This is a *many-to-many* (m:m) merge.

Here we will demonstrate the second of these, a many-to-one merge.

Merging part of a Dataset

We will also look at how to merge only part of a dataset, i.e. bring in a subset of the variables from the using dataset. Quite often, when carrying out a merge, we may only wish to bring in a in a subset of variables from the 'using' dataset i.e. not the whole dataset. We can do this easily in Stata with the keepusing (varlist) option.

Below are listed the first 5 observations from the *fup_egfr.dta* dataset having sorted on the patient id variable and visit.

- . use fup egfr, clear
- . sort ptid visit
- . list in 1/5

	+			+
	ptid	visit	visdate	egfr
1. 2. 3. 4. 5.	C10011001 C10011001 C10011001 C10011001 C10011001	Screening Month 5 Month 13 Month 21 Month 29	20ju12006 19dec2006 05sep2007 30apr2008 08jan2009	52.82 58.34 56.37 53.67 56.92
	T			

We can see that the values of the linking variable *ptid* are duplicated e.g. C10011001 appears 5 times, once for each visit.

We want to add on to this dataset the variables sex, age and treatment group from *combined1.dta*. Below we list the first 5 observations from *combined1.dta* to show that *ptid* is not duplicated, e.g. C10011001 appears only on the first row.

- . use combined1, clear
- . sort ptid
- . list ptid age sex trt in 1/5

	+			+
	ptid	age	sex	trt
1.	C10011001	63	Male	Active
2.	C10011002	66	Male	Placebo
3.	C10011004	62	Male	Active
4.	C10011005	66	Male	Active
5.	C10011006	68	Male	Active
	+			

To merge these two files we first load fup egfr.dta and then merge on hfs combined1.dta.

Chapter 4: Creating and Combining Stata Datasets

The merge command includes the following:

m:1 indicating a many-to-one merge
ptid the linking variable
using combined1 indicating which dataset we are merging; the using file
is in the current working directory otherwise we would
also need to specify the directory

also fleed to specify the directory

keepusing(sex age trt) bring in only these three variables

Save this dataset as fup_egfr1.dta.

Chapter 5: Housekeeping

Aims and Objectives of Chapter 5

By the end of this chapter you should:

- Be aware of the value of housekeeping
- Know how to attach labels to variables
- Know how to define value labels and attach them to variable values
- Be able to amend value labels
- Know how to rename variable names
- Know how to get rid of unwanted variables or observations
- Know how to add and manage notes to variables
- Know how to manage labels, names and notes in the Variables Manager

The following commands are used in this chapter: label variable, label define, label values, label list, label book, rename, drop, keep.

5.1 Housekeeping

By housekeeping we mean the part of data management that is related to keeping your dataset in good order, i.e. not cluttered with redundant variables, clearly labelled, etc. This can be incredibly helpful for you when it comes to descriptive statistics and statistical analyses. A messy dataset often leads to messy analyses.

Additionally, as medical research is often collaborative, it is likely that at some point you will pass on your data to other people. If the dataset is clean, clearly labelled etc. this makes this much less painful than it might otherwise be.

In this chapter we will look at a few of the essential housekeeping commands. There are many more. Much of what we will look at can also be done through the *Variables Manager*.

5.2 Labelling Variables

It is good practice to keep *variable names* as short as possible. This helps to keep the dataset simple, and simplifies the process of referring to variables during analyses, e.g. it is much simpler to refer to <code>sbp</code> than to <code>systolic_blood_pressure</code>.

However, keeping variable names short can make it difficult to identify what each variable is e.g. what is *wc* or *lvef*? To overcome this we can attach a lengthier more detailed label (up to 80 characters in length) to each variable. These will be saved with the data file and will appear when describing, tabulating and graphing the variables. For example, when we do a describe of the *bl demog.dta* dataset:

describe

Contains data from H:\Stats Computing\Stata\Exercise 5\bl demog.dta

obs:	2,500	
vars:	21	14 Sep 2015 16:09
size:	250,000	

variable name		display format		variable label
ptid birthdt age agegroup sex randdt trt smkstat smoke race hfdiag diagnosis wt ht wc wc_unit sbp dbp hrate	byte float str7 long str7 str5 byte double double double str2 float float int	%d %8.0g %9.0g %8.0g %d %9s %13.0g %9s %9s %10.0g %10.0g %10.0g %10.0g %9s %9.0g %9.0g %8.0g	agegroup sex	Sex Date randomized Treatment allocation Smoking status Smoking status Race Heart failure Weight (kg) Height (cm) Waist circumference WC units
egfr lvef diab	double double byte	%10.0g		eGFR (ml/min/1.73msq) LVEF (%)

Sorted by: ptid

Here we see that in general the variable names (first column) are much shorter than the variable labels (fifth column). The variable ptid has the label "Patient ID", the variable wt has the label "Weight (kg)". The syntax for labelling a variable is:

```
label variable varname "variable label"
```

Here label is the command and variable is a subcommand indicating the type of label being defined. The word *varname* tells Stata to which variable the label should be attached.

In the data description above the variable *sbp* has not been labelled. To add a variable label the syntax is:

```
. label variable sbp "Systolic Blood Pressure (mmHg) " \,
```

The variable label will now appear when we describe the data, plot the data, etc. E.g.

. describe sbp

```
storage display value
variable name type format label variable label
-----
sbp float %9.0g Systolic Blood Pressure (mmHg)
```

Variable labels can be amended without specifying modify, replace or overwrite. For example, if we wished to abbreviate the above label we could amend our command and rerun as

. label variable sbp "SBP (mmHg)"

5.3 Labelling Values

Above we added labels to variable names. Here we will learn how to add labels to the values of a variable. Stata calls these value labels.

Often a categorical variable (e.g. sex) will be recorded as real numeric values (e.g. 1, 2) which indicate some category (e.g. Male, Female). For example, in our dataset the variable *hfdiag* records the type of heart failure which the patient was diagnosed with on entry to the study and takes the values 1 or 2 where 1 = Ischaemic and 2 = Non-Ischaemic.

. tab hfdiag

Heart failure diagnosis	 Freq.	Percent	Cum.
1 2	1,730 770	69.20 30.80	69.20 100.00
Total	2,500	100.00	

It can be very useful to attach labels to these values so that we can easily identify what the values refer to without continually having to look this information up.

Adding value labels to a variable in Stata is a two-stage process. Firstly, a value label is *defined*, and then secondly, the value label is *attached* to the appropriate variable.

(i) Defining a Value Label

Each value label has a name, and a series of associations, between integer values and text. To define a value label we use the label define command. We will start by defining a value label called *hf lab*

. label define hf lab 1 "Ischaemic" 2 "Non ischaemic"

The words label define are the Stata command for defining a value label, hf_lab is the name we have decided to call this value label. The rest are the values and the labels for each value.

When we run this command the value label is created or defined but is not yet attached to any variable. When the dataset is saved the value label would be saved as an unattached value label along with the data.

(ii) Attaching a Value Label to a Variable

Having defined the value label we now need to tell Stata to which variable this value label should be attached.

To attach the value label *hf_lab*, created above, to the variable hfdiag:

. label values hfdiag hf lab

Here *label value* is the Stata command, *hfdiag* is the name of the variable we are attaching the value label to, and *hf_lab* is the name of the value label we defined above.

. tab hfdiag

Heart failure diagnosis	Freq.	Percent	Cum.
Ischaemic Non-ischaemic	1,730 770	69.20 30.80	69.20 100.00
Total	2 , 500	100.00	

Amending or replacing a value label

To change or modify an existing value label we need to specify the option modify along with the modified label define command. For example, if we wanted to modify the labels of the hf lab value label,

. label define hf la 1 "Ischaemic HF" 2 "Non ischaemic HF", modify

We can completely overwrite a value label by specifying the option replace.

Dropping a Value Label

To drop an existing value label:

. label drop labelname

Where label drop is the Stata command and labelname is the name of the value label.

Detaching a Value Label

To detach a value label from a particular variable, without deleting the value label itself, we simply use the label values command specifying the variable name but no value label. For example,

. label values agegroup

Will break the association between agegroup and its current value label, but the value label itself will not be deleted.

Getting a list of value labels

There are two useful commands for getting summaries of one, several or all the value labels that exist in the dataset in memory.

The command label list [labelname] can be used to obtain a list of any value labels defined, including the value label name, the values and what they map to. E.g.

value label agegroup

The command labelbook [labelname] can be used to obtain a codebook style report for the specified value label or, if none are specified, for all value labels in the dataset.

. labelbook agegroup

0 30-1 65-2 70-3 75-4 100-

variables: agegroup

Adding or Removing Numeric Prefixes to Value Labels

The command numlabel can be used to add (or remove) prefix numeric values to the value labels. The syntax for the command is:

numlabel [labelname], {add/remove}

For example:

. tab sex

Cum.	Percent	Freq.	Sex
77.68 100.00	77.68 22.32	1,942 558	Male Female
	100.00	2,500	Total

- . numlabel sex, add
- . tab sex

Sex	Freq.	Percent	Cum.
1. Male 2. Female	1,942 558	77.68 22.32	77.68
Total	2,500	100.00	

- . numlabel sex , remove
- . tab sex

Sex	Freq.	Percent	Cum.
Male Female	1,942 558	77.68 22.32	77.68 100.00
Total	2,500	100.00	

Saving value labels to a do-file

The command label save can be used to save value labels to a do-file i.e. to save a series of commands that can redefine the value labels. Value labels currently not attached to at least one variable are not saved. The file to which the value labels are to be saved is specified with using filename. The syntax for the command is:

label save using filename, [options]

For example to save the value labels from the bl demog dataset:

. label save using val_labs1
file val_labs1.do saved

The do-file created is shown below.

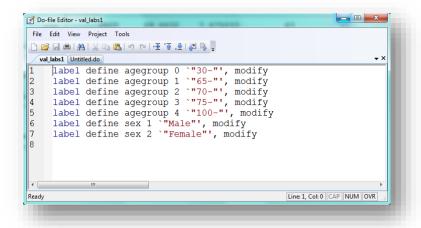


Figure 5.1: Do-file created by label save

5.4 Dropping Variables

Sometimes it can be helpful to reduce the size of your dataset by dropping either certain variables (columns) or observations (rows) from a dataset. For example, one or more variables that have been collected may not be required or perhaps an error has been made when generating a new variable. Alternatively you may want to drop all subjects that are under a certain age. We can use the command drop for either case.

For example, if you have made a mistake when creating a variable called *smoke2* and you wish to recreate it correctly, first you will need to drop the erroneous variable

. drop smoke2

In the situation where the number of variables you want to drop is greater than the number that will be left in the dataset we can use the keep command. This does the opposite to the drop command in that it keeps the variables specified and drops all others. For example:

describe

Contains data from bl demog.dta

obs: 2,500 vars: 18 size: 232,500

23 Sep 2014 14:15

variable name	_	display format	variable label
ptid birthdt age agegroup sex smkstat race hfdiag wt ht wc wc_unit sbp dbp hrate egfr	str9 str12 byte float byte long str5 byte double double str2 float float int double	%9s %12s %8.0g %9.0g %8.0g %13.0g %13.0g %10.0g %10.0g %10.0g %10.0g %9s %9.0g %9.0g %8.0g %10.0g	 Patient ID Sex Smoking status Race Heart failure diagnosis Weight (kg) Height (cm) Waist circumference WC units eGFR (ml/min/1.73msq)
lvef diab	str5 str7		 LVEF (%)

Sorted by: lvef

keep ptid age sex describe

Contains data from bl demog.dta

obs: 2,500 vars: 3 size: 27,500

2 Sep 2014 19:20

variable name	storage type	display format	value label	variable label
ptid	str9	%9s		Patient ID
age	byte	%8.0g		~
sex	byte 	%9.0g	sex	Sex
				

Sorted by: ptid

Note: dataset has changed since last saved

5.5 Dropping Observations

You may wish to carry out a series of analyses which are restricted to just a subset of all the observations in a dataset. You could do this using an if expression and keeping all the observations in the dataset – but this can add to the complexity of an analysis. An alternative is to create a separate dataset that contains just the observations that you want to include in

your analysis. We can do this with the ${\tt drop}$ or ${\tt keep}$ commands combined with an if expression.

For example if you wanted to carry out a series of analyses on people aged 50 or above we could drop all observations/records where age was less than 60 years as follows.

- . use bl demog, clear
- . summ age

Variable		Obs	Mean	Std.	Dev.	Min	Max
	+						
age		2500	68.6632	7.675	5033	43	95

- . drop if age<60
 (272 observations deleted)</pre>
- . summ age

Variable	Obs	Mean	Std. Dev.	Min	Max
	+				
age	2228	70.10727	6.819218	60	95

This command has dropped the entire record (row) for any person age under 60 years. We could have done the same thing using keep if age >= 60.

There is not an undrop or unkeep command so take care. However, remember any changes you make such as dropping variables or observations are only made to the dataset in memory and not to the data on disk.

5.6 Changing Variable Names

Sometimes we may wish to modify variable names. We can do this using the rename command.

The basic syntax is:

```
rename oldname newname
```

Where *oldname* is the original name of the variable and *newname* is the new variable name. For example, to change the variable name *diab* to *diabetes*:

```
rename diab diabetes
```

We can also rename groups of variables. Some examples are given below.

1. To rename two variables at same time (birthdt as dob and randdt as dor):

```
rename (birthdt randdt) (dob dor)
```

2. To swap two variable names:

```
rename (a b) (b a)
```

- 3. To rename all variables beginning/ending with the same prefix/suffix:
- (i) To rename all variables beginning with bl_ by removing bl_ and adding _1 to end of name:

```
rename bl * * 1
```

(ii) To remove the prefix bl_ from all variable names:

```
rename bl * *
```

(iii) To remove the suffix _fup and replace with _2

```
rename *_fup *_2
```

We can also use rename to change the case of variable names. As Stata is case sensitive with variable names it is generally simplest to have all variable names in lower case. The syntax for this is:

```
rename varname, lower
```

Where *varname* is the name of the variable to be changed. We could also specifiy upper or proper for upper and proper case respectively – though this is not advised for variable names.

