Intro to Stata

1. Basics

If you're used to SAS, my condolences. Important differences: Stata commands are almost always on a single line, perhaps with options after a comma, and can be issued interactively at a command line or in a file of commands. A SAS **program** is a Stata **do file**. A SAS **macro** is a Stata **program**. Roughly. Also, the data structure is a bit different, and handling data is very different, primarily because Stata has all the data in memory at one time, whereas SAS has one line at a time. The main difference between SAS and Stata is that you can see inside much of Stata's code and get good help very easily. Also, Stata is not an acronym, so it is not spelled in all caps. For an alternative to these notes, see http://www.ats.ucla.edu/STAT/stata/.

Getting Started

Stata is an extremely flexible program for working with data, and the tradeoff for that flexibility is that it is not the simplest program in the world to use, but it is easier than most. There are few other programs that have comparable strengths: SAS is slightly less flexible, and R is slightly more flexible than Stata, but both of these are much harder to use for beginners, and there are easier programs for beginners to use (SPSS) which are not useful for doing statistical or data manipulation work past a certain point.

As an example, consider running a basic OLS regression in Stata: you just type **`regress y x`** to regress y on x and get a variety of related statistics. It's not that easy in any other program. To run an instrumental variables regression, you type **`ivreg y (x=z)`** and to run the same regression getting statistics quoted in a paper that came out in 2002, but are not available in any official Stata 9 program, you download a new program with **`ssc install ivreg2`** then run **`ivreg2 y (x=z)`** to get the output. This is the kind of flexibility and ease of use I am talking about.

I'll assume you've just started Stata. There are four windows open, the big Results window, and below it the small Command window where you type commands. On the left are the Review window, showing commands you've already run, and the Variables window, showing variables in the data you are using, both empty right now, of course. You can try moving around the windows, and changing their size, etc.

Now click on Prefs, and choose General Prefs, and the Windowing tab. Let's check "Lock splitters," and uncheck "Enable ability to dock, undock, pin, or tab windows" so we don't accidentally move a window to where we can't see it anymore. If it ever happens that you accidentally move a window to where you can't see it anymore, you can restore the factory defaults like so: in Stata 9 and earlier, click on Prefs, and choose Manage Prefs, and Load Prefs and click on Factory Settings; in Stata 10, click on Edit, choose Prefs, choose Manage Prefs, and Load Prefs and click on Factory Settings.

Updating and Getting Help

The command to get free updates is **`update`** and you can check if your Stata is up to date with **`update qu.`** You shouldn't ever have to update if you're using Stata on a network and your network administrator is up to snuff, but if you update on your home computer, make sure you do that last step of updating the executable—if Stata starts producing weird behavior, it is almost certainly because you did a partial update. Let's try **`query`** and just notice how many options you can set with the **`set`** command. We'll come back to some in a moment. Then type **`about`**. This is the kind of info you will want to include if you ever send an email asking for help from Stata's

Tech Support, and you should include the first half (not the license codes, but the version number and "birthdate") in an email to Statalist (http://www.stata.com/statalist/).

Speaking of help, most of your questions can be answered by typing **`help some_command_name`** or **`findit some keywords`** so let's try **`findit instrumental`** and scroll down to see some of the relevant commands, both official and user-supplied, and FAQ files. You could also be more specific: **`findit instrumental first-stage`** (the user-supplied program **`ivreg2`** is one of my favorite programs)

If **`help`** and **`findit`** don't give you an answer, Google will (often from the archives of stata.com or the Statalist; for example if you try to install Stata 10 on a Windows 2000 machine, it will complain that you don't have gdiplus.dll but a quick Google search turns up http://www.stata.com/support/faqs/win/gdiplus.html with a fix). There is also a large collection of FAQ's at Stata's website (http://www.stata.com/support/faqs).

As a last resort, you can subscribe to the Statalist (http://www.stata.com/statalist/) and ask the experts, but be sure to read the Statalist FAQ first (http://www.stata.com/support/faqs/res/statalist.html), and I would recommend reading some posts and replies before you send your own post to the list. Make sure you specify your problem carefully—if you alienate the experts on Statalist, you may ruin your best chance at an answer to a difficult question. I say "last resort" only because 80% of the questions posted on Statalist can be answered by looking at a help file, and another 15% by searching the Statalist archive.

Syntax

Let's install my favorite: **`ssc install ivreg2, replace`** and read the help file: **`help ivreg2`**. Like the basic regress command, the **`ivreg2`** command operates on a list of variables—click on **`varlist`** for help on how to specify a variable list. You can also specify weights—the square brackets indicate that weights are optional. You can also specify restrictions with **`if`** or **`in`**, which we will come back to. Then you can specify a variety of options after the comma (the open square bracket and comma indicates that all the options are optional—not so surprising, I guess). Some of the options, e..g. **`cueoptions()`** and **`robust`** have parts of the word underlined. The underlined part is a minimal abbreviation of the option, i.e. you can just type those letters and the meaning is the same as if you had typed the whole thing.

Let's look at **`help su`**. Note the minimal abbreviation on the whole command. Now try **`help sum`**. Stata tries to help you as much as it can here—do you mean the **`summarize`** command or the **`sum()`** function?

The **`command varlist [weights] [if] [in] [, options]`** layout is one of the two most common basic syntax diagrams—the other has a **`=exp`** part which we will see when we come to generating variables. The **`if`** qualifier restricts any command to operate only on observations where the statement is true, and the **`in`** qualifier restricts any command to the set of observation numbers specified in a list of numbers (see **`help numlist`**). Weights are covered below.

Stata Files

Mostly, you need to know about 5 kinds of files to use Stata: do files (with the .do extension), log files (usually with the .log or .smcl extension), .dta files, .dct files, and .ado files. There are help files, too, with the .hlp extension up through Stata 9.2 and .sthlp for Stata 10 and up (the main reason for the new extension is ongoing problems with Windows trying to open .hlp files as if they were Microsoft Help Format files, after MS improperly appropriated the extension). Only occasionally will you run into .mo or .mlib files (see **`help m1_first`**), or .exe or .dll files (see **`help plugins`**). In short, a do file is a list of commands, a log file is a .dta file is a Stata dataset, a .dct file is a dictionary (see **`help infile`**) that specifies how some raw file can be turned into a Stata dataset, and an ado file is an "automatic do-file" that loads a program (see Programming below).

Recordkeeping: do files and log files

Everything in this file you can do interactively, which means type stuff in one line at a time, but the right way to do things is in a do-file. This is a text file of commands, all of which are executed one after another, and provide a good way of making sure you can reproduce your results, which is a basic requirement for good research. Once you've typed commands in a do-file called "profile.do", you can run the do-file with the command "do profile" and see everything run. You can open a do-file using the Window...Do-file editor...New file command or type **`doedit`** or just hit Ctrl-8. Write **`set mem 100m`** and save the file as d:\ado\profile.do (create the \ado folder if necessary). Then go back to the command window and type "**`cd /ado`**" (makes c:\ado the current directory) and **`do profile`** (runs the do-file profile.do). The **`set mem`** command increases the amount of memory available to Stata, which makes it happy.

File environment commands

Of course, you need to work with other files, too, so these may prove handy:

`cd "c:\Program Files"`	change directory to "c:\Program Files"
`pwd`	shows your current directory (path)
`erase /ado/auto*`	erase the files in D:\ado whose names start with "auto"
`copy x y`	copy file at location x (could be a URL or a path) to location y
`!del auto*`	The ! or shell command runs a program in the operating system (like del)
`winexec "C:\Program Files\Internet Explorer\IEXPLORE.EXE" http://google.com`	Also runs a program in the operating system, but doesn't wait for it to finish before Stata goes on to the next thing.
`type profile.do`	Displays the contents of the text file "profile.do" in the Results window.

You can use a text editor such as Textpad or Stata's built-in editor (though Stata's built in editor only allows about 32KB of commands per file, that is really not a binding constraint, since one do file can call another, e.g. myfile1.do can end with the line do myfile2.do) but *don't ever use Word* or another non-text editor to make your do-files—it's too easy to introduce non-text gibberish. See http://fmwww.bc.edu/repec/bocode/t/textEditors.html for more info on text editor choices and configurations.

You should really start every do-file out by first stating what version of Stata you're using with e.g. **`version 9.2`** (this ensures the do file will run the same way in a subsequent version, and won't accidentally run incorrectly in a prior version) and then making a log file, or a record of everything run, with a command like **`log using myfile1, text replace`** and put the **`about`** command right after it so you can see what version of Stata you ran in. I find it usually helps to put the command **`capture log close`** right before opening a log with **`log using`**, which closes any open log file (the **`capture`** command suppresses any error message that results from no log file being open).

Another handy command, especially for when you first start up Stata, is **`cmdlog`**, which opens a log file that just saves just the commands you type, not their output. If you like to just type willy-nilly and see what happens, then write the real do-file later, the **`cmdlog`** command can help you make your do-file easily. Just type whatever you want, then edit out the dross after the fact. (I open a cmdlog at the beginning of every session using profile.do, just in case I need to look up something I typed later).

Comments are a necessity in do-files and log files, so you will want to know that you can put anything you want between **`/*`** and **`*/`** and the contents will be ignored. Any line that starts with **`*`** will be ignored, and the rest of any line after **`///`** will be ignored, too. So if you want to put a long command on more than one line you can

```
set mem /*
    */ 100m
```

and Stata will read it all as one line or

```
set mem ///
     100m
```

with the same result. You can change the end-of-line delimiter to a semi-colon or back to a carriage return with the **`#delimit`** command on a line all by itself.

Useful commands for controlling the flow of output to the Results window include **`set more on`**, **`more`**, and **`set more off`**. If a command produces more output than can be shown in the Results window on the screen size you're using, the command will pause until you hit a key—sometimes you would prefer that Stata keep going through all the commands, rather than waiting for you. The **`set more off`** command at the start of a do file will ensure that Stata doesn't wait for you to hit a key. Other times, you'd like Stata to pause until you've had a chance to review output (after changing the data, as with a **`merge`**, for example), and the commands **`set more on`**, **`more`**, and **`set more off`** in that order will make Stata pause.

The **`quietly`** command can preface any other command, and hide its output, which is often handy. You can also enclose a block of commands inside **`qui {`** and **`}`** to suppress the output of each command in the block. Inside the block, you can preface a command with **`noi`** to show output for that command. If you want to see under Stata's hood, and have Stata show everything that a command does (including programs that it calls, and programs that the programs call), you can **`set trace on`**. If you **`set traced 1`**, you will see only what the command does, and if you **`set traced 2`**, you will see only what the command and any programs it call do. These commands are especially useful when debugging programs and loops (q.v.). To turn off this verbose output, you just **`set trace off`**.

Data

After you've got Stata up and running, and you've got some kind of record of your work in place, you need to get some data. A lot of the time, you will be given data in Stata format, which you can load with the **`use`** command. Sometimes you will be converting data from SAS or SPSS format using StatTransfer (best) or DBMSCopy (lame, but available on the UI network) or importing text files using **`infile`** or related commands. The infiling situations are often idiosyncratic, and covered by **`help infiling`**, so I will just touch on two things that may be helpful: **`insheet`** and dictionary files (see **`help infiling`** for more) . The command **`insheet`** will import tab-delimited or comma-delimited files in one step, and if the first line is a bunch of variable names, it's pretty automatic, but you might wind up with text or string variables where you wanted numeric—see **help destring** for a quick fix (also helpful are **encode** and **decode**, which turn string variables into numeric variables and vice versa). More complicated situations usually require two files—one is a dictionary file with format information, and the other a do-file that uses the dictionary to import data via an **infile using X** command, and then does all the data manipulation you need.

As an example of some really complicated infiling problems and how to easily address them, you can check out the files provided at http://www.nber.org/data/cps_progs.html for reading CPS supplements in raw text files, then assigning labels (see **help label**), and turning household and family records into household and family variables attached to individuals.

We'll skip over this, and use some data that comes with Stata: The **sysuse** command loads a dataset that Stata finds on its search path, so if you type **sysuse auto**, you will load a commonly used dataset. You can see the variables show up in the variables window. These little toy datasets are good to know about (as are the datasets available via **webuse**), because if you ever have a problem that you want to get help with, you should recast it as a problem on one of the little toy datasets that ship with Stata, since most of the people who might answer your question will stop paying attention if you spend the first paragraph describing the variables on the NSAF or SASS, or whatever massive esoteric dataset you're using that no one else cares about.

Try out another **set** command, to see what kinds of things you can do to your environment:

```
set varlabelpos 8
set varlabelpos 30
```

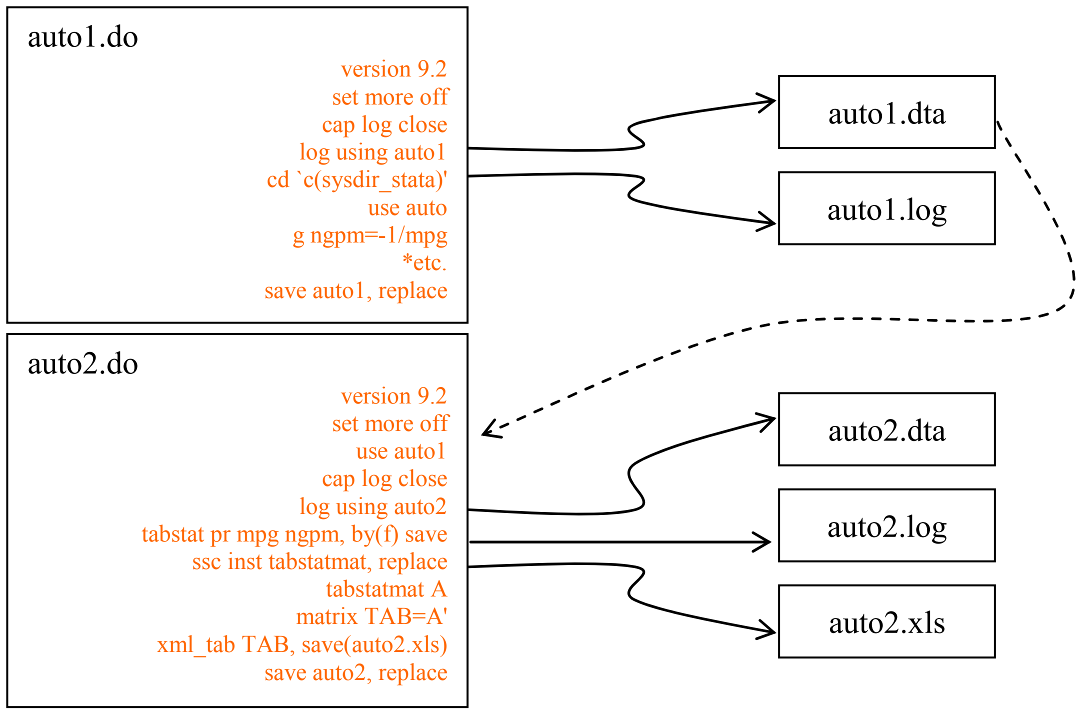
Did you see what happened in your variables window? This is especially handy when someone else has made your data, and named the variables some really long names like my_data_came_with_nice_short_names_but_I_made_these _vars_impossible_to_use.

The **clear** command gets rid of the data in memory, and is therefore a very dangerous command—until you save your data to disk, it is all held in memory, and if your computer shuts down unexpectedly or your clear when you didn't mean to, you will lose your changes. No different than using Word, I guess, but worth emphasizing more than once.

The **save** command is crucial, and often dangerous. Stata will not let you **save** over an existing dataset, unless you specify the **replace** option—but this is very dangerous. It is all too easy to change your data in some irrevocable way and then overwrite your good data with bad data. It's good practice to start every do file by using or infiling data, and do stuff to the data, and save a different dataset under a new name at the end of the do-file. Note you can also screw up the replicability goal by saving multiple different versions of your data under the same name in different directories: try **save auto** and see: you saved auto.dta in the /ado folder, so now you have two copies, and you could make changes to one, then open the other, and get incorrect results.

Some of these problems can be avoided with naming conventions. I like to have a do-file which saves the data at the end with the same name as the do-file. So you might have raw data in cps.txt read in by cps05dropouts1.do which saves an analysis file cps05dropouts1.dta, then cps05dropouts2.do makes some new variables and runs some tabs and saves cps05dropouts2.dta, and then cps05dropouts3.do drops a bunch of data to make an estimation sample and saves cps05dropouts3.dta.

Simple Naming Conventions Can Save You a Lot of Headache



```
version 9.2
set more off
cap log close
log using auto1
cd `c(sysdir_stata)'
use auto
g ngpm=-1/mpg
*etc.
save auto1, replace
```

```
version 9.2
set more off
use auto1
cap log close
log using auto2
tabstat pr mpg ngpm, by(f) save
ssc inst tabstatmat, replace
tabstatmat A
matrix TAB=A'
xml_tab TAB, save(auto2.xls)
save auto2, replace
```

Annotating the Data

The **label** and **note** commands are invaluable. You should always **label** every variable, describing what it measures, or when you open the data again in 5 years, or someone else does, no one will have any idea.

```
la var rep78 "Repair Record, 1978"
```

You should also label the values of any categorical variable.

```
la def replab 1"Good" 5 "Bad", modify
la val rep78 replab
```

You can also add notes on any variable with

```
notes rep78: not sure if 1 is good or bad
```

and add notes to the whole dataset:

```
note: rep78 badly labeled
```

and list the notes by typing **notes**.