Sometimes many or all of the variable names in a dataset contained upper case characters and we wish to make them all lower case. We can do this simply using _all to indicate the variable list. E.g.

```
rename all, lower
```

5.7 Adding Notes

The command notes attaches notes to the dataset in memory. As with labels these notes become a part of the dataset and are saved when the data file is saved. Also as with labels we can attach notes generically to the dataset or to specific variables within the dataset.

The note facilities can be accessed using the Data > Data utilities > Notes utilities menu.

Notes are numbered sequentially, with the first note added being 1, the second being 2 etc. When one note is deleted the numbering is not reordered. Up to 9,999 notes can be added to the dataset generically, and up to 9,999 notes added to each variable! Each note can be up to 67,784 characters in length! Note that notes are not saved until the dataset is saved.

Some examples are given below:

1. Adding a note to the dataset in memory

. notes: Data used for Intro to Stata Module

2. Adding a note to a variable

. notes wc: Note that some waist circumferences are measured in $\ensuremath{\mathsf{meters}}$

3. Listing notes

. notes

_dta:

1. Data used for Intro to Stata Module

WC:

1. Note that some waist circumferences are measured in meters

Just specifying the command notes requests a listing of all notes. To specify a list of notes for the dataset

```
. notes _dta
```

_dta:

1. Data used for Intro to Stata Module

And for a particular variable:

. notes wc

WC:

1. Note that some waist circumferences appear to be measured in $\ensuremath{\mathsf{meters}}$

4. Deleting notes

Notes can be deleted using the notes drop command. For example, to drop the first note attached to wc

. notes drop wc in 1
 (1 note dropped)

5.8 Managing Labels and Notes in the Variables Manager

If you forget the command syntax for labelling, notes etc, then variable labels, value labels and notes can be managed very easily through the Variables Manager (Figure 7.2). Remember that the Variables Manager can be opened using the *Window > Variables Manager* menu or through the shortcut on the toolbar.

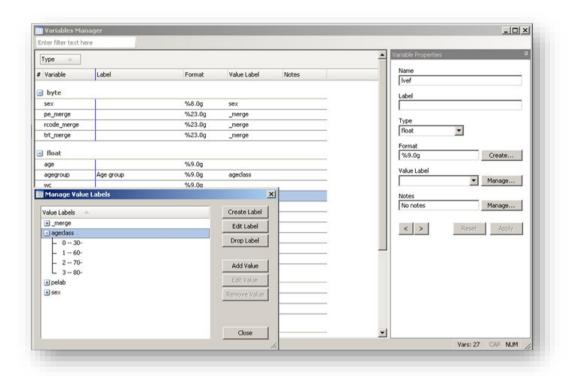


Figure 5.2 Variables Manager and Manage Value Labels dialog box

To add a variable label, selecting the variable from the left frame and fill in the details in Variable properties frame. Click on the Manage... button next to the Value Label field to open the Manage Value Labels dialog box. With this it is possible to create, edit, drop, and attach value labels. Notes are dealt with similarly.

Chapter 6: Essential Data Processing

Aims and Objectives of Chapter 6

By the end of this chapter you should:

- Know how Stata deals with data in memory and on disk
- Be able to correct or change values of existing variables
- Be able to convert string variables to numeric
- Understand how Stata stores missing values
- Be able to create new variables

The following commands are used in this chapter: replace, encode, destring, recode, generate, egen and mydecode.

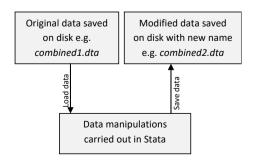
6.1 Data Processing

So far in this module we have learnt how to create Stata datasets, to examine data for errors and to carry out basic housekeeping. The goal of this process is to create a dataset that is ready for analysis. In this chapter we will continue along this process and look at some of the essential data processing commands for correcting errors and creating new variables ready for our analysis.

6.2 Processing Existing Variables

It is often the case that we will want to modify some existing variables. For example, we may wish to change the units (e.g. from days to years or grams to kilograms), or correct errors, or convert from string to numeric. Here we will look at a few of the most essential commands you will need: replace, encode, destring and recode.

It is important to recall that when we make changes e.g. drop variables, rename variables, generate new variables we are only affecting the data currently in memory, not the data saved on disk. The modifications are only saved when the dataset is saved. It is important to keep one completely unmodified copy of your original or raw data.



1. Replacing values

The **replace** command can be used to change the values of an existing variable. The syntax for the command is:

```
replace varname=expression [if] [in]
```

where expression could be a number or a missing value, or a function of some variables.

Replace example

The variable wc has values that were recorded in metres or centimetres. We want the units to be consistent e.g. to create a new variable where all the values are in cm. First we will generate a new variable, wc_cm, which is an exact copy of wc, using the generate command (we will come back to this command shortly) and then replace the values that were measured in metres.

```
. generate wc_cm = wc
. replace wc_cm = wc_cm*100 if wc_unit=="M"
(319 real changes made)
```

We have replaced wc_cm with itself times 100 if wc_unit equals "M". Note use of single equals for assigning the values and the double equals for if condition.

We should now check that the changes have worked.

```
. summ wc wc_cm
```

Variable	Obs	Mean	Std. Dev.	Min	Мах
wc		85.88955	35.65602	. 69	165
wc_cm		99.27214	13.28178	58	165

2. Encoding Categorical String Variables

Most of Stata's analytical commands require numeric rather than string variables. When strings are encountered Stata treats them as if they were missing values. By a categorical string variable we mean variables such as sex containing values "Male" or "Female" or smoke containing "Never", "Ex" or "Current" or race containing "Asian", "Black", "White" etc.

We can convert such categorical string variables into numeric variables using the <code>encode</code> command. This command allocates numeric values to the different strings (default is in alphabetical order). A value label is automatically created.

The basic syntax for the command is:

```
encode varname , gen(newvarname)
```

where *varname* is the name of the variable to be encoded; gen(newvarname) must be specified.

Encode example 1

The variable *sex* is a string variable recorded as "Female" or "Male". To encode this into a numeric variable with value labels attached:

- . encode sex , gen(sex2)
- . tab sex2

Cum.	Percent	Freq.	Sex
22.32 100.00	22.32 77.68	558 1 , 942	Female Male
	100.00	2 , 500	Total

Specifying the option nolabel we see that *sex2* is a numeric variable with value labels attached

. tab sex2 , nolab

Cum.	Percent	Freq.	Sex
22.32 100.00	22.32 77.68	558 1 , 942	1 2
	100.00	2 , 500	Total

By default with encode the new variable takes values 1, 2, etc. based on the alphabetical ordering of the string values.

Encode example 2

If we wish the variable to take some ordering other than alphabetical we need to first define the *value label* indicating the ordering and then include the option label (labelname) with the command. For example, we may wish to encode the variable *race* but due to the numbers in the different categories it makes sense to use an ordering other than alphabetical.

. tab race

Cum.	Percent	Freq.	Race
11.80 14.20 17.36 100.00	11.80 2.40 3.16 82.64	295 60 79 2,066	Asian Black Other White
	100.00	2,500	Total

- . label define race lab 1"White"2"Asian"3"Black"4"Other"
- . encode race , gen(race2) label(race lab)

. tab race2

Cum.	Percent	Freq.	Race
82.64 94.44 96.84 100.00	82.64 11.80 2.40 3.16	2,066 295 60	White Asian Black Other
	100.00	2,500	Total

3. Converting "Number" Strings to Numeric

With the <code>encode</code> command above we converted categorical string variables into numeric variables. The original categories contained strings which consisted of non-numeric characters e.g. Female, Black. In each case there was a discrete number of categories.

In this example we will be converting numeric variables that have been stored as strings into a numeric storage type. These are variables that may have all numeric characters but have been imported as strings or could be variables that are mostly numeric but have a few non-numeric characters. For these examples we will use the destring command. The syntax is:

```
destring varlist , {replace/gen(newvarlist)} [force ignore("")]
```

One of the options replace or gen (newvarlist) must be specified. If replace is used the existing variable is overwritten.

Destring example 1

First we will look at the variable lvef (Left ventricular ejection fraction (%)). This is a numeric variable that can in theory take values between 0 and 100. In the bl_demog dataset this variable has been imported as a string.

We can see from the codebook command that *lvef* is stored as a string, but the examples are just numeric characters. If you browse lvef you will see that the variable contains just numeric characters but that they are displayed in red i.e. they are stored as a string.

We therefore cannot calculate a mean or other summary statistics since Stata does not allow this for string variables e.g. see summarize output below.

. summarize lvef

Variable	Obs	Mean Mean	Std. I	Dev.	Min	Max
lvef	+ ()				

To convert this to a numeric variable:

```
. destring lvef , replace
lvef has all characters numeric; replaced as double
(137 missing values generated)
```

Stata reports that all the characters were numeric and that lvef has been replaced as double i.e. as one of Stata's numeric storage types. Now we can use summarize to obtain some summary statistics.

. summ lvef

Variable	Obs	Mean	Std. Dev.	Min	Max
	+				
lvef	2363	26.07964	4.671837	6	40

Destring example 2

In this second example we have a variable diab that has been recorded as 0 or 1 i.e. as a numeric variable. However, for one observation the entry is recorded as "Missing". This is obviously not a number and therefore the variable *diab* has been stored as a string.

. codebook diab

diab (unlabeled)

type: string (str7)

unique values: 3 missing "": 0/2500

tabulation: Freq. Value
1716 "0"
783 "1"
1 "Missing"

If we try the same approach as for lvef Stata will report that this variable contains some non-numeric characters and therefore that it cannot replace. A variable can only be numeric if all the characters are numeric. To force Stata to convert this to a numeric variable we either must specify which non-numeric characters to ignore or specify the force option.

- . destring diab , replace
 diab contains nonnumeric characters; no replace
- . destring diab , replace ignore("missing")
 diab: characters m i s n g removed; replaced as byte
 (1 missing values generated)
- . tab diab

Cum.	Percent	Freq.	diab
68.67	68.67 31.33	1,716 783	0 1
	100.00	2 , 499	Total

4. Recoding numeric categorical variables

We may sometimes wish to combine categories of an existing variable (e.g. combine Current and Ex smokers into Ever smokers or change a binary variable coded as 1=No 2=Yes to be 0=No and 1=Yes).

The most appropriate command for this in Stata is recode. The basic syntax for recode is:

recode varname rules , gen(newvarname) label(labname)

Where (rules) takes the form (oldvalue(s) = newvalue). Some examples of rules are shown in the table below.

Recode rules

Example	Meaning
(3 = 1)	3 recoded to 1
(4/6 = 2)	4 to 6 (inclusive) recoded to 2
$(7 \ 9 = 3)$	7 and 9 recoded to 3
(min/2=0)	Minimum value to 2 (inclusive) recoded as 0
(11/max=4)	11 to maximum value (inclusive but not including missing values) recoded to 4
(* = 5)	All other values (including missing) recoded to 5
(. = 99)	Missing values recoded to 99

The option <code>gen(newvarname)</code> indicates that we want to create a new variable (newvarname) which contains the recoded values i.e. we do not recode the values of the original variable. If this option is not specified then the values of the original variable (varname) will be recoded. We should only do this if varname is a new variable we have previously copied using <code>generate</code>.

Recode example 1

Suppose we wish to create a new variable evsmk that takes the value 0 for never smokers and 1 for those who have ever smoked. In our dataset we have a variable smoke that takes value 1 = Never, 2 = Ex-Light, 3 = Ex-Heavy, 4 = Current-Light and 5 = Current-Heavy.

```
.recode smoke(1=0"Never smoker")(2/5=1"Ever smoker"),gen(evsmk)
label(evsmk_lab)
(2500 differences between smoke and eversmoke)
```

Note that within the brackets we have specified the recode rules followed by value labels. In the options we have specified the name of the value label with label (evsmk lab).

We can check the distribution of the new variable with a table.

. tab evsmk

RECODE of smoke (Smoking status)	Freq.	Percent	Cum.
Never smoker Ever smoker	1,114 1,386	44.56 55.44	44.56
Total	2,500	100.00	

It is worth cross-tabulating the two variables to check we have not made a mistake in the recoding:

. tab smoke evsmk

 Smoking		status)	
status	Never smo	Ever smok	Total
Never Ex-Light Ex-Heavy Current-Light Current-Heavy	1,114 0 0 0 0	0 576 541 132 137	1,114 576 541 132 137
Total	1,114	1,386	2,500

See help recode for more details.

Recode example 2

Here we will create a categorical variable called *agegroup* by recoding the variable age; as above we do not want to change the values of the variable age. The minimum age is 43 years and maximum is 95 years.

```
. recode age (40/59=1 "<60 years" ) (60/69=2 "60-69 years" ) (70/\text{max}=3 "70+ years" ) , gen(agegroup) label(age_lab) (2500 \text{ differences between age and agegroup})
```

. tab agegroup

RECODE of age (Age (years))	Freq.	Percent	Cum.
<60 years 60-69 years 70+ years	272 1,125 1,103	10.88 45.00 44.12	10.88 55.88 100.00
Total	2 , 500	100.00	

6.3 Creating New Variables

We will now look at two key commands for creating new variables: generate and egen.

Generate

The basic syntax for the generate command is:

```
generate [type] newvar = expression [if] [in]
```

newvar is the name of the new variable being created;

expression could be a number, a string, a variable or some function to be evaluated;

type is the storage type for the new variable. Type can be one of:

byte	integer (range from -127 to +100)	1 byte
int	Integer	2 bytes
long	integer (range -2,147,483,647 to 2,147,483,620)	4 bytes
float	$-1.7014117 \times 10^{38}$ to $+1.7014117 \times 10^{38}$	4 bytes
double	$-8.9884656 \times 10^{307} \text{ to } +8.9884656 \times 10^{307}$	8 bytes
str#	string of maximum length # where 1\le #\le 244	1-244 bytes

If type is not specified and the new variable is numeric Stata will default to float. If type is not specified and the new variable is a string Stata will automatically select str# where # is the maximum length of the string variable.