Seeing the Data

You can type **list** to list your data in the Results window, and I use this command with various options often, to see what I've done to the data. But try typing **browse** to take a look at the auto data in spreadsheet form. As you can see, the data is a big matrix with variables as columns and observations as rows. Suppose we know that the AMC Pacer really has 10 cu ft of trunk space. Click on the 11 under **trunk** on the AMC Pacer line and type 10, enter. Nothing happens—this is the beauty of **browse**—you cannot accidentally screw up your data. Now type **edit** and do the same thing—you've changed the value. Close the window—Stata asks you if all the changes you made were actually intentional, and then records the commands that produce those changes on the results screen (and your log file, if you've got one open, but nothing to your

`cmdlog` file, since you didn't actually type the commands). But you have now changed only the data in the computer's memory—not the data on the hard drive. If you type **`sysuse auto`**, you will be told NO, but type **`sysuse auto, clear`** to force Stata to lose the data it has in its head at the moment, and **`brow`** to see that the value on the HDD is unchanged.

You can also see subsets of the data by typing **`edit varlist`**, e.g. **`edit make trunk`** or **`edit if some condition`**, e.g. **`edit if trunk==11`** (note two equal signs), or in some obs numbers e.g. **`edit in 1/3`**. The **`list`** command will show the same info as **`browse`** in the Results window (and therefore in the log file).

Note that the **`if`** qualifier restricts any command to operate where the statement is true, and the **`in`** qualifier restricts any command to the set of observation numbers specified in a list of numbers (see **`help numlist`**). There are two uses of the word **`if`** in Stata—we will talk about the second later, but see **`help if`** and **`help ifcmd`** for details.

Descriptive Statistics

To get an overview of your data, the **`describe`**, **`codebook`**, **`inspect`**, and **`summarize`** commands are quite handy. Type **`su`** to get summary stats on all the vars, or **`su trunk`** for just one. You can get more detail with options, e.g. **`su trunk, d`**. Probably **`su`** is the one command I use the most. Another most-commonly-used command is **`tabulate`**, abbreviated **`tab`**, which (along with its, produces simple tabs, e.g. **`tab trunk`** (from which we see that the median is 14), and crosstabs, e.g. **`tab trunk for`**. Cousins **`table`** and **`tabstat`** can produce more complicated tables of summary statistics.

Weights and Survey Data

Weighted tabs can be produced by specifying a weight variable, e.g. **`tab trunk for [aw=wei]`**. But you should be careful with weights, and remember that there are at least three kinds of weights:

`aweight` Analytic weight capturing the precision with which data points are measured

`pweight` Probability weight measuring how many population units a data unit represents.

`fweight` Frequency weight measuring how many data points a data point represents.

Mostly, you will want to use pweights (common on surveys) and you will want to go one step further: you will want to use the survey commands, which are regular commands prefixed with **`svy:`** e.g. **`svy: tab region race`**. Read **`help svy`** for more detail, and **`help svyset`** for how to specify the characteristics of your survey.

The consequences of using the wrong weight type are severe enough that Stata will not let you produce a regular tab with pweights, e.g. try **`tab trunk for [pw=wei]`**. But it's handy to know that aweights produce the same point estimates as pweights, so if you don't care about variance or sd or std errors, you can pretend (tell Stata) that your pweight is an aweight and run the non-survey command. In general, pweights equal aweights plus robust variance estimation (see **`help _robust`**). When it comes time to construct a confidence interval, or do some hypothesis testing, however, you will have to go back to **`svy`**. You can test the null hypothesis that two cell proportions are the same using this syntax:

```
webuse nhanes2
svy: tab race highbp
test _b[p12] = _b[p22]
```

or test any linear combination of **`_b[p{row}{col}]`** more generally. You can test the null hypothesis that two row or column proportions are the same using:

```
svy: tab race highbp, row se
test _b[p12] = _b[p22]
```

Note that you need to specify **`se`** or **`ci`** as an option to make the row or column proportions overwrite the cell proportions.

Making new data

Most of the time, you have to make the variables before you run **`tab`**, right?

The **`generate`** command makes a new variable, and the **`replace`** command replaces values in an existing variable. You specify **`gen`** (or **`replace`**), then a variable name, then a single equal sign and an expression or function (see **`help functions`**, **`help exp`**, **`help operators`**, **`help subscripting`**, and **`help _variables`**):

```
 gen met=tru* (12*.0254)^3
 su met tru

    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+--------------------------------------------------------
         met |        74    .3891653     .121417   .1415842   .6512875
       trunk |        74    13.74324      4.2878          5         23
```

Now let's make a dummy variable indicating trunk size at the median:

```
 gen met=(trunk==14)
```

Whoops. We already have that variable. Let's say we don't care about the old met var and drop it:

```
 drop met
 gen met=(trunk==14)
```

But the other thing we could do is just replace it like so:

```
 replace met=(trunk==14)
```

Note that the single equal sign means "assign" in a command like **`gen y=x`** but the double equal sign means a test of equality as is **`gen y=x if z==1`**.

Logical Statements and Missing Values

What is that **`replace met=(trunk==14)`** expression doing? It's a logical statement, i.e. it is true or false that trunk==14, so the statement **`(trunk==14)`** evaluates to one (true) or zero (false). So it is doing the same thing as:

```
 gen met2=1 if trunk==14
 replace met2=0 if trunk!=14
```

which first makes met2 equal one whenever trunk equals 14, with a missing value shown as a single period everywhere else, then puts zero whenever trunk doesn't equal 14 –see **`help operator`** for more operators. Note that != means "not equal to" (and see NOT below). You could also

```
 gen met3=1 if trunk==14
 replace met3=0 if mi(met)
```

which first makes met2 equal one whenever trunk equals 14, then puts zero whenever the new variable is missing (undefined), and seems like the same thing as

```
gen met4=1 if trunk==14
replace met4=0 if trunk<14 | trunk>14 & trunk<=23
su met*
```

where the | symbol means "or" and the & symbol means "and" but that's not quite true—know why?

Try the following:

```
tab rep78
gen medr=(rep 78==3)
gen medr2=1 if rep 78==3
gen medr2=0 if rep78==1 | rep78==2 | rep78==4 | rep78==5
su medr*
```

The problem is, "missing" is a value too. There are actually a variety of missing values (see **`help missing`**), which are helpful if you want to code the reason something is missing (e.g. **`.a`** means "Refused interview" and **`.b`** means "Not at home"), and they are all bigger than any real number (i.e. they also represent infinity—a handy interpretation if you code **`gen undef=1/0`** for example). So

```
gen hir=(rep 78>=3)
```

will include all missing rep78 values in the hir "High Rep" category. The better way to code the creation of the hirep dummy variable is

```
gen hirep=(rep 78>=3) if !mi(rep78)
```

which will put a missing value in every obs where rep78 is missing, though you could also

```
gen hirep=(rep 78>=3) if rep78<.
```

because the missing value **`.`** is bigger than any real number, and extended missing values are bigger than the missing value **`.`** (and **`.a`** is smaller than **`.z`**).

You should **always account for any potential missing values** when you write a **`generate`** or **`replace`** statement—failure to do so may result in incorrect calculations. This goes for any statistical software, of course. You cannot simply put values in for some missing values (which is what failing to account for missings will do) as that will bias your results—see **`findit imputation`** for ways to fillin for missings).

On NOT: the NOT EQUAL operator says A does not equal B, e.g. **`trunk!=14`** means trunk is not 14 for a given observation and evaluates to one or zero. The NOT operator gives the opposite of a true-or-false statement, so **`!(trunk==14)`** means the same as **`(trunk!=14)`**.

System variables

What if you wanted not just the median value but the middle observation (or the first of two middle observations)? Then you would need to reference the observation number directly, or you could

```
gen med=1 in 37
replace med=0 if mi(med)
```

but it's much more direct to use a built-in variable which is equal to the current observation number and is always available on every dataset: _n

```
gen med2=(_n==37)
```

But what if you didn't know how many observations you had in your dataset, and you didn't want to have to figure it out interactively before you wrote your do-file? Then you just use _N, which is a built-in variable containing the number of the last observation:

```
gen med3=(_n==_N/2)
```

```
su med*
```

What if you want instead to change the value of some variable in that middle observation, e.g. change medr2 to 2 in that observation? It's just **`replace medr2=2 in _N/2`** right? NO, you can't put calculations after the "in" qualifier. But you can use a trick to force calculations in these kinds of spots that nominally don't allow expressions, but only numbers: put the expression inside a left single quote, equal sign and a right single quote.

```
replace medr2=2 in `=_N/2'
```

and Stata will calculate the thing inside **`` `= ``** and **`'`** before running the command. In this case, you could also

```
replace medr2=2 if _n=_N/2
```

but the trick is handy when you have no alternative.