Generate example 1: creating a variable that is a function of two variables

Suppose we wish to create a new variable called bmi containing the body mass index of each individual (defined as kg/m^2). Note that in our dataset weights are recorded in kilograms but heights are recorded in centimetres rather than metres. We therefore need to divide height by 100 within the expression:

```
. generate bmi = wt/(ht/100)^2
(14 missing values generated)
```

Note that 14 missing values are generated since we have some missing values for *ht* and/or *wt* and therefore *bmi* cannot be calculated.

Once a new variable has been created it is always worthwhile checking its distribution using histogram or summarize. It is possible that we might uncover problems with ht and wt that were not obvious when considered individually. There are 2 values of bmi over 50 kg/m².

. list pt wt ht bmi wc sex if bmi>50 & bmi~=.

+	 ptid			bmi		sex	
İ		149.9	173	57.77778 50.0852	1.46	Male	İ

A twoway scatter plot can be helpful. The darker markers relate to the 2 cases where bmi>50.

```
. twoway (scatter wt ht if bmi>50, ms(o) mc(gs1)) /// (scatter wt ht if bmi<50, ms(oh) mc(gs12)), legend(off)
```

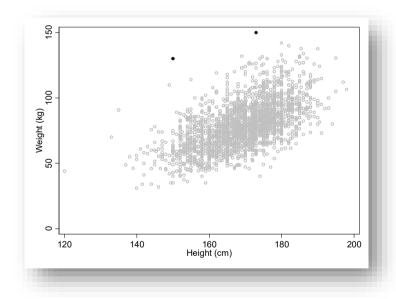


Figure 6.1 Scatter plot of weight versus height

Generate example 2: generating a log-transformed variable

Quite often we will want to create a new variable equal to the log-transformation of another, generally where the original variable is skewed.

```
. gen log egrf = log(egfr)
```

Creates a new variable called *log_egfr* that is the natural logarithm of *egfr*. We can use histogram to compare the two distributions.

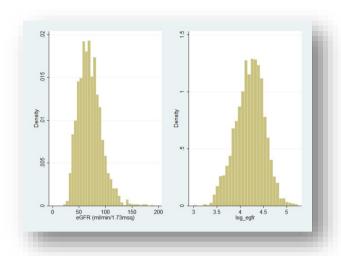


Figure 6.1: Histogram of egfr and log_egfr

The log transformed variable looks slightly less positively skewed though there may be some negative skew.

. summ egfr log_egfr, detail

		eGFR (ml/min/1.	.73msq)	
1% 5%	Percentiles 32.6 39	Smallest 20.2 25		
10% 25% 50%	44.5 55.2 68.7	26.3 26.8 Largest	Obs Sum of Wgt. Mean Std. Dev.	2491 2491 70.70273 21.89467
75% 90% 95% 99%	83.8 98.3 109.2 137.7	172.5 176.2 178 190.5	Variance Skewness Kurtosis	479.3766 . 8156039 4.494325
		log_egfr		
1% 5%	Percentiles 3.484312 3.663562	Smallest 3.005683 3.218876		
10% 25% 50%	3.795489 4.010963 4.229749	3.269569 3.288402 Largest	Obs Sum of Wgt. Mean Std. Dev.	2491 2491 4.21123 .3101085
75% 90% 95% 99%	4.428433 4.588024 4.693181 4.925077	5.150397 5.17162 5.181784 5.249652	Variance Skewness Kurtosis	.0961673 163848 2.964581

Generate example 3: generating a binary variable

A useful feature of the generate command is that when combined with a condition it is possible to generate a binary 0, 1 variable depending on whether the condition is satisfied or not. For example, to generate a variable called *age70* taking the value 1 if the subject is greater than or equal to 70 and 0 otherwise.

- . gen age70 = (age>=70)
- . tab age70

Cum.	Percent	Freq.	age70
55.88 100.00	55.88 44.12	1,397 1,103	0 1
	100.00	2,500	Total

CAUTION: Care needs to be taken when using > or < conditions where there are missing values. This is because of the way Stata handles missing values. Stata stores numeric missing values as "large positive values" which will be greater than any non-missing value and which will therefore certainly satisfy the condition "> some real value" and certainly not satisfy the condition "< some real value". So to avoid having a subject with a missing bmi returned as being obese we need to add *if bmi*~=. as follows.

```
. gen obese = (bmi>=30) if !missing(bmi)
(14 missing values generated)
```

. tab obese

Cum.	Percent	Freq.	obese
73.25 100.00	73.25 26.75	1,821 665	0 1
	100.00	2 , 486	Total

If we had omitted the !missing(bmi) condition we would have got the following:

- . gen obese = bmi >= 30
- . tab obese

Cum.	Percent	Freq.	obese
72.84	72.84 27.16	1,821 679	0
	100.00	2 , 500	Total

Note that this time Stata does not report any missing values generated and that we have an extra 14 observations in category 1 (the BMI 30+ group).

More than one condition can be specified, e.g.

```
. gen hyper = (sbp>=140 \mid dbp>=90) if !missing(sbp,dbp) (1 missing value generated)
```

. tab hyper

Cum.	Percent	Freq.	hyper
76.55 100.00	76.55 23.45	1,913 586	0 1
	100.00	2,499	Total

However, you need to think carefully when doing this. If sbp was missing and dbp was 95 then by our definition the person has hypertension no matter what the missing sbp value is. However if sbp was missing and dbp was 89 the missing sbp is important.

<u>Egen</u>

The command egen is an extension to the generate command and has many useful functions which can be used to create a new variables.

A particularly useful function specific to egen is cut(varname) which can be used to 'cut up' or categorize a continuous variable. We can either specify the exact cut-points to be used with the option at(numlist) or specify the desired number of equal-sized groups (e.g. quarters or fifths) using the option group(#).

Egen example 1: Categorising a continuous variable at specific cut-points

Here we will create a new variable *sbpcat* based upon an existing variable *sbp*. We will create four categories: <120, 121-129, 130-139 and 140+. The lowest value we will accept is 80mmHg and maximum value will be 200mmHg i.e. any values below 80 or above 200 will be treated as missing. The command syntax for this is:

```
. egen sbpcat = cut(sbp), at(80, 120, 130, 140, 201) label
```

The option at () tells Stata where we want the cut-points. The first number is the lowest value of the first category; the next value is the lowest value in the second category and so on up to the final number which is the value at and beyond which we will treat as missing. So in our example here the first category will extend from 80 to 119 mmHg inclusive; values below 80 would be returned as missing. The second category will include values from 120 to 129 mmHg and the third 130 to 139 mmHg. The fourth category will extend from 140 to 200 mmHg and any values of 201 or above will be returned as missing.

The option label requests that the categories are given integer-coded values and that a value label (using the left-hand ends of each interval) is automatically defined and attached. If the label option is not used then the by default the categories will be coded with values equal to the left-hand end of the intervals e.g. 80, 120 etc. in the example above.

. tab sbpcat

Cum.	Percent	Freq.	sbpcat
35.21 58.46 79.31 100.00	35.21 23.25 20.85 20.69	880 581 521	80- 120- 130- 140-
	100.00	+ 2 , 499	Total

Note that one missing value was generated because we have one value missing for sbp.

The number list in the at () option could also be specified as #1(#2)#3 meaning from #1 to #3 in steps of #2. For example, at (40(10)90) would be create categories from 40 to 90 in steps of 10 where the top category would be 80-89.

Egen example 2: Categorising a continuous variable into equal sized groups

To categorize a variable into equal sized groups (e.g. quarters, fifths) we use the option group (#) rather than specifying the actual cut-points. For example, to categorise *bmi* into four equal size groups:

```
. egen bmi4 = cut(bmi), group(4) label
  (14 missing values generated)
```

. tab bmi4

Cum.	Percent	Freq.	bmi4
24.98 49.92 74.98 100.00	24.98 24.94 25.06 25.02	621 620 623 622	13.21179- 24.4418- 27.0538- 30.27371-
	100.00	+ 2,486	Total

Note that the groups are not exactly equal-sized because there are a few tied values.

Egen example 3: Creating a row summary variable

In the bl_medhis1.dta dataset there are four binary (0/1) variables (*strisch strhem stremb stroth*) that record whether or not the patient had previously experienced any of four different types of strokes. The four variables are tabulated below.

. tab1 strisch strhem stremb stroth

strisch	Freq.	Percent	Cum.
0	2,297 187	92.47 7.53	92.47
Total	2,484	100.00	
strhem	Freq.	Percent	Cum.
0	2,413 15	99.38 0.62	99.38
Total	2,428	100.00	
stremb	Freq.	Percent	Cum.
0	2,397 35	98.56 1.44	98.56 100.00
Total	2,432	100.00	
stroth	Freq.	Percent	Cum.
0	2,404	99.05 0.95	99.05
Total	2,427	100.00	

We want to create a single variable that takes the value 1 if any of these four variables is 1 and 0 otherwise. As a patient could have had more than one type of stroke a row total would not necessarily work. What we could use for this task is a row maximum.

. egen stroke_any = rowmax(strisch strhem stremb stroth)
(1 missing value generated)

. tab stroke

Cum.	Percent	Freq.	stroke_any
90.00	90.00	2,249 250	0 1
	100.00	2,499	Total

1 missing value has been generated. This will be a patient who has missing values for all four of the stroke types.

Egen example 4: calculating the number of missing values in a set of variables

In example 3 we saw that 1 missing value had been generated. This was for a patient who had missing values for all four of the stroke types. However, you may have noted from the tables above that each of the stroke type variables has more than one missing values. The rowmax function will calculate a row maximum as long as at least one value is not missing. The missing values do not count towards the row maximum. Essentially we have to assume here that if one stroke type has been reported then all other missing values can be treated as a 0. We might be interested in exploring how serious this issue might be by finding out how many missing values each person had.

To calculate the number of missing values among these four stroke variables for each patient we can use the rowmiss () function of egen.

- . egen stroke_miss = rowmiss(strisch strhem stremb stroth)
- . tab stroke_miss

stroke_miss	Freq.	Percent	Cum.
	+		
0	2,418	96.72	96.72
1	9	0.36	97.08
3	72	2.88	99.96
4	1	0.04	100.00
	+		
Total	2,500	100.00	

Here we see that 1 patient has all four missing, 72 have three missing and 9 have one missing value. The majority have all 4 values present.

We could explore further by creating a cross-tabulation of *stroke_any* and *stroke_miss* to see how many of the 81 with partially missing data had previously had a stroke.

. tab stroke miss stroke any, miss

stroke_mis		stroke_any	7	
s	0	_ 1	•	Total
0	2,226	192	0	2,418
1	8 15	1 57	0	9 72
4	1 0	0	1	/2
	.+			+
Total	2,249	250	1	2,500

We can see that 58 out of the 81 with some missing value had previously experienced a stroke. The missing data is therefore not important – since whatever values they would take the row maximum would still be 1. There are 23 patients (8+15) who we are uncertain about. We must either assume that missing is equivalent to "no" for these patients or perhaps code them as missing for the *stroke_any* variable.

6.4 Missing values

Missing data are common in medical research. It is rare to find a dataset with complete data on all subjects on all variables, even from the most carefully conducted trials.

Stata has 27 numeric missing values. They are,

The "system missing value" is generated by Stata when it is not able to assign a specific value. The "extended missing values" can be specified by the user when it is important to keep track of reasons for a missing value. Value labels can be attached to .a, .b etc. The advantage of having more than one missing value code is that measurements that are missing because of say non-response can be distinguished from those missing due to withdrawal from the study.

As described above, numeric missing values are represented by very large positive values. The ordering is:

```
"all non-missing numbers" < . < .a < .b < .c < ... < .x < .y < .z
```

Stata ignores any of these missing values when carrying out analytical commands e.g. when summarizing a variable. However, it *is very important* to note that sometimes missing values can be recorded in a database as a real number e.g. 9999 or -999. When this is the case Stata will treat these as real values and so they would, for example, contribute towards the calculation of a mean. Such values need to be recoded as Stata missing values. We can do this with the recode or mydecode commands.

Missing Values Example 1: recoding numeric values to missing

First look at a summary of hemaglobin (hb).

. summ hb

Variable		Obs		Mean	Std.	Dev.	Min	Max
 	-+							
hb		2500	425	.1898	1984	.981	8.8	9999

We see that the maximum value is 9999 which was the numeric value chosen to indicate a missing value. Although we know that this is not a real value Stata does not and had treated it as a genuine value and used it in calculating the mean and standard deviation (SD). Such values need to be recoded as missing values. We can do this is a number of ways, including using replace, recode or mydecode.

For example to use the recode command:

```
. recode hb 9999=.
(hb: 103 changes made)
```

If we do a summary now we see a big change in both the mean and SD.

. summ hb

Variable	Obs	Mean	Std. Dev	. Min	Max
	+				
hb	2397	13.79959	1.560654	8.8	20

Missing values Example 2: recoding missing values for multiple variables

Alternatively Stata has a specific command (mvdecode) for decoding missing values across multiple variables and if required multiple variables.

Here we just have one numerical missing value (9999) that has been recorded in four variables.

```
. mvdecode hb pot sodium totbil , mv(9999)
    hb: 103 missing values generated
    pot: 26 missing values generated
    sodium: 87 missing values generated
    totbil: 156 missing values generated
```

Missing values Example 3: taking care with greater or less than

Since Stata stores missing values as (impossibly) large values we need to be careful when generating new variables based on values of existing variables using > or < statements. For example,

```
. generate sbp140=(sbp>=140)
```

will return 0 if sbp<140, and 1 if sbp≥140 OR if sbp is missing.

To overcome this problem it is necessary to add a condition outside the brackets:

```
. generate sbp140=(sbp>=140) if sbp\sim=.
```

If we have extended missing values then we would need to use exclude observations by conditioning on whether the value is less than ".". For instance,

```
. generate hyper=(sbp>=140) if sbp<.
```

Alternatively we could use the 'not missing' function e.g.

```
. generate hyper=(sbp>=140 | dbp>=90) if !missing(sbp, dbp)
```

Obs<.

Exploring missing data patterns

Above in egen example 4 we encountered some issues with missing data. A neat way of exploring that example further is with the misstable command along with its various subcommands.

The summarize subcommand produces a basic summary table for the variables specified.

. misstable summarize strisch strhem stremb stroth

We see here the number of missing values for each variable plus a brief summary of the non-missing values.

The patterns subcommand allows an exploration of any patterns of missing values among the set of variables.

. misstable patterns strisch strhem stremb stroth, freq

Missing-value patterns (1 means complete)

		P	att	ern	
Frequency		1	2	3	4
	-+-				
2,418		1	1	1	1
	-				
58		1	0	0	0
8		0	0	0	1
8		1	1	1	0
5		0	1	0	0
1	1	0	0	0	0
1	1	0	0	1	0
1		0	1	1	1
	-+-				
2,500					

Variables are (1) strisch (2) stremb (3) strhem (4) stroth

This allows us to see that for 2418 people all the values are non-missing. The most common missing pattern among the four variables is for number 1 (see key below = strisch) to be present but for the remaining 3 to be missing.

Chapter 7: Descriptive Statistics and Simple Hypothesis Tests

Aims and Objectives of Chapter 7:

By the end of this chapter you should be able to:

- Obtain univariable summaries of location and spread for continuous variables
- Produce one-way tables summarising categorical variables
- Produce simple graphs for describing univariable distributions
- Describe associations between categorical and continuous variables
- Describe associations between continuous variables
- Carry out a two-sample t-test and chi-square test
- Copy and paste output from the Results Window as text or tables

The following commands are used in this chapter: summarize, table, tabulate, tabstat, graph (histogram, box, twoway scatter, matrix), pwcorr, ttest, tabodds

7.1 Summarising and describing data

Having checked for errors in the data the next step is to produce simple descriptive summaries of the data. It is tempting to overlook this stage and rush into more complicated statistical modelling. However a good initial description of the data is essential. Such summaries usually involve tables and/or figures. It is fairly easy to produce both tables and figures, though not so easy to produce tables and figures that convey information effectively. It can be helpful to look at how data are presented in tables and figures in journals such as the New England Journal of Medicine, the BMJ or the Lancet.

How to summarize data is determined mostly by the format and distribution of the data. For example we would summarize age (in years) and sex (male/female) very differently, the first being a continuous numeric variable and the second being categorical (could be stored as string or numeric).

For continuous numeric variables it is important to check the shape of the distribution. Variables that are approximately normally distributed can be appropriately summarised using the mean and standard deviation of the distribution whereas skewed distributions may best be described using the median and perhaps the inter-quartile range or 5th and 95th centiles. The shape of the distribution is best checked visually using the histogram command (as described above) or the qnorm command.

For categorical variables we are generally interested in absolute numbers and relative frequencies e.g. row or column percentages.

7.2 Summarising continuous variables

For quantitative continuous variables, you will usually be interested in summary measures like means, medians and standard deviations, as well as maximum and minimum values and percentiles. These describe the location and spread of the distribution.

Most of this information can be obtained using the summarize command. Typing summarize on its own provides the number of observations, the mean, the standard deviation, the minimum value and the maximum value for all the variables in the dataset. You can restrict the number of variables which are summarised by including a list of variable names with the command.

For the following examples we will load *bl_combined2.dta*.

For example, to obtain summaries of the variables wt and sbp, submit the command,

. summ wt sbp

Variable	Obs	Mean	Std. Dev.	Min	Max
	+	70 10040	16 07250	21	140.0
wt	2497	79.19049	16.87359	31	149.9
sbp	2499	124.1012	16.81271	72	189

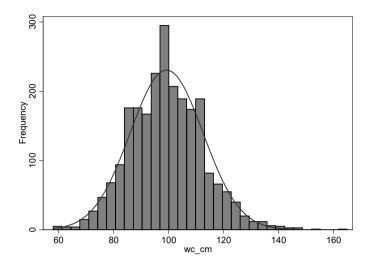
Additional information can be obtained by specifying the option $\underline{\mathtt{detail}}$ (can be abbreviated to d). Stata will then present the number of observations, measures of location e.g. the mean and median (50th percentile), measures of spread e.g. the standard deviation, variance, various percentiles and the four smallest and four largest observations and measures of skewness and kurtosis. For example,

. sum sbp, detail

	Systo	lic Blood Press	ure (mmHg)	
	Percentiles	Smallest		
1%	90	72		
5%	98	74		
10%	101	80	Obs	2499
25%	110	85	Sum of Wgt.	2499
50%	123		Mean	124.1012
		Largest	Std. Dev.	16.81271
75%	135	180		
90%	145	180	Variance	282.6673
95%	150	187	Skewness	.2785866
99%	170	189	Kurtosis	3.111947

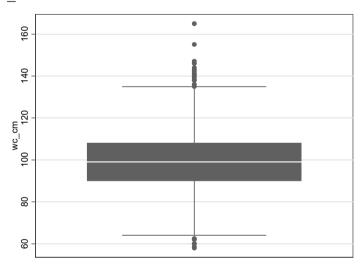
Distributional plots for continuous variables

Useful graphical summaries for continuous numeric variables include histograms and boxand-whisker plots. Two examples are shown below. . histogram wc cm, freq normal



The option freq requests frequencies rather than density and normal overlays with a normal distribution given the mean and standard deviation of the variable.

. graph box wc cm



The line within the box is the median value. The box extends from the 25th to 75th centiles of the distribution i.e. the interquartile range. The whiskers extend up to 1.5 times the interquartile range above the 75th centile and below the 25th centile. If there are no values at or beyond these points the whiskers extend to the lowest or highest value within this range. Values beyond these points i.e. outlying values, are plotted individually. See help graph box and the pdf documentation for more information on the history of box plots.

Other distributional plots can be found under the *Graphics > Distributional Plots* menu.

Summarising a continuous variable over levels of a categorical variable.

Often we will want to examine the association between a continuous variable and a categorical variable, e.g. does systolic blood pressure vary across categories of age-group or categories of over-weight?

Here we want to obtain a summary of sbp for patients (i) who are obese and (ii) are not obese.

As there are just two categories of obese (0/1 = no/yes) we could do this quite simply using an if statement e.g.

. summ sbp if obese=		ese==1	if	sbp	summ	
----------------------	--	--------	----	-----	------	--

Variable	Obs	Mean	Std. Dev.	Min	Max
sbp	+ 665	127.3564	16.16868	74	187

. summ sbp if obese==0

Variable	1	Obs		Mean	Std.	Dev.	Min	Max
shn	+	 1820	 122	9052	16 86	 5602	 72	189

Alternatively we could use the bysort prefix e.g.

. bysort obese: summ sbp

-> obese = 0

Variable		Obs	Mean	Std.	Dev.	Min	Max
sbp	-+ 	1820	 122.9052	16.86	602	72	189

-> obese = 1

Variable	Obs	Mean	Std. Dev.	Min	Max
+					
sbp	665	127.3564	16.16868	74	187

 \rightarrow obese = .

Variable	Obs	Mean	Std. Dev	. Min	Max
sbp	+ 14	124.9643	20.41536	90	168

Note that with the bysort prefix Stata treats patients with a missing obese value as a separate group and automatically returns a summary for this group of patients.

However, almost certainly it would be better to produce these summary statistics in a table format using the table command. This command can be used to produce basic frequency tabulations for categorical variables, but is most useful when used with the statistic (...) option which a range of statistics to be specified, including frequency, mean, median, standard deviation (sd), and percentiles (p1, p2 etc).

For example, to produce a table of the number, mean and standard deviation of systolic blood pressure (sbp) for each category of obese:

table (obese), statistic(count sbp) statistic(mean sbp) statistic(sd sbp)

	Number o	f nonmissing	values	Mean	Standard deviation
BMI 30+ BMI<30 BMI 30+ Total			665	122.9137 127.3609 124.1038	16.8668 16.16739 16.79512

Note: The table command must be typed in full. Tabulate may be abbreviated as tab.

We can reduce the number of decimal places reported with the nformat option, e.g.

table (obese), statistic(count sbp) statistic(mean sbp) statistic(sd sbp) nformat(\$4.1f mean sd)

			nonmissing		 Mean	deviation
BMI 30+ BMI<30 BMI 30+ Total	 			1,820 665 2,485	127.4	16.9 16.2 16.8

The % indicates that this is a format; the 4.1 specifies 1 decimal place and a minimum of 4 characters in width; the f indicates a fixed format. The format will be applied to the variables listed after the format in the brackets.

The command tabstat can also be used to get summaries of one or more continuous variables over levels of a categorical variable. In the following example we build up from a simple summary of *sbp* and *dbp*.

Firstly, to get the means of *sbp* and *dbp* in the whole dataset:

. tabstat sbp dbp

stats	sbp	_
	124.1012	

With the stats() option we can request various statistical summaries. Here we request counts, means and standard deviations:

. tabstat sbp dbp , stats(count mean sd)

stats		sbp	dbp
	'	2499	2499
mean		124.1012	74.58944
sd			10.20323

Using the ${\tt by}\,()\,$ option we can obtain these summary measures over levels of a categorical variable:

. tabstat sbp dbp, by(bmi4) stats(count mean sd)

Summary statistics: N, mean, sd
by categories of: bmi4

bmi4	sbp	dbp
16-	272 119.318 17.50248	272 71.97243 10.46185
22-	466 120.9421 17.36223	466 72.91309 10.07976
25-	1074 124.784 16.19471	1074 74.94274 9.87823
30-	665 127.3564 16.16868	665 76.25338 10.20251
Total 	2477 124.1516 16.7733	2477 74.5866 10.16568

See help tabstat for more options.

Two-sample t-test

The two-sample t-test can be used to compare the mean levels of a normally distributed continuous variable in two independent groups.

Below we have carried out a t-test to calculate the mean difference in systolic blood pressure and its 95% confidence interval between patients who were/weren't obese.

```
. ttest sbp, by(obese)
Two-sample t test with equal variances
 Group | Obs Mean Std. Err. Std. Dev. [95% Conf. Interval]
_____+
   0 | 1820 122.9052 .3953456 16.86602 122.1298
   1 | 665 127.3564 .6269946 16.16868 126.1253
______
combined | 2485 124.0964 .336914 16.79509
                          123.4357
______
         -4.451171 .7559186
                          -5.933467 -2.968875
______
 diff = mean(0) - mean(1)
                              t = -5.8884
Ho: diff = 0
                     degrees of freedom = 2483
```

There are four rows of results plus some hypothesis tests and p-values below.

The first two rows (0 and 1) are the means, 95% CIs etc. in the two groups separately. In this case 0 = not obese and 1 = obese; compare these to the tables on the previous page.

The third row (combined) presents the results for the whole sample pooled i.e. both groups combined.

The fourth row (diff) contains the results we are most interested in i.e. the mean difference and its 95% CI. Here the mean difference is estimated to be -4.45 with 95% CI (-5.93, -2.97). Since the 95% CI does not include 0 (no difference) we can infer that the difference is statistically significant.

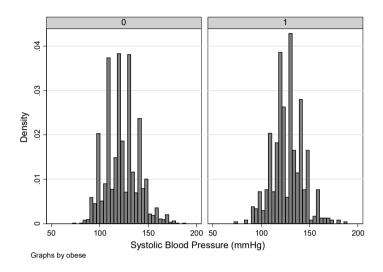
Stata presents three p-values – we are usually interested in the middle p-value which is from a two-sided test. The p-values on the left and right of the output are from one-sided tests. Here the two-sided p-value is <0.0001 which is strong evidence against the null hypothesis that the means in the two groups are equal.

An additional assumption is that the variances in the two samples are equal, though there is a correction to the t-test that can account for non-equal variances. In the example above we have assumed that the variances in the two samples. If we suspected that they were not equal we could add the option unequal.

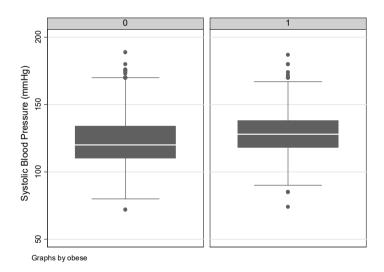
Graphs of associations between continuous and categorical variables

Both the histogram and box plots can be used to describe the distribution of continuous variables over categories of another variable.

. histogram sbp, by(obese)



. graph box sbp, over(obese)



Correlation - association between continuous variables

One common method used to describe the linear association between continuous variables is the correlation coefficient. The correlation coefficient can take values between -1 (perfect negative correlation) and +1 (perfect positive correlation). A value of 0 indicates no association between the two variables.

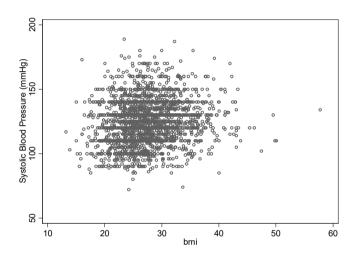
To calculate the correlation between sbp and bmi:

. correlate sbp bmi
(obs=2485)

Here the correlation between sbp and bmi is 0.16 (to 2dp). The number of patients with both measurements is 2485.

We could also produce a twoway scatter plot:

. twoway scatter sbp bmi, ms(oh)



We can add more variables to the variable list:

. corr sbp bmi age wt ht wc_cm hrate
(obs=2348)

	sbp	bmi	age	wt	ht	wc_cm	hrate
sbp	1.0000						
bmi	0.1579	1.0000					
age	0.0669	-0.1532	1.0000				
wt	0.1287	0.8485	-0.1903	1.0000			
ht	0.0038	0.0791	-0.1085	0.5850	1.0000		
wc cm	0.1152	0.7847	-0.0895	0.8138	0.3313	1.0000	
hrate	-0.0594	-0.0076	-0.0473	-0.0248	-0.0456	0.0332	1.0000

Note that the number of observations is now 2348. In calculating these correlation coefficients Stata has used only those patients with complete data on all the variables specified.