Subscripting and tsvarlist

Often, you want to refer to other observations when making a variable, e.g. the value before or after the current one. This is when you want to use explicit subscripting (see **`help subscripting`**) such as

```
gen med2lag=med2[_n-1]
edit med2 med2lag
```

You can even put a variable name in the brackets indicating which observation you want to reference:

```
gen med2lag=med2[wave]
```

This set of tricks for looking at neighboring observations is one of the minor advantages of keeping all the data in memory (as opposed to reading it in a line at a time as SAS does), but the cost is that you have to have enough memory to keep all the data in memory. There is a whole suite of functions (see **`help tsvarlist`**) for making lags and leads and differences without subscripting, which is safer, since a one-period lag is not always the prior observation (if years were 1989, 1990, 1992, 1993, the lag should only be defined in the second and fourth observations).

Functions

When I wrote

```
gen medr2=0 if rep78==1 | rep78==2 | rep78==4 | rep78==5
```

above, I really should have used a handy function:

```
gen medr2=0 if inlist(rep78,1,2,4,5)
```

and of course there is a long list of handy functions at **`help functions`** organized into categories: Mathematical functions, Probability distributions and density functions, Random-number functions, String functions, Programming functions, Date functions, Time-series functions, and Matrix functions.

By groups

A lot of tricks in generating variables are used so much, they are coded in the "extensions to generate" command **`egen`** and you can learn a lot just by reading **`help egen`**. Even more are included in **`egenmore`**, which you can get by typing **`ssc install egenmore`**. But you should know that none of these tricks are that complicated to write using the basic **generate** and **replace**, possibly with a **by** command or loop thrown in (loops will be covered in detail later).

The **by** command steps through each unique value of a variable, and treats each set of observations as a little separate dataset. The data must be sorted by values of the by-group variable before using the **by** command (see **help sort**). Suppose we wanted to calculate the minimum value of rep78 for foreign and domestic cars—we could:

```
sort for rep78
by for: gen minrep=rep78[1]
```

since the first line orders all the cars by repair record within for==0 or for==1 (Foreign) and the second line looks only within each group, and assigns the value of rep78 in the first observation to the new variable minrep.

Note that the _n variable which records the current observation number resets within each by-group, i.e. each group is treated like its own little dataset.

You can combine these two steps with the **bysort** command (abbreviated **bys**):

```
bys for (rep78): gen minrep=rep78[1]
```

where the variables after **bys** but before the parentheses are the variables you want to perform the command **by**, and the variables inside the parentheses specify the sort order of each little dataset you are performing the command on.

For more, see: http://www.stata.com/support/faqs/data/group.html and many other related FAQs on data management, or the Data Management manual.

Data manipulation

To destroy the data in memory, and turn it into useful summary statistics, and quickly, the **collapse** command is invaluable. Of course, you may want to save a copy of your data to disk before you destroy the copy in memory—if you want to save a temporary copy, you can use **preserve**, then type **restore** when you want it back. If you wanted to calculate the weighted mean of income at the family level, you could **preserve**, then **collapse income [pw=finwt], by(familyid)** and **save fminc** to save the calculated means and then **restore** to get the full dataset back, and **merge** the mean income back onto the main data.

The **merge** command matches two datasets, one in memory and on the hard drive, usually using an identifier, such as family or person IDs. It is a relatively straightforward command, with a good help file, but for some reason, people always seems to get something wrong in merging. So be careful about checking the diagnostics that the command supplies, and always look at a few observations to make sure it went like you thought it would.

The **append** command just adds data to the end of the existing data (like stacking one matrix on top of another). If you had foreign auto data in for.dta and domestic in dom.dta, you could **use for**, then **append using dom**, then **save auto**. It's important to remember that if variables are named differently, they will not be missing in half the data (well, not half, but you get the idea). If variables that are named the same have different value labels (corresponding to different coding), the appended data will lose its coding and use the master data's coding. For example, if gender is 1 for male in one year and 2 for female, and you have defined value labels that reflect that in your data, and then you append the next year's data where 0 is female and 1 is male, you will see:

```
tab gender
```

```
     gender |      Freq.     Percent        Cum.
------------+-----------------------------------
          0 |    390,003       25.03       25.03
       Male |    612,066       39.28       64.31
     Female |    556,212       35.69      100.00
------------+-----------------------------------
      Total |  1,558,281      100.00
```

The **reshape** command changes the shape of the data in very useful ways. If you have panel data on earnings, but each year of data are saved as variables, such as e1951, e1952, etc. then you will want to reshape the data to have observations as person-year data points (so you can run regressions—which we will talk about later):

```
li persid e19??, noo

  +-------------------------------+
  | persid   e1951   e1952   e1953 |
  |-------------------------------|
  |      1    1800    1800    1900 |
  |      2    2600    3100    3200 |
  |      3    3000    3800    5500 |
  |      4    4700    5400    6500 |
  |      5    5900    6500    8200 |
  +-------------------------------+

reshape long e, i(persid) j(year)

Data                               wide   ->   long
-----------------------------------------------------------------------
Number of obs.                        5   ->      15
Number of variables                   4   ->       3
j variable (3 values)                     ->   year
xij variables:        e1951 e1952 e1953   ->   e
-----------------------------------------------------------------------

li persid e*, noo sepby(persid)

  +---------------+
  | persid      e |
  |---------------|
  |      1   1800 |
  |      1   1800 |
  |      1   1900 |
  |---------------|
  |      2   2600 |
  |      2   3100 |
  |      2   3200 |
  |---------------|
  |      3   3000 |
  |      3   3800 |
  |      3   5500 |
  |---------------|
  |      4   4700 |
  |      4   5400 |
  |      4   6500 |
  |---------------|
  |      5   5900 |
  |      5   6500 |
  |      5   8200 |
  +---------------+
```

Returned saved results, precision, scalars

A lot of times, you want to use a value that appears on the screen, either to generate a new variable, or to do some other kind of calculation. Returned saved results are the most useful way to do that. After any command, you can type `return list` to see a list of items you might want to use, e.g.

```
su trunk, d
ret li
gen mt=r(p50)
```

or sometimes you might get a number that way that doesn't show up on the screen explicitly, e.g.

```
tab trunk
ret li
gen nvals=r(r)
```

where `r(r)` is the number of distinct values in the table.

There's really no reason to generate a variable that takes on one value for every observation, as I just did, especially on a big dataset (where space in memory is at a premium). If we want to use a single number later in our do-file, we can save it as a scalar like so:

```
scalar nval=r(N)
```

which is just the number of observations summarized in the table, but you have to exercise some caution referring to a scalar, thanks to Stata's eagerness to interpret pieces of expressions as variables:

```
gen test=nval
gen test2= scalar(nval)
su test* nvals
```

Here Stata wanted very badly to interpret the `nval` you typed as a variable, and there was a variable named `nvals` that `nval` was a good abbreviation for, so Stata used that and bypassed your scalar—a good reason to always use the `scalar(name_of_scalar)` construction, even when it seems redundant.

Display, Formats, Datatypes, and Precision

If you just want to do a simple calculation, say average number of observations per cell, which is `r(N)` divided by `r(r)`, you can use the `display` command:

```
tab trunk
di r(N)/r(r)
```

which is very handy as a calculator, too:

```
di _pi, ln(_pi), tan(_pi/4), norm(1.96)
```

and you can change the display format of the numbers on the screen easily:

```
di %20.18f _pi
```

using the same kinds of formats available to assign to variables (see `help format`) which are really helpful for variables mainly when it comes to displaying dates (see `help dates`) in my experience. But the mention of display formats for variables brings up a related point that always seems to trip people up:

```
gen tenth=_n/10
su tenth if tenth==6
su tenth if tenth==5.9
```

Stata finds no observation with tenth equal to 5.9 but we clearly think that observation 59 should have that value, and if we look:

```
list tenth in 58/60
```

it sure looks like it does. The problem here is that Stata thinks in double precision (see **`help data_types`**) using 8 bytes per number, but variables are usually defined in float precision (4 bytes), and tenths have no exact representation in binary numbers. If you write out the value of 5.9 that was used in **`su tenth if tenth==5.9`**, and the value of tenth in observation number 59, you can see the source of the problem more clearly:

```
di %20.18f 5.9
  5.900000000000000400
di %20.18f tenth[59]
  5.900000095367431600
```

and these two numbers are not equal. You could create you variable as a double (with higher precision):

```
gen double t2=_n/10
su t2 if t2==5.9
```

or you could round to float precision:

```
su tenth if tenth==float(5.9)
```

to get around this problem. It doesn't come up that often, but it does seem to confuse people when it does. If you always use integer values, you will never run into this problem.

The Stata Macro

What are called "variables" or "literals" in other programming languages are macros in Stata. Before any command is run, all the macros in the command get interpreted.

Globals

Global macros (see **`help global`**) are defined as a number or string, with or without =

```
global test="seven"
global test "seven"
global test=7
```

Global macros are referenced using a dollar sign:

```
display $test
display ${test}
```

The brackets are better style, since **`display $test7`** is interpreted as **`display ${test7}`** which is evaluated as **`display`** which displays nothing, but **`display ${test}7`** is interpreted as **`display 77`** which displays the number you wanted.

Locals

Local macros (see **`help local`**) are

Defined as a number or string, with or without =

```
local test="eight"
local test "eight"
local test=8
```

Referenced using two kinds of single quotes:

```
display `test'
```

Make sure you get that first quote right—it's on the same key as the tilde ~

What does the = do? The equal sign denotes immediate evaluation, instead of assignment, i.e. Stata figures out what goes in the local now, rather than looking back to see what's there when you reference the macro later. Note that immediate evaluation limits length of a local to about 245 characters, and immediate evaluation means the local won't change if other stuff changes.

What's the difference between locals and globals? Globals stick around, and overwrite existing globals (bad practice when avoidable). Locals disappear, and occupy a safe part of memory (but can't be seen when your do-file or program is done).

Why use them? They don't just save retyping—they save making mistakes. There are also many useful extended functions (see **`help extended_fcn`**, which is linked from **`help macro`**). In particular, anything you can **`display`**, you can put in a macro with e.g. .

```
  local t: display _pi " is the ratio in question"
```

which can come in handy for putting numbers in a given display format (rounding, significant digits, dates, etc.).

Tricky: order of interpretation

If you have a local called test that contains 7 and a global called row7 that contains _pi, you could **`display ${row`test'}`** As with expressions enclosed in parentheses in math operations, macros are evaluated from the "insidemost" out.

Trickier:

All of the local macro extended functions are available without first defining a local macro:

```
local t: display _pi " is the ratio in question"
gen tvar="`t'"
```

is equivalent to

```
gen tvar="`: display _pi " is the ratio in question" '"
```

which is just a shortcut, but can really come in handy.

Scalars (similar to macros, but...)

Scalars are defined only with the = (evaluation, not assignment)

```
scalar test=7 scalar test="seven"
```

Scalars are best referenced using scalar(name): **`display scalar(test)`** Why? Try this:

```
clear
range test 0 1 2
display test
list test in 1
display scalar(test)
```

Again

The “trick” of condensing a local definition into a command turns out to be very handy, and is especially important to understand when reading other people’s code. As an example, consider the following:

```
sysuse auto, clear
ins rep
local n=r(N)
local u=r(N_unique)
local l: var lab rep
hist rep78, ti("`l', `g' obs") bin(`u')
```

versus this:

```
sysuse auto, clear
```

```
ins rep
hist rep78, ti("`:var lab rep', `=r(N)' obs") bin(`=r(N_unique)')
```

both of which do the same thing. Sometimes only the first of these approaches will work, but it's often easier to use the latter approach.

Ifcmd

We saw the **`if`** qualifier already, which restricts the scope of a command like **`generate`**, but there is another **`if`** which is a command in its own right (not a qualifier) with a help file at **`help ifcmd`**. The **`if`** command executes a block of code (enclosed in curly brackets) once if the condition that follows the command is true, or skips the block of code if it's not. So it's related to **`while`**, except it only runs once. The related command **`else`** follows an **`if`** command, and executes a block of code (enclosed in curly brackets) once if the previous **`if`** command failed to execute its block.

This is particularly handy if you're looping in a do-file, and want to execute some additional code only for certain values, or if you want to use a returned result (the mean, say) and execute code only if it falls in some range.

One thing that always seems to confuse people is the difference between the two uses of **`if`** so make sure you know the help files at **`help if`** and at **`help ifcmd`**. What output do you think

```
sysuse auto, clear
if for==1 {
 g dom==0
 }
su dom
```

produces? I don't exactly understand how people seem to get this wrong at the rates they do, but I suspect if comes from some *faux ami* analogy to SAS or SPSS. It's common enough to warrant a FAQ: http://www.stata.com/support/faqs/lang/ifqualifier.html

2. Graphs

We've seen a plot produced by the **`inspect`** command, and a similar histogram can be produced by the **`hist`** command. Most graphs are produced by the **`graph`** command, which has a number of subcommands, including **`twoway`**, **`bar`**, **`box`**, **`pie`** and many others. The bulk of the good graphs will be produced by **`twoway`**, a **`graph`** subcommand for graphing some variable(s) on the y axis (ordinate) versus some variable on the x axis (abscissa), that has its own subcommands, including:

`scatter`	`scatterplot`
`line`	`line plot`
`area`	`line plot with shading`
`bar`	`bar plot`
`rarea`	`range plot with area shading`
`tsline`	`time-series plot`
`lowess`	`LOWESS line plot`
`lfit`	`linear prediction plot`
`qfit`	`quadratic prediction plot`
`function`	`line plot of function`
`histogram`	`histogram plot`
`kdensity`	`kernel density plot`

all with their own very useful help files. Note that bar graphs can be produced by **`graph bar`** or by **`graph twoway bar`**, the first with an easier syntax for some people, and the second with a lot more powerful control over placement and look of bars.

Most of the examples we will see today are linked from **help tw** but if you read no other graph help file, you should read **help scatter** at least. I also recommend reading **help schemes** (I have **set scheme s2mono, perm** on my computer). If you want 3D graphics, you will have to go to another program—it is one of the few gaps in Stata's repertoire.

There are some nice FAQs at http://www.stata.com/support/faqs/graphics/ but to really see what Stata can do, check out A Visual Guide to Stata Graphics by Michael Mitchell (a new edition is slated to come out this year).

One alternative to the **graph** command is the Stata 7 graph command, now available as the **gr7** command. This command produces twoway graphs, including scatter and line graphs, but very quickly, though they are not as pretty.

Scatter or Line Graphs

The **scatter** command, part of the **twoway** suite, is the workhorse of graph commands, and really the workhorse of descriptive statistics (and regression diagnostics as well). Here's a quick example:

```
sysuse uslifeexp2, clear
scatter le year
```

where you can see immediately the impact of the Spanish Flu relative to various wars.

You can add options to pretty it up, if you like:

```
sysuse uslifeexp2, clear
scatter le year, subti("Life expectancy at birth, U.S.") note("1")
    caption("Source:  National Vital Statistics Report, Vol. 50 No. 6")
```

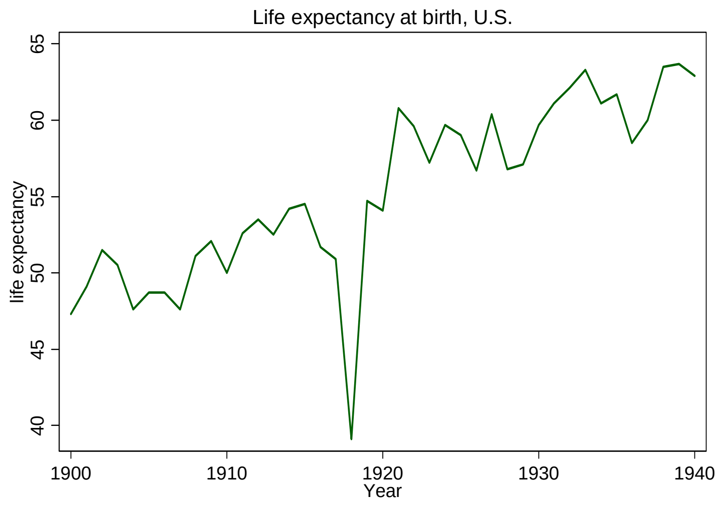
and there are a few hundred thousand ways you might modify that graph with options, so I won't go into detail. It's all in the help files.

One of the common options on a scatter plot is to connect the dots:

```
sysuse uslifeexp2, clear
scatter le year, c(l)
```

and sometimes to suppress the dots after connecting them:

```
scatter le year, c(l) m(i)
```



The last is so common, in fact, there is a separate command to make it easier to type:

```
sysuse uslifeexp2, clear
line le year
```

but note that the dots are graphed in the sort order of the data, which can result in some unpleasant looking graphs unless you specify the **sort** option:

```
sysuse auto, clear
line mpg weight
line mpg weight, sort name(s)
```

The **name** option is handy when you want to have a number of graphs open at once for comparison.