We can obtain all the pair wise correlations using the pwcorr command. With this command each correlation coefficient is calculated using the patients with complete data for that pair.

. pwcorr sbp bmi age wt ht wc cm hrate

1	sbp	bmi	age	wt	ht	wc_cm	hrate
sbp	1.0000						
bmi	0.1575	1.0000					
age	0.0737	-0.1524	1.0000				
wt	0.1312	0.8488	-0.1839	1.0000			
ht	0.0054	0.0755	-0.1057	0.5812	1.0000		
wc_cm	0.1180	0.7845	-0.0852	0.8135	0.3314	1.0000	
hrate	-0.0463	-0.0059	-0.0455	-0.0260	-0.0514	0.0307	1.0000

Options for pwcorr include obs (number of observation) and sig (p-value for test of correlation is equal to zero).

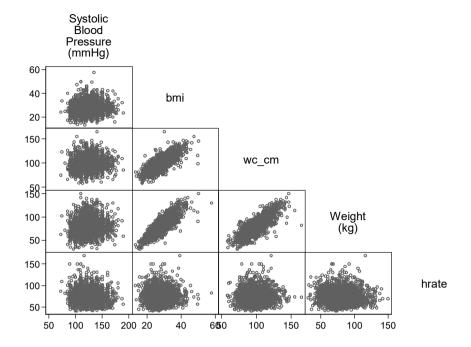
. pwcorr sbp bmi age wc hrate, obs sig

	sbp	bmi	age	WC	hrate
sbp	1.0000				
	2499				
bmi	0.1575	1.0000			
	2485 I	2486			
age	0.0737	-0.1524 0.0000	1.0000		
	2499 	2486	2500		
WC	0.1222		-0.0321 0.1180	1.0000	
	2369 	2360	2369	2369	
hrate	-0.0463 0.0210		-0.0455 0.0234		1.0000
	2486	2472	2486	2357	2486

Stata presents the p-values to 4 decimal places. For some correlations e.g. sbp and bmi the p-value is presented as 0.0000. You should report the p-values such as this as p<0.0001. Or you could be a bit more precise and report as p<0.00005 – since Stata would have presented anything greater than this rounded to 0.0001. e.g. 0.00008 would have been reported as 0.0001.

We can also produce multiple twoway scatter plots as a quick way of examining the association between multiple continuous variables.

. graph matrix sbp bmi wc cm wt hrate, ms(oh) half msize(*0.85)



7.3 Summarising categorical variables

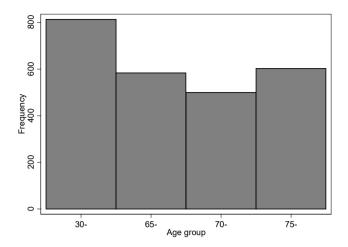
The distribution of categorical variables can be viewed in Stata using the tabulate command, which allows one-way or two-way tabulations. For example,

. tab agegroup

Age group	Freq.	Percent	Cum.
30- 60- 70- 80-	245 1,121 946 257	9.54 43.64 36.82 10.00	9.54 53.17 90.00 100.00
Total	2 , 569	100.00	

The distribution can be displayed graphically using a graph twoway histogram with the discrete option.

. graph twoway histogram agegroup, discrete xlab(0(1)3, value) freq



This is a different command to the histogram command we have used before. The graph twoway histogram command has extra options.

The xlab() option relates to the x-axis labelling. The 0(1)3 is shorthand for label the values 0 to 3 in steps of 1. The option value within xlab() says use the value label rather than the numeric values.

Two-way associations between categorical variables

To obtain a two-way table of age-group and smoking, submit the command,

. tab agegroup smoke

	Sm	oking status		
Age group	Current	Ex	Never	Total
30-	129	361	323	813
65-	73	260	251	584
70-	41	228	231	500
75-	26	268	309	603
Total	269	1,117	1,114	2,500

To obtain row or column percentages, use the row or col options. For example,

. tab agegroup smoke, row

+-			+
	Key		
-			٠
	fı	requency	
	row	percentage	
+-			+

Smoking status					
Age group	Current	Ex	Never	Total	
30-	129 15.87	361 44.40	323 39.73	•	
65-	73 12.50	260 44.52	251 42.98		
70-	41 8.20	228 45.60	231 46.20	•	
75-	26 4.31	268 44.44	309 51.24		
Total	269 10.76	1,117 44.68	1,114 44.56		

To carry out a general chi square test i.e. a test of the null hypothesis of no association between agegroup and smoke:

. tab agegroup smoke, row chi
[key omitted]

Age group	Si Current	moking stat Ex		Total
30-		361 44.40	323 39.73	813 100.00
65-	73	260 44.52		•
70-	41 8.20	228 45.60	231 46.20	•
75-	26	268 44.44	309 51.24	'
Total	269 10.76	1,117 44.68	1,114 44.56	2,500

Pearson chi2(6) = 58.7493 Pr = 0.000

Note as pointed out above that Stata often presents p-values to just 3 or 4 decimal places. Here the p-value is 0.000 to 3dp. We could report this as p<0.0005.

The p-value is obtained from the chi-square test statistic which in the example above is 58.7493 on 6 degrees of freedom. We could use Stata's <code>chiprob()</code> function. This function takes two arguments; first the degrees of freedom and second the chi-square statistic. We can use the display command and use a format to get the p-value to 10 decimal places.

```
. disp %12.10f chiprob(6, 58.7493)
0.0000000001
```

So the first significant figure is at 10 decimal places. You should report such a p-value as p<0.0001 at most.

By default Stata omits any missing values. If we want to a table including a row/column for missing values i.e. treat missing values in the same way as non-missing values we must specify the missing option. For example,

. tab agegroup smoke, miss

	I	sm	noke		
Age group	[Current	Ex	Never	Total
30- 60- 70- 80-	0 1 0 0	48 151 64 9	102 504 432 111	95 465 450 137	245 1,121 946 257
Total	,	272	1 , 149	1 , 147	2,569

Here we see that there is one person missing smoking status who is in the 60-69 year agegroup.

Association between a binary outcome and a categorical variable

Here we are interested in investigating the association between the outcome of all cause mortality (acdeath) and the categorical variable sbpcat (created above).

We start with a simple two-way tabulation with column percentages and a chi square test.

. tab acdeath sbpcat , col chi

All cause	sbpcat				
death	70 - +	120-	130-	140-	Total
0	697 79.20	470 80.90	452 86.76	461 89.17	2,080
1	183 20.80	111 19.10	69 13.24	56 10.83	419
Total	880 100.00	581 100.00	521 100.00	517 100.00	2,499

Pearson chi2(3) = 30.1937 Pr = 0.000

There is clearly a trend across the categories of *sbpcat* with the risk of dying decreasing with increasing *sbp*.

We now use the tabodds command to estimate the odds of dying in each category

. tabodds acdeath sbpcat

 sbpcat	cases	controls	odds	[95% Conf.	Interval]
70-	183	697	0.26255	0.22311	0.30897
120-	111	470	0.23617	0.19204	0.29044
130-	69	452	0.15265	0.11849	0.19666
140-	56	461	0.12148	0.09205	0.16030

Test of homogeneity (equal odds): chi2(3) = 30.18

Pr>chi2 = 0.0000

Score test for trend of odds: chi2(1) = 28.91Pr>chi2 = 0.0000

The output shows the number of cases (deaths) and controls (alive), the odds of death and a 95% CI for the odds in each category. It also shows a test of homogeneity of the odds (same as the general chi square test above) and a test of trend in the odds. The odds of the outcome will always be greater than the risk of the outcome – compare the percentages and the odds in the two outputs above.

The test for trend suggests that there is a trend in the odds of dying across the categories of *sbpcat*.

Using the tabodds command we can also get odds ratios:

. tabodds acdeath sbpcat , or

sbpcat	Odds Ratio	chi2	P>chi2	[95% Conf.	Interval]
70- 120- 130- 140-	1.000000 0.899512 0.581423 0.462667	0.62 12.64 22.78	0.4304 0.0004 0.0000	0.691240 0.429610 0.334496	1.170536 0.786882 0.639951

Test of homogeneity (equal odds): chi2(3) = 30.18Pr>chi2 = 0.0000

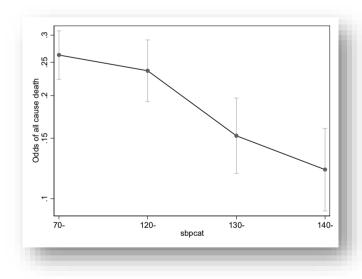
Score test for trend of odds: chi2(1) = 28.91Pr>chi2 = 0.0000

The lowest level of *sbpcat* is used as the reference group. The odds ratio for dying in the 140-group compared to the 70- group is 0.46, 95% CI 0.33 to 0.64, i.e. the odds of dying in the highest category of *sbp* is 54% lower than that in the lowest category.

We can also produce a graph of the odds with the graph option.

. tabodds acdeath sbpcat, graph ci yscale(log) xlab(,value) ytitle(Odds of death)

[output omitted]

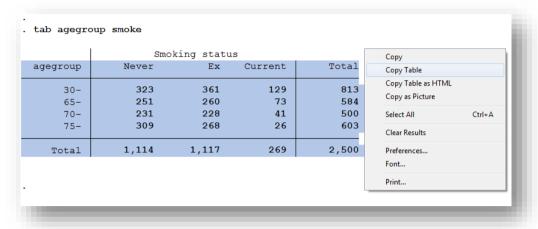


Extra graph options have been specified:

graph plot of odds against categories ci plot the 95% CIs xlab(, value) use value labels for the x-axis ytitle(Odds of death) specifies the y-axis title yscale(log) use a log scale for the y-axis.

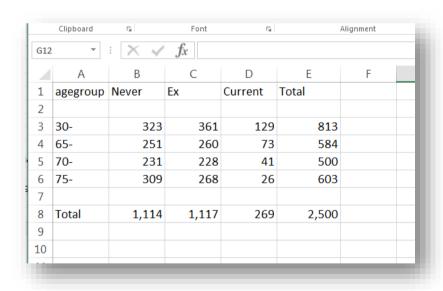
7.4 Moving tables into Word or Excel using Copy & Paste

It is possible to copy and paste tables straight from the Results Window into Word or Excel. Use the mouse to highlight the table and right-click. The first two options are *Copy* and *Copy Table* (see figure below). Selecting 'Copy Table' will allow the table to be pasted as a tab-delimited table directly into Excel or Word. Note here that we have selected the column headers but not the overall columns title.



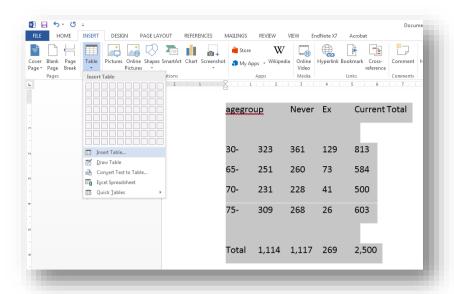
Copying a table directly from the results window

When pasting into an Excel worksheet the cells of the table will occupy separate cells of the spreadsheet.



Inserting a table into Excel

To create a table in Word, follow the same procedure as above i.e. select table in the Results Window, copy as a table and paste the table into Word. You then need to select the pasted table in Word and then select *Insert > Table > Insert Table* as shown in the figure below.



Creating a table in Word

Tables can be pasted as plain text into a Word document using the *Copy* option rather than *Copy Table*. Having copied and pasted into Word you will need to select a non-proportional font such as Courier New or Consolas, otherwise the table columns will not correctly align – see figures below.

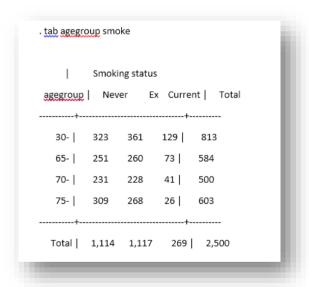
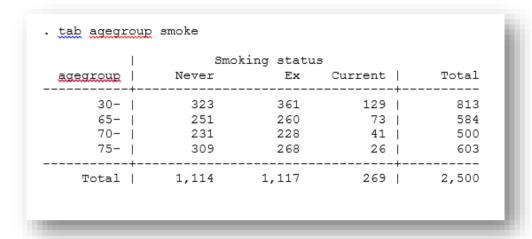


Table will be misaligned if a proportional font such as Calibri or Times New Roman is used



Same table using Courier New font

In version 14 Stata introduced a new command <code>putexcel</code> for exporting results, matrices and images directly to Excel, and in version 15 added <code>putdocx</code> and <code>putpdf</code> for writing paragraphs, images and tables to Office Open XML (Word) and PDF documents, respectively. This suite of commands allows the user to automate, for example, the generation (and formatting) of regular reports. We will not look in detail at these commands during this introductory module, but would encourage you to explore them yourself as you become more familiar with Stata. See <code>help putexcel</code> (or <code>putdocx</code> or <code>putpdf</code>) for details.

Chapter 8: Advanced Data Management

Aims & Objectives of Chapter 8

By the end of this chapter you should:

- Know how to work efficiently using loops
- Be able to process string variables
- Understand Stata's elapsed date format
- Be able to manage and create date variables
- Be able to manage repeated measures data
- Know how to create summary datasets
- Be able to reshape datasets into wide and long formats

The following commands and functions are used in this chapter: forvalues, foreach, generate, lower(), upper(), substr(), strpos(), egen, bysort, mdy(), date(), contract, collapse, reshape wide and reshape long. We also deal with subscripts and Stata's system variables _n and _N.

8.1 Creating Loops

A loop in Stata is simply a sequence of commands that are continually repeated until a condition is fulfilled e.g. a pre-specified sequence is completed or the end of a list is reached. Being able to create and used loops can save time and lines of Stata code in a do-file i.e. it is about working efficiently and making best use of time and space.

There are a number of ways of creating loops in Stata. Here we will look at how to create loops using the forvalues and foreach commands.

1. Looping with forvalues

The forvalues command is the simplest way to create a loop which runs over consecutive numeric values (e.g. 1, 2, 3, 4, 5) or a sequence of values (e.g. 0, 5, 10, 15, 20).