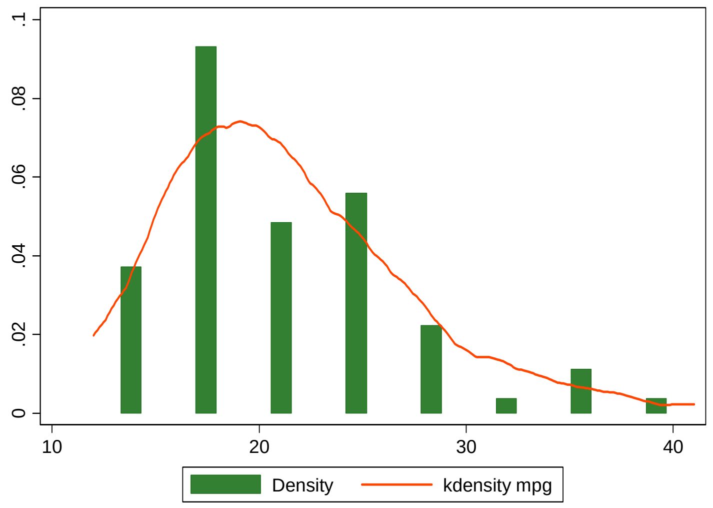
Density and Local Polynomial Graphs

The last graph (**line mpg weight, sort**) is getting close to specifying an empirical model: mpg declines as weight increases. As useful as scatter/line plots and histograms are in small datasets, they rapidly become untenable in large datasets. A good way to get sense of the distribution of a variable (or a residual after a regression) or the functional relationships between pairs of variables in a large dataset is to use kernel estimators like **kdensity** or **lpoly**. Kernel estimators use subsets of the data and reweight to construct local estimates, for example of the proportion of cars with mileage "near" 21 mpg (a kernel density estimator), or the effect of another 100 pounds on mpg "near" 3000 lbs (a kernel regression estimator).

```
sysuse auto, clear
hist mpg, name(h)
kdensity mpg, name(k)
```

You can get the values that **hist** uses with the undocumented command **twoway__histogram_gen** and then graph them with **tw bar**, which is handy for combining graphs:

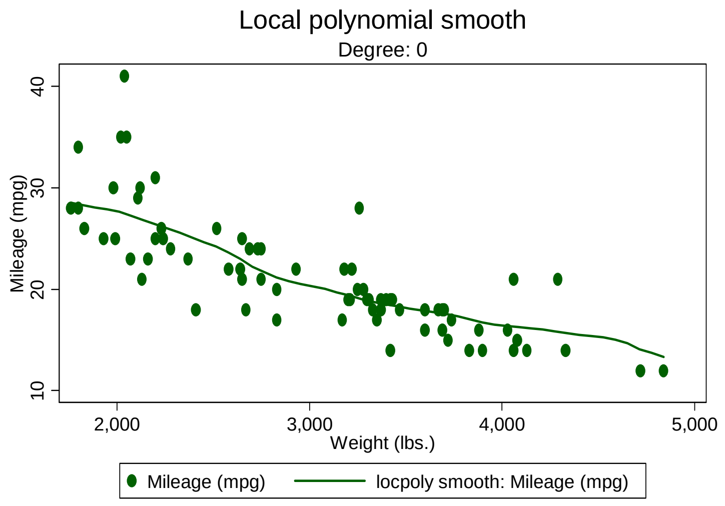
```
twoway__histogram_gen mpg, bin(8) start(12) gen(f x)
tw bar f x || kdensity mpg
```



The user-written **kdens** (**ssc install kdens**) offers even more flexibility than **kdensity**.

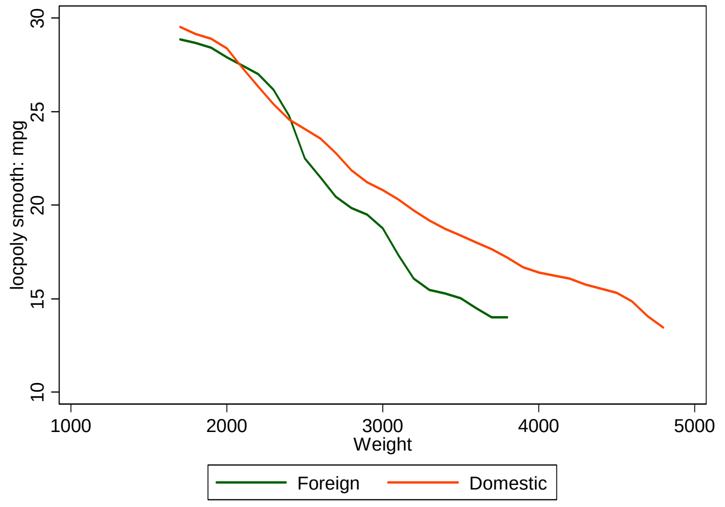
In Stata 10, local polynomial regression is performed with the command **lpoly**, but the near-equivalent command **locpoly** is available via **findit** (http://www.stata-journal.com/software/sj6-4) for prior versions.

```
net from http://www.stata-journal.com/software/sj6-4/
net inst  st0053_3
line mpg wei, sort name(bumpy)
locpoly mpg wei, name(smooth)
```



The **lowess** command is also available in Stata versions before Stata 10, but I've never liked it as much, mainly because it does not offer the **at()** option with the **generate()** option, and does not give the same control over kernels. The **at()** option and **generate()** option are especially helpful if you want to overlay two smoothed graphs:

```
sysuse auto, clear
g m=(16+_n)*100 in 1/32
la var m "Weight"
locpoly mpg wei if for==1, nogr at(m) gen(mfor)
locpoly mpg wei if for==0, nogr at(m) gen(mdom)
line mfor mdom m, leg(lab(1 "Foreign") lab(2 "Domestic"))
```



Bar Graphs

You can get simple bar graphs with **graph bar** but more flexibility with **twoway bar**:

```
sysuse sp500, clear
gr bar high in 1/4, over(date)
```

where the legend on categories shows their numeric value (dates measured as days since January 1, 1960) instead of a more legible format. With **twoway bar** the defaults are a bit friendlier:

```
twoway bar high date in 1/4, yla(1300(20)1340) barw(.5)
twoway bar high date in 1/4, yla(1300(20)1340) barw(1.5)
```

and you can alter the data in clever ways to get total control over the look of the graph, e.g. overlapping bars of arbitrary width, different labels, etc.:

```
replace date= date+(2-_n)/3 in 1/4
twoway bar high date in 1/4, yla(1300(20)1340) xla(14977 "Jan 2" 14979 Jan 5")
```

A related command is **twoway dropline**:

```
sysuse sp500, clear
tw dropline change date in 1/57, yline(0, lstyle(foreground))
```

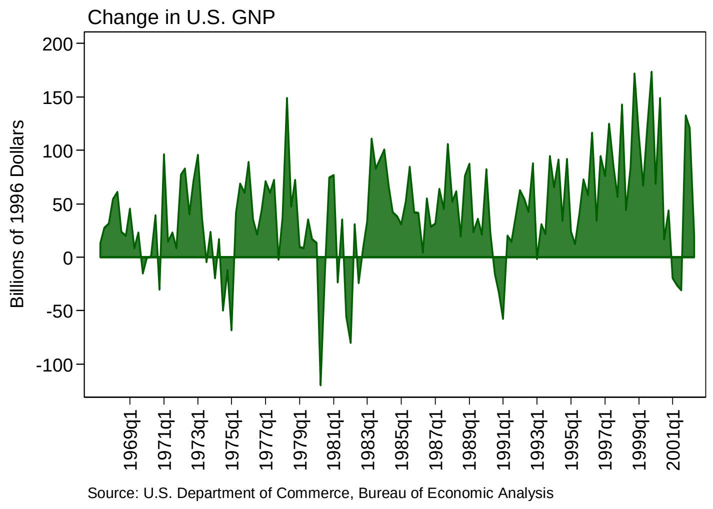
and a handy command when there is a lot of data is **twoway spike**:

```
sysuse sp500, clear
tw spike change date in 1/57
tw spike change date
```

Area Graphs

Area graphs are handy for showing meaningful areas between a curve and an axis (if the running integral has some real interpretation):

```
sysuse gnp96, clear
twoway area d.gnp96 date
twoway area d.gnp96 date, xla(36(8)164, angle(90)) yla(-100(50)200, angle(0))
    yti("Billions of 1996 Dollars") xti("") subti("Change in U.S. GNP", position(11))
    note("Source: U.S. Department of Commerce, Bureau of Economic Analysis")
```



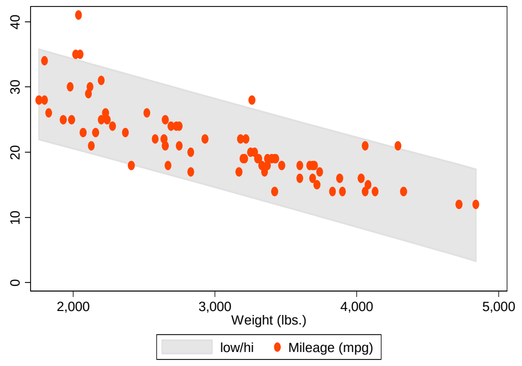
And a range plot with area shading (**tw rarea**) is useful when the area between two functions is informative:

```
sysuse sp500, clear
twoway rarea high low date in 1/57
```

This is handy for custom standard error graphs (but see **help lfitci** for an automated solution):

```
sysuse auto, clear
qui regress mpg weight
predict hat
predict s, stdf
```

```
gen low = hat - 1.96*s
gen hi  = hat + 1.96*s
tw rarea low hi weight, sort color(gs14) || scatter mpg wei
```



Note that we graphed the shaded area first and then the scatterplot. Typing

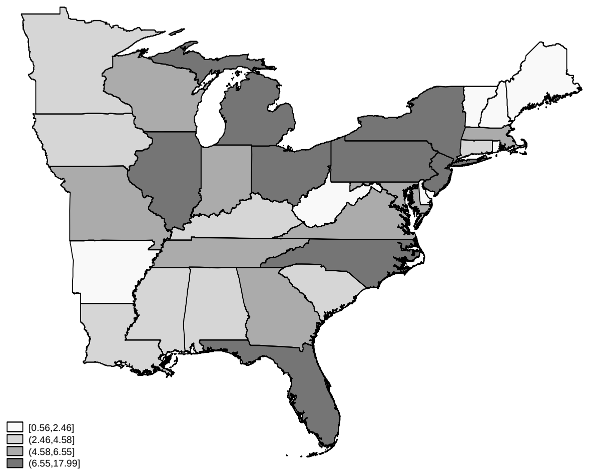
```
tw scatter mpg wei || rarea low hi weight, sort color(gs14)
```

would superimpose the shading on the scatter, obscuring the dots.

Mapping

There is a nice guide to mapping in Stata at http://mysite.verizon.net/huebler/2005/20051106_tmap.html, and there are FAQs on the Stata website (e.g. http://www.stata.com/support/faqs/graphics/tmap.html). The relevant commands are **`tmap`** for Stata 8 and **`spmap`** for more recent Stata versions, both available from SSC.

```
cap ssc install tmap
cap copy http://pped.org/stata/uscoord.dta /uscoord.dta
use http://pped.org/stata/spop90.dta, clear
gen East=(LON>=-98)
tmap cho p if East==1, id(id) map(\uscoord.dta)
```



Adding Text and Lines

Many lines can be added with options **`xline()`** or **`yline()`**. See **`help added_line_options`** and **`help added_text_options`** for more. Arrows can be added via **`tw pcarrow`** tricks.

The New Graph Editor

In Stata 10, you can click on a graph and add graphic elements such as text or lines interactively, using the new Graph Editor, but there is no way to store those changes as commands, so it behooves you to learn the command syntax approach. Otherwise, when you change your graph, you'll be stuck clicking and dragging and typing *ad nauseam*. I would recommend you not use the new Graph Editor, unless there is no other way forward.

3. Looping, Programming, and Automating Output in Stata

Good Programming Style

Thm: Reproducibility, error reduction, ease of use, and portability all depend on good programming style.

Cor 1: Don't type any parameter (a number or string of characters that you might later change) more than 3 times in a program or do-file. If you do, you are inviting a situation where you change 2 instances and forget the third, and never notice the output is flawed.

Cor 2: Comments are good, but clean code is better. Comments tell you what the programmer intended, but might not help you fix or adapt the code easily. Clean code does both.

Cor 3: A little bit of programming sophistication goes a long way. If you are reformatting tables of output more than once when the output changes, you would have been better off programming the output (table layout and number display format) in the first place. If you are doing the same thing over and over (similar regression, similar graphs, similar paper topics), you are at risk of becoming a dull boy. Doing the same thing over and over is what computers are for.

Looping

This is how you make the computer do your work for you, and save yourself some carpal tunnel: Use **`foreach`** or **`forvalues`**, not **`for`** (note **`while`** and **`for`** still work, but are harder to use, and the **`for`** command had some problems—just avoid it). **`foreach`** works beautifully, and is simple:

```
foreach v in some list of stuff {
 does this 4 times, for `v'="some" and `v'="list" etc.
 presumably does something with `v' itself
 }
```

Make sure the curly braces are as shown (no code after the first, and the second on a line by itself).

Here's a fun example (though outdated, as **`tmap`** has been replaced by **`spmap`**):

```
qui ssc install tmap
cap copy http://pped.org/stata/uscoord.dta /uscoord.dta
use http://pped.org/stata/spop90.dta, clear
gen East=(LON>=-98)
gen West=(LON<-98 & id!=13 & id!=56)
foreach v in East West {
 tmap cho p if `v'==1, id(id) map(\uscoord.dta)
 graph rename `v', replace
*makes a popn map for the west, then the east
 }
erase /uscoord.dta
```

The similar command **`forvalues`** steps through a numeric list:

```
forvalues v=1/10 {
 does this 10 times, for `v'=1 and `v'=2 etc.
 presumably does something with `v' itself
 }
```

Note that **`forvalues v=1/10 {`** is equivalent to **`foreach v in 1 2 3 4 5 6 7 8 9 10 {`**

Perhaps handiest is the second syntax of **`foreach`**, i.e. one of the following:

```
foreach lname of local lmacname {
foreach lname of global gmacname {
foreach lname of varlist varlist {
foreach lname of newlist newvarlist {
foreach lname of numlist numlist {
```

so you can store any list in a macro, or have Stata parse a variable list for you. Note also that

```
foreach v of numlist 1/10 {
```

is equivalent to

```
forvalues v=1/10 {
```

All of these loops can be nested: just make sure you use different names for the local macros created:

```
foreach v of numlist 1/10 {
 foreach v of numlist 1/10 {
  di "Row `v' and Column `v' value is "
  }
 }
```

will obviously not work, but this is fine:

```
foreach r of numlist 1/10 {
 foreach c of numlist 1/10 {
  di "Row `r' and Column `c' value is "
  }
 }
```

See also the **`continue`** and **`break`** commands for exiting a loop prematurely or preventing exit from a loop or program.

The **`levelsof`** command works very nicely with **`foreach`** to do something for every value of a variable, e.g.

```
webuse nhanes, clear
levelsof race, local(r)
foreach v of local r {
 svy, subpop(if race==`v’): tab sex higbp, row
 }
```

Output: The `file`*,* `estout`*, and* `xmlsave` *Commands*

The **`file`** command allows you to read or write to text or binary files. This means that you can write anything you can think of to a file. You could have a whole paper (text, tables, graphics, etc.) written out by one do-file, in theory, or even write out a file that would be an executable program (not that anyone would ever do that) and then run it.

In particular, you can write out in any format the output from tabulations or regressions available via **`return`** or **`ereturn`** or built-in shortcuts like **`_b[var]`** (gives the coefficient on var) or **`_se[var]`** (gives the SE on var). For example:

```
webuse nhanes2, clear
qui svy: tab race diab, row ci
mat rowpc=e(b)
file open d using /b.txt, write replace
file write d "Race" _tab "Percent Diabetic"
forv r=1/3 {
 file write d _n "`: lab (race) `r''"
 file write d _tab "`: di rowpc[1,`=`r'*2']'"
 }
file close _all
type /b.txt
local excel="C:\Program Files\MSOffice2000\Office11\Excel.exe"
winexec `excel' \b.txt
```

And it would be easy to embed the preceding in a larger loop that stepped through a list of diseases, and did tests of significance, etc., and then opened it all up in Excel, if you like that kind of thing.

The **estout** command from SSC automates the creation of tables of coefficients from estimation commands or of summary statistics, and is far better than crappy alternatives like **outreg**. Install it with **ssc install estout**. This is a really useful command, and has myriad options, so the command has its own website at http://fmwww.bc.edu/repec/bocode/e/estout/ with plentiful examples.

The **xmlsave** command allows you to save a Stata dataset in an XML file format: either Stata's .dta or Microsoft Excel's SpreadsheetML format. So you can **collapse** your data into a dataset of means by year, say, then save in Excel format.

A user-written command **xml_tab** (**findit xml_tab**) offers a way to write out various formatted tables to Excel-type files. You may find it especially handy when used to create and output a simple table of the means:

```
tabstat price mpg rep78 headroom trunk weight length, by(foreign) save
ssc inst tabstatmat, replace
tabstatmat A
matrix TAB=A'
xml_tab TAB, replace
```

where **tabstat** generates a table of means for the list of variables categorized by foreign. **tabstatmat** saves the results to matrix A with three rows for Domestic, Foreign and Total. In the columns of matrix A are the means for the listed variables. The transposed matrix A is the matrix TAB, which **xml_tab** outputs into the default XML file. You can see more examples of using **xml_tab** in xml_tab_example.do (**findit xml_tab**).

The `program` *Command, and ado Files*

Any bit of code you want to repeat should be coded as a program. So a bit of text, or a number, should be coded as a macro, but some lines of code that, say, calculate convert some amounts into real dollars, or write out a table of estimates, can be written as a program, and then to run the code, you just type the name of the program:

```
cap program drop dtab
program dtab
syntax varname
webuse nhanes2, clear
qui svy: tab race `varlist', row ci
mat rowpc=e(b)
file open d using /b.txt, write replace
file write d "Race" _tab "Percent suffering from `varlist'"
forv r=1/3 {
 file write d _n "`: lab (race) `r''"
 file write d _tab "`: di rowpc[1,`=`r'*2']'"
 }
file close _all
```

```
type /`varlist'.txt
end
```

Now you can type, e.g.

```
dtab diab
dtab heart
dtab highlead
```

ad infinitum. If you saved that bit of code in a file called dtab.ado, you could type those lines (e.g. **`dtab diab`**) to get an instant table at the command prompt, or in an unrelated do-file. The ado file loads a program automatically; that is how a lot of Stata's official commands are written (and you can read their code, with the **`viewsource`** command, which is instructive, to say the least). There's a lot more about **`program`** in the Programming manual, of course.