The syntax is:

```
forvalues macname = range {
    command(s) to be executed repeatedly
}
```

Taking the syntax in order:

- forvalues is the Stata command
- macname is a local macro name provided by the user and which will act as the counter

- range specifies the values over which the local macro will be incremented e.g.
 - o 1/5 meaning 1 to 5 in steps of 1
 - o 0(2)10 meaning 0 to 10 in steps of 2
 - 3 6 to 36 meaning 3 to 36 in steps of 3 i.e. the step is determined by the interval between the first two numbers in the sequence
- { the open brace (a curly bracket) must appear at the end of the forvalues line; nothing may follow the open brace (except comments)
- Commands to be executed repeatedly until the end of the loop. These commands will usually include a reference to the local macro defined by the forvalues command. When referring to a local macro (called dereferencing) the macroname must be punctuated correctly i.e. enclosed by a left single quote and a right single quote (see Figure 8.1 and text below).
- the close brace appears on a line on its own following all the commands that are to be repeated.

Local macros

Macros are the variables of Stata programs. They consist of a macro name and macro content. The content of a macro is accessed by dereferencing using precise punctuation. When dereferencing a *local macro* we must put a left single quote (generally located on the key immediately left of the 1 key) immediately before the macro name and a right-single quote, usually on the @ key, immediately following the macro name.

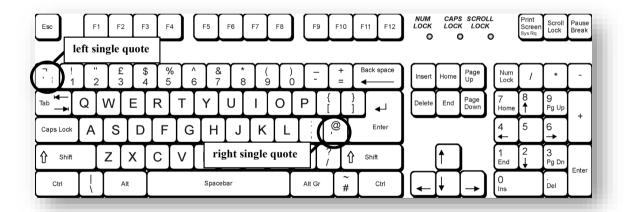


Figure 8.1: Location of left and right single quotes

Forvalues: Example 1

Type the following commands in a do-file and then run (you will need to run all three lines at the same time).

```
forvalues i = 1/5 {
disp "This is loop number: `i'"
}
```

The forvalues command creates a local macro called i, which takes the value 1 on the first loop, then 2 on the second loop, etc., through to 5 on the final loop. While i is less than or equal to 5 Stata continues to execute the commands in the loop. The command inside the loop asks Stata to display "This is loop number: `i'" where local macro i has been dereferenced appropriately. On the first pass through the loop Stata reads this as display "This is loop number 1".

The output in the *Results Window* should be as follows:

```
. forvalues i=1/5 {
   2. display "This is loop number: `i'"
   3. }
This is loop number: 1
This is loop number: 2
This is loop number: 3
This is loop number: 4
This is loop number: 5
```

Note that Stata first prints out the forvalues loop in full before executing the commands in sequence.

Forvalues: Example 2

Copy and run the following three lines in a do-file.

```
forvalues k = 10(-2)0 {
  disp "Local macro k is now equal to `k'"
}

. forvalues k = 10(-2)0 {
    2.
    disp "Local macro k is now equal to `k'"
    3.
    }

Local macro k is now equal to 10
Local macro k is now equal to 8
Local macro k is now equal to 6
Local macro k is now equal to 4
Local macro k is now equal to 2
Local macro k is now equal to 0
```

2. Looping with foreach

The foreach command is similar to forvalues in that it enables looping through batches of commands, but is more flexible in that it allows looping through a list of numbers (not necessarily consecutive), a list of variable names, the elements of a local (or global) macro or indeed through any list. The syntax for foreach is:

```
foreach macname of list_type list {
    command(s) to be executed repeatedly
}
```

Taking the syntax in order:

- foreach is the Stata command
- macname is a local macro name provided by the user e.g. A, var, k, bob
- of list type tells Stata what to expect e.g.
 - o of varlist meaning *list* will consist of names of variables in memory
 - o of numlist meaning *list* will consist of numbers
 - o of local meaning list will consist of a local macro name
 - o of global meaning that list will consist of a global macro name
- { the open brace (a curly bracket) must appear on its own at the end of the foreach line
- Commands to be executed these are the commands which will be repeated until the end of the loop. These commands will usually include a reference to the local macro defined by the foreach command.
- } the close brace appears on a line on its own following all the commands that are to be repeated.

Foreach: Example 1

Open bl_combined2.dta. Type the following commands in a do-file and run.

```
foreach V of varlist diab angina cvd {
     tabulate bmicat `V' , row chi nokey
}
```

The output from the *Results Window* appears below. There are three variables (diab, angina and cvd) in the variable list. On the first pass through the loop the local macro V contains the variable name *diab*, on the second pass *angina* and on the final pass *cvd*.

. foreach V of varlist diab angina cvd {
 2. tabulate bmicat `V' , row chi nokey
 3. }

BMI categories	Diabetes 0	1	Total
12-	208 74.29	72 25.71	
22-	332 71.24	134 28.76	466
25-	755 70.30	319 29.70	1,074
30-	412 61.95	253 38.05	665
Total	1,707 68.69	778 31.31	2,485 100.00

Pearson chi2(3) = 20.8086 Pr = 0.000

BMI categories	Angina No	Yes	Total
12-	190 67.86	90 32.14	280
22-	287 61.59	179 38.41	466
25-	573 53.35	501 46.65	1,074
30-	344 51.73	321 48.27	665
Total	1,394 56.10	1,091 43.90	2,485

Pearson chi2(3) = 29.8654 Pr = 0.000

BMI	cvd		
categories	0	1	Total
12-	105 37.50	175 62.50	280 100.00
22-	154 33.05	312 66.95	466
25-	298 27.75	776 72.25	1,074 100.00
30-	205	460 69.17	665 100.00
Total	762 30.66	1,723 69.34	2,485 100.00
P€	earson chi2(3)	= 11.7064	Pr = 0.008

Foreach: Example 2

Open fup_pot_long1.dta. What values does the variable visit take? In this example we loop through the categories of visit; within each loop we draw a box plot of potval (potassium value) over trt (treatment group) and then carry out a 2-sample t-test. Type and run the following commands.

```
foreach N of numlist 1 3/11 {
  graph box potval if visit==`N', over(trt) name(visit`N',replace)
  disp
  disp "Two-sample t-test of potassium by treat at visit `N'"
  disp
  ttest potval if visit==`N', by(trt)
}
```

Here the values of visit do not follow a complete arithmetic sequence as potassium was not measured at visit 2. The Stata output for the first few loops is shown below.

```
. foreach N of numlist 1 3/11 {
   2. graph box potval if visit==`N', over(trt)
name(visit`N',replace)
   3. disp
   4. disp "Two-sample t-test of potassium by treat at visit `N'"
   5. disp
   6. ttest potval if visit==`N', by(trt)
   7. }
```

Two-sample t-test of potassium by treat at visit 1 Two-sample t test with equal variances ______ Group | Obs Mean Std. Err. Std. Dev. [95% Conf. Interval] ______
 1
 |
 1232
 4.32017
 .0124056
 .4354335
 4.295832
 4.344509

 2
 |
 1242
 4.329605
 .0126359
 .445315
 4.304815
 4.354396
 combined | 2474 4.324907 .0088533 .4403582 4.307546 4.342268 ______ diff | -.009435 .0177094 -.0441617 .0252917 ______ diff = mean(1) - mean(2)t = -0.5328Ho: diff = 0degrees of freedom = 2472 Ha: diff < 0 Ha: diff != 0 Ha: diff > 0Pr(T < t) = 0.2971 Pr(|T| > |t|) = 0.5942 Pr(T > t) = 0.7029Two-sample t-test of potassium by treat at visit 3 Two-sample t test with equal variances Group | Obs Mean Std. Err. Std. Dev. [95% Conf. Interval] ______
 1
 |
 1206
 4.444867
 .0143625
 .4987732
 4.416689
 4.473046

 2
 |
 1219
 4.359688
 .0135591
 .4734041
 4.333087
 4.38629
 ______ combined | 2425 4.402049 .0099087 .4879487 4.382619 4.42148 _____ diff | .0851791 .0197462 .0464579 .1239002 ______ t = 4.3137diff = mean(1) - mean(2)Ho: diff = 0degrees of freedom = 2423

8.2 Processing String Variables

Datasets often contain complex string variables, such as identification codes, post-codes, drug names, adverse event narratives etc., which are often considerably more difficult to process than numeric variables. One of Stata's great strengths is its ability to manage string variables. It has many very useful string functions. We will consider just a few: lower(), upper(), substr(), strpos(), length(), trim().

1. Changing Case

Stata is case sensitive. When it comes to searching for string characters "a" is not equal to "A" and therefore, as long as case is not important, a good starting point when dealing with string variables may be to make the case consistent i.e. change to all lower or all upper case characters. This makes it easier to search for a string of characters. To convert characters to lower case use the lower () function and for upper case the upper () function. For example:

```
lower("Body Mass Index") = "body mass index"
upper("Body Mass Index") = "BODY MASS INDEX"
proper("BODY MASS INDEX") = "Body Mass Index"
```

2. Substrings

The function substr() can be used to decompose a string into parts. The function takes 3 arguments:

- argument 1 is the string or string variable which we are extracting from
- argument 2 is a number which indicates the starting position of the substring within the overall string; this is counted from the first character of the string unless the number is negative when this is taken as counting backwards from the last character.
- argument 3 is a number which indicates the length of the substring; a "." can be used to indicate all characters to the end of the string.

For example:

```
substr("abcde12345",1,3) = "abc"
substr("abcde12345",4,4) = "de12"
substr("abcde12345",-5,2) = "12"
substr("abcde12345",-4,.) = "2345"
```

In each example "abcde12345" is the string we are going to extract from. In the first example, the second and third arguments are 1 and 3 respectively meaning extract the substring starting from character position 1 and of length 3 characters. In the third example the second argument is negative, and therefore the starting position is interpreted as 5 characters from the end of the string. In the fourth example the third argument is given as missing indicating that all characters from the starting position (argument 2) to the end of string.

Substr: Example 1

Open bl_combined2.dta. The patient identifier (ptid) in our datasets is a string variable consisting of a centre id (first five characters) and a subject id (characters 6-9). See below.

We now wish to create a separate variable for centre id (cid) so that we could merge in information at the country level if we wished. We will use the generate command and the substr() function to do this.

```
. generate cid = substr(ptid, 1, 5)
```

We have generated a new variable called *cid*, which contains a substring of the variable *ptid*. The substring we have specified starts with the first character of ptid, and is 5 characters in length. It is a good idea to list a few of the old and new variable to check all has gone according to plan.

. list ptid cid in 1/5

	+		+
	İ	ptid	cid
1.		C11461001	C1146
2.		C11461002	C1146
3.		C13511001	C1351
4.		C11421001	C1142
5.		C11381001	C1138
	+		

3. Searching for a String

The strpos() function can be used to search for the occurrence of a string of characters within a longer string. The function takes two arguments:

- argument 1 is the string or string variable which we are searching
- argument 2 is the string of characters we are searching for.

The function returns the starting position of the string of characters if it is found and 0 otherwise. For example:

```
strpos("15mg Aspirin", "15") = 1 strpos("15mg Aspirin", "aspirin") = 0 strpos("15mg Aspirin", "Asp") = 6
```

Note that in the second example Stata returns a 0 since we are searching for the entire string "aspirin" and this is not found. This is a reminder that Stata is case-sensitive and that "a" is not equal to "A". When searching for a string where case is not important it can be helpful to first change the case of all the characters to either lower or upper case using the <code>lower()</code> or <code>upper()</code> functions as explained above.

Strpos: Example 1

Open bl_meds.dta. In this dataset we have records of medications that were being taken by at baseline by patients in the study. The database allowed for up to 10 medications to be recorded (med1-10).

. list ptid med1 med2 med3 in 1/5

-	+			
	ptid	med1	med2	med3
1.	C10011001	Paroxetine	Aspirin	Enalapril
2.	C10011002	Losartan	Aspirin	Carvedilol
3.	C10011003	Losartan	Insuline	Aspirin
4.	C10011004	Enalapril	Amiodarone	Thiazides
5.	C10011005	Carvedilol	Enalapril	Amiodarone
_	+			+

Suppose we wish to identify all patients taking aspirin and create a variable called *asp* that is 1 if aspirin is being taken and 0 otherwise. We have a number of issues: the word aspirin may occur alone or with a dose; the string "aspirin" may vary in terms of case (e.g. aspirin or Aspirin); the word aspirin may appear in one of 10 different variables or not at all.

We can deal with the problem of case by use of the lower() string function. We can deal with problem of the string "aspirin" occurring at various points within a longer string using the strpos() function. We can loop through each of the variables med1 to med10 using the forvalues command that we met above.

```
gen asp = 0
forvalues K = 1/10 {
replace med`K' = lower(med`K')
replace asp = strpos(med`K', "aspirin") if asp==0
}
```

The first command creates a variable called *asp* which takes the value 0 for all patients. We then use forvalues to create a local macro called K that will enable us to loop through the commands within the brackets. On the first pass through the loop K=1; so the first line within the loop changes med1 to lower case; the second line replaces *asp* with the position of "aspirin" within med1 if it is found or zero if not.

It is important to note the expression if asp==0. Suppose within the first loop that "aspirin" is found at string position 1 in med1 for the patient in row number 1. The variable asp (which starts with all values=0) is then replaced with the value 1 in row 1. Now on loop two it is unlikely that the string "aspirin" will be found in med2 for the same patient and therefore strpos(med2, ``aspirin'') will evaluate to 0. Since we have already found the string "aspirin" in med1 and set asp=1 we do not want to replace 1 with 0. Hence we only replace asp if asp is currently equal to 0 i.e. if the string aspirin has not been found in any previous variable.

We should now tabulate the variable asp.

. tab asp

asp	Freq.	Percent	Cum.
0	1 , 112	76.11	76.11
1	323	22.11	98.22
5	1	0.07	98.29
7	17	1.16	99.45
8	1	0.07	99.52
10	2	0.14	99.66
11	1	0.07	99.73
15	1	0.07	99.79
24	1	0.07	99.86
25	1	0.07	99.93
29	1	0.07	100.00
Total	1,461	100.00	

For 1112 observations no occurrences of the substring "aspirin" were found. Where it was found it was generally at the beginning of the string (asp=1). We should now recode all values greater than 1 to be equal to 1.

```
. recode asp 1/max=1
(asp: 26 changes made)
```

. tab asp

Cum.	Percent	Freq.	asp
76.11 100.00	76.11 23.89	1,112 349	0 1
	100.00	1,461	Total

Save the data in memory as bl_meds1.dta.

4. Converting Numbers to Strings and Vice Versa

From numbers to strings

It can sometimes be useful to convert a numeric variable into a string variable. We can do this in Stata using the string() function. This takes a single argument which must be a numeric variable or a number and returns the variable or number as a string. A second optional argument can be used to specify the format.

For example:

```
string(2014) = "2014" string(23.57, "%3.1f") = "23.6"
```

From strings to numbers

The real() function performs the opposite task. This converts a string to a real numeric value, provided that the string consists of numeric characters only.

For example:

```
real("15") = 15
real("20.4") = 20.4
real("12.5kg") = .
```

5. How long is a string?

The final string function we will consider now is the length() function. This takes a single argument – the string to be evaluated – and returns the length of the string. For examples,

```
length("abcde") = 5
length("WC1E 7HT") = 8 (includes the embedded space)
length(" abc ") = 5 (includes a leading and trailing space)
```

The problem of leading or trailing spaces can be dealt with using the trimming functions:

```
ltrim(" s") returns "s" with leading blanks removed.
rtrim("s") returns "s" with trailing blanks removed.
trim(" s ") returns "s" with leading and trailing blanks removed.
```

There are many other useful string functions. See help functions or help strfun for more information.

8.3 Dates in Stata

Dates are often recorded as strings e.g. "09/12/1973" or "Sept 7 1965". Dates in this format are not convenient for any data manipulation. For example, if we have recorded a person's date of birth and the current date it would be possible to calculate the number of days or years that person has been alive. Dates that are stored as strings do not allow us to easily carry out such calculations. Stata deals with this by storing dates as elapsed dates (see below) and has functions that enable the user to easily convert string dates into elapsed dates.

Stata stores dates as integers with 0 corresponding to 1 January 1960, 1 to 2 January 1960 and so on. Dates prior to 1 January 1960 are stored as negative integers with –1 corresponding to 31 December 1959 and so on. These are known as *elapsed dates*. Time between dates can therefore be calculated by subtraction. For example, given a person's date of birth and a screening date, the age at screening can be calculated as date of screening minus date of birth. This would give the "number of days old" which could, for example, be divided by 365.25 to convert to years.

Stata has two main functions that can be used along with generate for creating elapsed dates. They are date() and mdy(). Which to use depends on the format of the variable being translated.

If the variable to be translated takes the form "07/12/1997" or "July 11, 1948" i.e. a single string variable with a standard date structure then we can use the date() function. If the date to be translated consists of three different variables i.e. the day, month and year then we would need to use the mdy() function.

The Date Function

The syntax for the date function is:

```
generate newdate = date(stringdate, "pattern")
```

Taking the syntax in order:

- generate is the Stata command for creating a new variable
- newdate is the name of the elapsed date being created i.e. decided by you
- date() calls Stata's date function which takes two arguments (in the simplest case).
- stringdate, specifies the name of the string variable that is to be translated
- "pattern" is the order in which month, day and year occur in the stringdate. E.g.:
 - o for "07-11-1956" pattern would be "DMY"
 - o for "June 11, 1962" pattern would be "MDY"
 - o for "1965/Sept/07" pattern would be "YMD"
 - o for "24-10-78" pattern would be "MD19Y"

The mdy Function

The syntax for the mdy function is:

```
generate newdate = mdy(mvar, dvar, yvar)
```

Taking the syntax in order:

- generate is the Stata command for creating a new variable
- newdate is the name of the elapsed date being created i.e. decided by you
- mdy () is the function which takes three arguments. The three arguments are:
 - o *mvar* the variable containing the month
 - o dvar the variable containing the day
 - o yvar the variable containing the year

Formatting dates

Once the new date variable has been generated, it can then be formatted so that it appears (i.e. is viewed in the browser) as a date rather than just as a number. For example,

format	newdate	%td	1jul1948
format	newdate	%tdd_m_cy	1 Jul 1948
format	newdate	%tdM/D/CY	July/01/1948

Elapsed date: Example 1

Open example_dates.dta which contains dates in different formats.

. list date 1-year in in 1/5 , noobs

+								-+
	date_1	date_2	date_3	date_4	day_in	month_in	year_in	
	10/Aug/1929	2006/07/03		20060330	2	3	2006	-
	6/Sep/1920	2009/12/13	04-24-06	20060424	21	3	2006	
	6/Dec/1925	2007/04/29	05-05-06	20060505	15	2	2006	
	20/Feb/1918	2009/01/16	05-10-06	20060510	16	3	2006	
	18/May/1940	2010/11/11	05-10-06	20060510	8	4	2006	

The variable <code>date_1</code> is a single string variable which contains the day, month and year separated by forward slashes. We therefore need to use the <code>date()</code> function to create an elapsed date. The syntax is:

```
. gen edate 1 = date(date 1, "DMY")
```

The next step is to apply a date format the elasped date, but before we do so we will look at date_1 and edate_1.

. list id date 1 edate 1 in 1/5

	+		+
	id id	date_1	edate_1
1.	P1001	10/Aug/1929	-11101
2.	P1003	6/Sep/1920	-14361
3.	P1004	6/Dec/1925	-12444
4.	P1005	20/Feb/1918	-15290
5.	P1006	18/May/1940	-7167
	+		+

We see here that *edate_1* is just a number. The values here are all less than zero since these dates are all prior to January 1st 1960. We will now apply a date format and list again.

- . format edate 1 %td
- . list id date 1 edate 1 in 1/5

	+		
	id	date_1	edate_1
1	P1001	10/Aug/1929	10aug1929
⊥•	•	_	_
2.	P1003	6/Sep/1920	06sep1920
3.	P1004	6/Dec/1925	06dec1925
4.	P1005	20/Feb/1918	20feb1918
5.	P1006	18/May/1940	18may1940
	+		+

The variable edate_1 now displays as a recognisable date, although it is still just a real number. It is good practice to check a few of the dates to make sure the conversion has worked properly. If we use the command codebook on these two variables we will get very different output.

```
. codebook date 1 edate 1
______
______
              type: string (str11)
       unique values: 50
                                       missing "": 0/50
           examples: "15/Feb/1933"
                    "18/Nov/1934"
                    "24/May/1936"
                    "31/Mar/1933"
    ·_____
              type: numeric daily date (float)
             range: [-15290,-56531
                                          units: 1
     or equivalently: [20feb1918,10jul1944] units: days
       unique values: 50
                                       missing .: 0/50
              mean: -9352.54 = 24 \text{may} 1934 \text{ (+ } -13 \text{ hours)}
           std. dev: 2502.23

    10%
    25%
    50%
    75%
    90%

    -13335
    -10835
    -9023
    -7433
    -6254

        percentiles:
                    29jun1923 03may1930 19apr1935 26aug1939 17nov1942
```

Elapsed date: Example 2

The variable date_3 is a single string variable which contains the month, day and year separated by hyphens. However, note that the year does not include the century i.e. it is in the format MM-DD-YY. As with example 1 we need to use the date() function but this time we will need to specify the century. The syntax is:

```
. gen edate_2 = date(date_3, "MD20Y")
```

. format edate 3 %td

As mentioned above it is always worth checking that the date conversion has worked by comparing a few of the original and new dates. Here everything appears to be in order.

. list date 3 edate 3 in 1/5

	+		
	id	date_3	edate_3
1. 2. 3. 4.	P1001 P1003 P1004 P1005	03-30-06 04-24-06 05-05-06 05-10-06 05-10-06	30mar2006 24apr2006 05may2006 10may2006 10may2006
	+		+

Elapsed date: Example 3

The final three columns in example_dates.dta contain the day_in, month_in and year_in i.e. the date_in is recorded in three variables. To translate this into an elapsed date we will need to use the mdy() function.

```
. gen edate_in = mdy( month_in, day_in, year_in)
. format edate_in %td
```

Note that the order is important. The function is mdy () and the three arguments must appear in that order. If month and day are switched then all the dates will be incorrect (apart from dates where the month and day are the same!) and some missing values will be generated.

Check that the date creation has worked.

. list day in month in year in edate in 1/5

	+			+
	day_in	month_in	year_in	edate_in
1.	2	3	2006	02mar2006
2.	21	3	2006	21mar2006
3.	15	2	2006	15feb2006
4.	16	3	2006	16mar2006
5.	8	4	2006	08apr2006
	+			+

Elapsed date: Example 4

The variable *date_4* is a numeric variable but is not an elapsed date. For example, consider the first observation 20060330, which we understand means 30th March 2006. Stata understands this as 20,060,330 i.e. as twenty million sixty thousand three hundred and thirty – in elapsed date terms that would actually equate to sometime in the 75th century.

In this case we cannot directly use the date() function, because it expects a string variable as input, and we cannot directly use the mdy() function because it expects three separate numeric variables as input.

The easiest way to convert such a variable is to first convert it to a string variable using tostring, and then apply the date () function to create the elapsed date.

```
. tostring date_4, replace
date_4 was long now str8

. gen edate_4 = date(date_4, "YMD")
. format edate 4 %td
```

Now check that the process has worked correctly.

Other date functions

Other date related functions allow the user to extract the month, day of month, day of year, day of week, quarter of year, etc from an elapsed date.

For example, to extract the day of the week we can use the dow () function

- . gen dow edate 1=dow(edate 1)
- . tab dow_edate_1

dow_edate_1	Freq.	Percent	Cum.
+			
0	6	12.00	12.00
1	5	10.00	22.00
2	4	8.00	30.00
3	12	24.00	54.00
4	6	12.00	66.00
5	8	16.00	82.00
6	9	18.00	100.00
+ Total	 50	100.00	

Where 0= Sunday, 1=Monday, through to 6= Saturday.

To extract the month or year we can use the month () or year () functions.

8.4 Managing Repeated Measures Data

Stata has a number of useful functions and tools for handling repeated measure data. By repeated measures data we mean data where measurements of a variable (or variables) for an individual have been measured on a number of occasions during a study. For example, in a randomised controlled trial each patient's blood pressure may be measured and recorded at baseline and then at each subsequent visit. We may then be interested in looking at the change in blood pressure from baseline or from the previous visit, or the time until blood pressure dropped below a given level or increased by a given amount. In this next section we will explore some of Stata's commands, system variables and other tools for dealing with such data through a series of example tasks.

Repeated measures: Example 1

Open fup_egfr1.dta. In this dataset we have patient id, visit number and date and the egfr value at each visit. We also have the patient's age at entry to the study, their sex and the treatment group. Our aim in this example is to create a variable containing the change from screening in egfr level.

- . use fup egfr1 , clear
- . sort ptid visit

. list in 1/10

	+						+
	ptid	visit	visdate	egfr	age	sex	trt
1. 2. 3. 4.	C10011001 C10011001 C10011001 C10011001	Screening Month 5 Month 13 Month 21 Month 29	20jul2006 19dec2006 05sep2007 30apr2008 08jan2009	52.82 58.34 56.37 53.67 56.92	63 63 63 63 63	Male Male Male Male Male	Active Active Active Active Active Active
6. 7. 8. 9.	C10011002 C10011002 C10011002 C10011002 C10011004	Screening Month 5 Month 13 Month 21 Screening	21jul2006 13dec2006 23aug2007 24apr2008 21aug2006	82.65 69.78 82.67 83.89 71.49	66 66 66 66 66	Male Male Male Male Male	Placebo Placebo Placebo Placebo Active

To calculate the change in egfr we will need to use the bysort prefix command, understand the Stata system variables n and N and how to use subscripts.

(i) Repeating commands using bysort

We have already met the <code>bysort</code> prefix which allows a command to be repeated over subsets of the data. This prefix is particularly useful when it comes to managing repeated measures data where results for a patient are recorded over several rows of a dataset.

Recall that,

```
bysort varname: command
```

will first sort the dataset in ascending order of *varname* and then repeat the command over each level of *varname*.

Now consider the following command:

```
bysort varname1 (varname2): command
```

Here we have specified two "bysort" variables, but the second of these is enclosed in parentheses. What this will do is sort the whole dataset in ascending order by *varname1* and *varname2*, but only repeat the command over levels of *varname1*.

We will see how this can be useful shortly.

(ii) System Variables _n and _N

Stata has a number of very useful "built-in" variables called system variables. The names of all the system variables start with the underscore character (_). Among the most useful system variables are _n and _N which are generally referred to as "little-n" and "big-n".

- n contains the row number in the dataset (as sorted)
- _N contains the total number of rows in the dataset

When combined with bysort varname: these then become the row number and total number of rows in the subset of observations within each level of *varname*.

For example, here we use bysort and generate to create two variables that are equal to _n and _N. We have sorted the dataset by *ptid* and *visdate*, but as *visdate* is in parentheses we only repeat the generate command by *ptid*.

```
. bysort ptid (visdate): generate n = _n . bysort ptid (visdate): generate N = _N . list ptid visit visdate egfr n N in 1/14
```

	+						+
	1	ptid	visit	visdate	egfr	n	N
1.	1	C10011001	Screening	20jul2006	52.82	1	5
2.	1	C10011001	Month 5	19dec2006	58.34	2	5
3.	1	C10011001	Month 13	05sep2007	56.37	3	5
4.		C10011001	Month 21	30apr2008	53.67	4	5
5.		C10011001	Month 29	08jan2009	56.92	5	5
6.		C10011002	Screening	21jul2006	82.65	1	4
7.		C10011002	Month 5	13dec2006	69.78	2	4
8.		C10011002	Month 13	23aug2007	82.67	3	4
9.		C10011002	Month 21	24apr2008	83.89	4	4
10.		C10011004	Screening	21aug2006	71.49	1	5
	-						
11.		C10011004	Month 5	01feb2007	85.2	2	5
12.	1	C10011004	Month 13	27sep2007	92.89	3	5
13.	1	C10011004	Month 21	05jun2008	64.5	4	5
14.	1	C10011004	Month 29	21jan2009	70.26	5	5
	+						+

We've listed the data for the first 3 patients.

Note that within each patient N is constant and indicates the number of rows for each patient; n varies within each patient and indicates the row number within each patient as currently sorted (i.e. by *visdate* within each patient).

Note that for each patient the first visit is where n=1 and the latest visit will be where n=N.

(iii) Subscripts

Specific rows of a dataset can be referred to using subscripts. Subscripts are specified by following a variable name with square brackets containing either a number or an expression. For example, using the display command to illustrate this:

```
. display ptid[1]
```

This is asking Stata to display ptid in row 1. Stata displays

```
C10011001
```

When combined with bysort varname: the subscript then refers to the row within each level of *varname*. For example, when combined with:

We now have all the tools we need to generate change in egfr from screening using a single line of Stata code.

```
. bysort ptid (visit): gen double egfr_chbl = egfr - egfr[1]
```

Running through the syntax in order:

- bysort ptid (visit) requests that the data is to be sorted by ptid and visit but that the command to be repeated by ptid only
- gen is the Stata command for creating a new variable
- double requests the new variable is calculated to double precision
- egfr chbl is the user specified name of the new variable
- egfr egfr[1] the new variable is equal to the value of egfr minus the value of egfr in the first row for each patient.
- . list ptid visit visdate egfr egfr chbl n in 1/9

	ptid	visit	visdate	egfr	egfr_c~l	n
1. 2. 3. 4. 5.	C10011001 C10011001 C10011001 C10011001	Screening Month 5 Month 13 Month 21 Month 29	20jul2006 19dec2006 05sep2007 30apr2008 08jan2009	52.82 58.34 56.37 53.67 56.92	0 5.52 3.55 .85 4.1	1 2 3 4 5
6. 7. 8. 9.	C10011002 C10011002 C10011002 C10011002	Screening Month 5 Month 13 Month 21	21jul2006 13dec2006 23aug2007 24apr2008	82.65 69.78 82.67 83.89	0 -12.87 .02 1.24	1 2 3 4

Repeated measures: Example 2

We will now create a new variable to indicate the time (in days) since the previous visit. This time we do not want to keep referring to the first row but rather the previous row. We can do this by using the n variable within the subscript.

```
. by sort ptid (visdate): gen double tsvis = visdate - visdate[n-1] (2500 missing values generated)
```

The first part of the syntax is exactly the same as for example 1. The key part here is the final section of code: visdate - visdate[n-1]

Note that the [_n-1] will equate to 0 (1-1) in the first row, 1 (2-1) in the second row, 2 (3-1) in the third row etc. So for the first row for each patient this code equates to:

```
visdate - visdate[0]
```

Since there is no row 0 for any patient this results in a missing value being generated (hence 2500 missing values generated above). This makes sense since there is no time since the previous visit for the first visit. In the second row for each patient this equates to:

```
visdate - visdate[1]
```

So for ptid C10011001 in the output above this equates to 19Dec2006 – 20Jul2006.

	+				+
	ptid	visit	visdate	tsvis	n
1. 2. 3. 4. 5.	C10011001 C10011001 C10011001 C10011001 C10011001	Screening Month 5 Month 13 Month 21 Month 29	20jul2006 19dec2006 05sep2007 30apr2008 08jan2009	152 260 238 253	1 2 3 4 5
6. 7. 8. 9.	C10011002 C10011002 C10011002 C10011002	Screening Month 5 Month 13 Month 21	21jul2006 13dec2006 23aug2007 24apr2008	145 253 245	1 2 3 4

. list ptid visit visdate tsvis n $\,$ in 1/9

8.5 Creating Summary Datasets

It can often be useful to create a summary dataset from a full dataset, particularly for producing table and figures. Here we will consider the two main Stata commands for creating summary datasets: contract and collapse.

Contracting Datasets

The command contract can be used to replace the dataset in memory with a summary dataset of frequencies.

Contract: Example

Open bl_combined2.dta. We will create a summary dataset containing the number of subjects within each combination of primary endpoint (pep), sex and treatment group (trt).

- . use bl combined2 , clear
- . contract trt sex pep
- . list, sep(4)

	+			+
	pep	trt	sex	_freq
1.	0	1	Female	230
2.	1	1	Female	51
3.	0	1	Male	751
4.	1	1	Male	210
5.	0	2	Female	201
6.	1	2	Female	76
7.	0	2	Male	703
8.	1	2	Male	278

The contracted dataset contains the variables *sex*, *pep* and *trt* and a new variable called _*freq* containing the frequencies. Note that all other variables will be dropped.

As there are 2 levels of *sex*, *pep* and *trt* we have just 8 observations in the contracted dataset. It is possible to analyse datasets such as this using Stata's frequency weight facility. For example:

. tab trt pep [fw= freq], chi row nokey

trt	pep 0	1	Total
1	981 78.99	261 21.01	1,242
2	904 71.86	354 28.14	1,258
Total	1,885 75.40	615 24.60	2,500 100.00

Pearson chi2(1) = 17.1071 Pr = 0.000

Note that the command contract overwrites the dataset currently in memory including any changes that have been made since last save. It is very important therefore to think carefully before using this command and to make sure all changes have been saved. Of course if you have been making all your changes using commands which have been saved in a do-file this is not an issue. The contracted file should be saved with a new name.

Collapsing Dataset

The command collapse replaces the dataset in memory with a dataset of statistics e.g. means, SDs, counts, medians, sums, etc. For a complete list of the statistics available see help collapse. The syntax for this command is best explained by an example.

Collapse: Example

Open fup_egfr1.dta. Suppose we want to create a summary dataset containing mean egfr at each visit by treatment group. We also wish to save the number of measurements and the standard deviation. The syntax for this is:

```
collapse (mean) m_egfr = egfr (sd) sd_egfr = egfr (count) n_egfr =
egfr, by(visit trt)
```

Running through the syntax in order:

collapse is the Stata command

There then follows three sets of statistics (we will run through first two):

•	(mean) m egfr	indicates that the first statistic we want is the mean specifies the name of the new variable to be <i>m</i> egfr
•	=egfr	indicates that it is the mean of $egfr$ that we want to calculate
•	(sd) sd_egfr =egfr	indicates that second statistic we want is the standard deviation specifies the new variable name for the second statistic indicates that it is the SD of <i>egfr</i> that we want to calculate

by (visit trt) indicates that we want all the statistics calculated for each combination of visit and trt

On the next page we list the collapsed dataset.

Note there is no "uncollapse" command. So if you are working interactively make sure any prior changes have been saved before collapsing a dataset – or make sure you are working within a do-file. The collapsed dataset should be saved with an appropriate name.

. list

_					
	visit	trt	m_egfr	sd_egfr	n_egfr
1.	Screening	Placebo	70.343079	21.883258 21.908973	1251
2.	Screening	Active	71.067814		1240
3.	Month 5	Placebo	71.263944	22.619153	1040
4.	Month 5	Active	68.680884	22.055378	
5.	Month 13	Placebo	71.076831	21.192192	830
6.	Month 13	Active	69.179988	22.900335	838
7.	Month 21	Placebo	70.973732	23.704579	613
8.	Month 21	Active	68.300883	22.3774	634
9. 10.	Month 29 Month 29 Month 29	Placebo Active	69.799057 70.07884	20.891014 22.528182	428 457
	•				ı

8.6 Reshaping data

The reshape command converts data from wide to long format or from long to wide format. It is particularly used when dealing with datasets containing repeated measurements e.g. data from a clinical trial with measurements taken at 3-monthly follow-up visits. Below we give hypothetical examples of long format and wide format datasets.

Long format data is where the dataset contains multiple rows per subject, each row corresponding to a repeated measurement. The dataset will generally contain variables indicating patient id and the visit number as well as the variable(s) being measured each time e.g. blood pressure, total cholesterol etc. The table below gives an example of a long format dataset for just two patients each with measurements of systolic blood pressure and total cholesterol at four visits.

patid	sex	visit	sbp	tchol
1	Male	1	120	6.1
1	Male	2	124	6.2
1	Male	3	124	6.2
1	Male	4	125	6.0
2	Female	1	135	7.2
2	Female	2	130	7.4
2	Female	3	140	7.4
2	Female	4	145	7.6

Wide format data is where the dataset contains one row per subjects, with multiple variables containing the measurements made at repeated visits. Generally the dataset will contain variables with names made up of a stub indicating the parameter being measured (e.g. sbp, tchol) and a subscript indicating the visit number (e.g. sbp1, sbp2, sbp3). The table below gives an example of a wide format dataset for just two patients each with measurements of systolic blood pressure and total cholesterol at four visits.

patid	sex	sbp1	sbp2	sbp3	sbp4	tchol1	tchol2	tchol3	tchol4
1	Male	120	124	124	125	6.1	6.2	6.2	6.0
2	Female	135	130	140	145	7.2	7.4	7.4	7.6

Note that these two examples contain the same information. In the long format dataset we have a variable called visit indicating the visit number, whereas in the wide format dataset the information about visit is contained in the subscript to the variable names. In long format the variable *sex* is constant within *patid*.

Sometimes it is more convenient to have the data in wide format and at other times it is more convenient to have the data in long format. The reshape command allows you to move between the two formats. We demonstrate the command with some examples.

Reshape: Example 1 - Moving from long to wide format

We will use the dataset *fup_egfr1.dta* to demonstrate moving from long to wide format. The dataset contains repeated measurements of egfr levels by visits.

- . use fup_egfr1, clear
- . list in 1/5

+ 	ptid	visit	visdate	egfr	age	sex	+ trt
1. 2. 3. 4. 5.	C10011001 C10011001 C10011001 C10011001 C10011001	Screening Month 5 Month 13 Month 21 Month 29	20ju12006 19dec2006 05sep2007 30apr2008 08jan2009	52.82 58.34 56.37 53.67 56.92	63 63 63 63	Male Male Male Male Male	Active Active Active Active

Note that id number C10011001 occupies 5 rows of the dataset, corresponding to 5 separate visits. The variable *visit* contains the visit number and the variable *egfr* contains the egfr level measured at each visit. Note that the variables *age*, *sex* and *trt* are constant within *ptid* whereas the variables *visit*, *visdate* and *egfr* are not.

Running through the syntax in order:

- reshape is the Stata command
- wide indicates that we are moving from long to wide format
- visdate egfr are the variables that change over visit
- i(ptid) is the unique subject identifier indicating which observations go together
- j (visit) is the name of the variable that indicates the repeat visits; the values of this variable will form the suffixes on the new variables.

The Stata output indicates we have moved from 8383 to 2497 observations and from 7 to 14 variables. The j variable which had 5 values is dropped and the variable value is now suffixed with values 1, 5, 7, 9 and 11 to indicate which visit number they represent.

Below we list the first 2 rows of the new dataset.

. list ptid trt sex egfr1 visdate1 egfr5 visdate5 in 1/2

+	ptid	trt	sex	egfr1	visdate1	egfr5	+ visdate5
			Male	52.82	20jul2006	58.34	19dec2006 13dec2006

Compare this listing of the data in wide format to that above in long format. We should now save this dataset; it is good practice to add the suffix _wide to the filename, and also indicate what it contains. So here egfr_wide.dta would be a good choice.

Reshape: Example 2 - moving from wide to long format

We will use the dataset *pot_wide.dta* to demonstrate moving from long to wide format.

. list ptid age trt sex potval1	. pot dt1 potval3	pot dt3 in	1/5
---------------------------------	-------------------	------------	-----

	+ ptid 	 age	trt	sex	potval1	pot_dt1	potval3	pot_dt3
1. 2. 3. 4. 5.	C10011001 C10011002 C10011004 C10011005 C10011006	63 66 62 66 68	1 2 1 1	Male Male Male Male Male	4.9 3.9 4.7 4.9	20jul2006 21jul2006 21aug2006 22aug2006 29aug2006	4.9 3.9 4.6 4.5 4.6	28jul2006 27jul2006 29aug2006 30aug2006 05sep2006

Note that the variables containing the potassium measurement at each visit all have the *same stub* (i.e. potval) and that the visit number is indicated by the suffix (i.e. 1, 3, 4, 5). The suffixes do not need to be consecutive. The variables sex, age and trt are only recorded once for each patient, but the visit date and potassium measurement are recorded for each visit.

To reshape from wide to long format.

Running through the syntax in order:

- reshape is the Stata command
- long indicates that we are moving from long to wide format
- potval pot dt are the stubs for the variables that change over visit
- i (ptid) is the unique subject identifier indicating which observations go together
- j(visit) is the name of the new variable that will be created to indicate the repeat visits; the values of this variable will come from the suffixes of *potval* and *pot_dt*.

The Stata output indicates we have moved from 2497 to 22473 observations and from 22 to 7 variables. The j variable is called visit and takes on 9 values. All the information contained in the variables *potval1-potval10* is now held in the *potval*.

. list in 1/9

	+						+
	ptid	visit	potval	pot_dt	age	trt	sex
1.	C10011001	Screening	4.9	20jul2006	63	1	Male
2.	C10011001	Week 1	4.9	28jul2006	63	1	Male
3.	C10011001	Week 4	4.6	17aug2006	63	1	Male
4.	C10011001	Month 5	4.7	19dec2006	63	1	Male
5.	C10011001	Month 9	4.6	26apr2007	63	1	Male
6.	C10011001	Month 13	4.5	05sep2007	63	1	Male
7.	C10011001	Month 17	4.2	09jan2008	63	1	Male
8.	C10011001	Month 21	4.5	30apr2008	63	1	Male
9.	C10011001	Month 25	4.5	03sep2008	63	1	Male
	+						+

Compare this listing of the dataset in long format to that above in wide format and make sure you understand how they relate. Save this dataset as pot_long.dta.