Automating Appendices

Michael Blasnick documented the MS Word trick of using a mail merge to put a series of Stata output files into a Word document at http://www.stata.com/statalist/archive/2004-06/msg00301.html and http://ideas.repec.org/p/boc/asug05/14.html. I've used it in e.g. the appendices of http://nber.org/papers/w13246, so I can attest that it can be quite handy in circumstances where you have to produce a lot of pages of the same type of thing.

4. Estimators

We've followed the path of many stats courses, doing some tabs and some graphs as exploratory data analysis, not worrying too much about standard errors or statistical significance. However, a tab of y versus x or a graph of y versus x usually is designed to elicit information about the "effect" of x on y. Thus, we don't simply want to know what proportion of dropouts by parent's marital status, we want to know the effect of parent's marital status on likelihood of dropping out. Returning to our auto data, we don't want to know the fuel efficiency by weight class, we want to know what the effect of an extra 100 pounds is on fuel efficiency.

In fact, a tabulation is an estimator, in the same way that an OLS regression is, and you can construct a confidence interval around a proportion (a tricky subject actually—see "Interval Estimation for a Binomial Proportion" by Lawrence D. Brown, T. Tony Cai, and Anirban DasGupta for details) from a tabulation, or test the equality of two proportions, using the tricks shown in the answers to Day 1's exercise 3.

There are various other programs to run hypothesis tests, including **`signrank, kwallis, nptrend, ranksum, runtest, bitest, ttest,`** etc. For example to test equality of mean mpg across foreign and domestic cars in the auto data, you can **`ttest mpg, by(for)`**. If you want to test the equality of means, however, the natural way to do that is in a regression, e.g. **`reg mpg fore`** will test whether foreign cars get better gas mileage on average. See http://www.ats.ucla.edu/stat/stata/webbooks/reg/default.htm for a gentle introduction to regression models in Stata.

Regression and Testing Hypotheses

We've already run a regression by fitting a line on a graph.

```
sysuse auto, clear
tw lfitci mpg wei, by(for) || scatter mpg wei
```

is running a regression (actually two OLS regressions), and showing the results in a graphical form. We could also

```
sysuse auto, clear
reg mpg wei if fore==1
est sto f1
reg mpg wei if fore==0
est sto f0
suest f0 f1
test [f0_mean]w=[f1_mean]w
```

or

```
gen forwei=fore*wei
reg mpg wei fore forw
test fore forw
```

both of which formally test that foreign and domestic cars exhibit the same relationship between mpg and weight, but the first approach allows the estimated error variance (the variance of residuals y-Xb) to vary across the two subsamples. See also

http://www.stata.com/statalist/archive/2007-07/msg00125.html

http://www.stata.com/statalist/archive/2006-12/msg00147.html

http://www.stata.com/statalist/archive/2006-12/msg00170.html

for more discussion.

The **mfx** command computes marginal effects, which for linear regression is just the coefficient, so doesn't have much effect until you run a nonlinear model. Note that to test the marginal impact when you have interaction terms or powers (e.g. squares or cubes), you need to do a little calculus before you specify a **test** command. The **test** command conducts a Wald test of joint significance, or any combination of linear hypotheses (see **help test** for more) e.g.

```
test wei=forw
test for, accum
```

tests that the effect of weight is exactly twice as big among foreign cars. Nonlinear tests can be done using **nlcom**.

To learn various techniques used to assess your model fit, you might want to read **help regress postestimation**. and see the manual at **[R] regress postestimation** (particularly helpful are scatterplots of residuals such as **rvfplot** and **rvpplot**).

To compare the importance of various coefficients, you might want to use the **beta** option of **regress**, which asks that standardized beta coefficients be reported instead of confidence intervals. The beta coefficients are the regression coefficients obtained by first standardizing all variables to have a mean of 0 and a standard deviation of 1. Or you might want to get the SPost commands from http://www.indiana.edu/~jslsoc/stata that allow you to do more. Type **findit spost9_ado** in Stata to get a short list.

We could also graph various pieces of the regression output directly, if we wanted to:

```
tw function y=_b[_cons]+_b[wei]*x*2000, range(1000 5000) || scatter mpg wei if fore==0
```

or save the coefficients and standard errors in macros for later calculations. You can use all the estimation results, though you may have to do some calculations yourself on the raw numbers (see **help ereturn**).

For now, let's focus on the first regression: the relationship between weight and (supposed) fuel efficiency for foreign cars:

```
reg mpg wei if fore==1
tw lfit mpg wei if fore==1 || scatter mpg wei if fore==1
```

and note that the spread of errors is much larger for lower-weight cars, i.e. we see heteroskedasticity, which results in incorrectly calculated standard errors—but it is a common enough condition to have an easy solution: use the **`robust`** option (do not look for robust regression—this is something else altogether).

```
reg mpg wei if fore==1, robust
```

Note that the standard errors are smaller when using **`robust`** here, which is unusual. Usually, a model specified without using **`robust`** will have improperly small standard errors, and lead researchers to find effects (reject the null of b=0) where there is no evidence of effects. Note the use of "no evidence of effects" instead of "no effects," which we cannot conclude when we fail to reject the null.

In general, computing heteroskedasticity-robust standard errors does not absolve misspecification (as I have committed above, since I know mpg is not a good measure of fuel efficiency, since the *inverse* gallons per mile would be a better measure of energy consumption). But it does seem to cover a multitude of misspecification-type sins in simulations, and its small-sample properties are surprisingly good.

The heteroskedasticity-robust standard errors calculated here are also called Huber-White standard errors, and the estimator the Huber-White or "sandwich" estimator, after

Huber, P. J. 1967. The behavior of maximum likelihood estimates under nonstandard conditions. In *Proceedings of the Fifth Berkeley Symposium on Mathematical Statistics and Probability*. Berkeley, CA: University of California Press, vol. 1, 221–223.

White, H. 1980. A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. *Econometrica* 48: 817–830.

or sometimes White standard errors, by folks who don't know Huber published first.

It's a good general rule to always use the robust option—if there is no heteroskedasticity, you will get the same answer with or without the robust option.

One thing heteroskedasticity-robust standard errors don't correct for is clustering of errors—when the error on an individual observation is correlated with errors on other individual observations. If multiple individuals are observed within households, there is almost always clustering of errors at the household level. Think of an x variable like a tax incentive to work more, and its effect on labor supply within a household—if it has an effect of increasing hours by 20% for a person living alone, it is almost certain not to increasing hours worked by each individual in a large household by 20% (some of them won't even be working), and may even depress the labor supply response of another household member—the bigger response by one person will be negatively correlated with a smaller (or opposite-signed) response by another.

Clustering also arises from survey design, and you can account for that type of clustering using the **`svy`** commands, which also specify weights and stratification. A useful way to correct for clustered error without using **`svy`** is to use the **`cluster( )`** option to get cluster-robust standard errors (this estimator is a direct result of Huber 1967 but sometimes called Rogers standard errors because Rogers 1993 was the first to put the details in writing):

The **`cluster( )`** option requires you to specify (by putting a variable name between the parentheses) the level at which the clustering of errors occurs—a good rule of thumb is that you need at least 50 clusters to get reliable estimates, but you want to cluster at the highest level where clustering is likely. In a regression of individual data on state-level regressors, you probably want to cluster at the state level.

The cluster-robust estimator of standard errors is also a “sandwich” estimator, but the ingredients are a bit different. Essentially, you assume that errors are independent across clusters, and use errors within each cluster to estimate the within-cluster correlations.

Panel regression

Longitudinal data or panel data, has single units observed at multiple points (in time, usually) and allows you to control for all kinds of unobservable factors that don’t vary over time. The suite of XT commands (see **`help xt`** and the XT manual) offer a whole panoply of techniques, but we’ll see two today.

```
use http://fmwww.bc.edu/ec-p/data/macro/abdata.dta
```

loads some macro data on employment in Britain.

```
tsset id year
```

tells Stata that id identifies units, indexed i in textbooks, and year identifies the points at which we observe them, indexed t in textbooks. Now regress industry output on capital stock and employment:

```
xtreg ys k n, fe
xtreg ys k n, fe robust
```

and note that you have controlled using fixed effects for any firm characteristics that do not change over time (a whole host of potential x variables spring to mind). If you wanted to measure the effect of some fixed firm characteristic, you would have to use another estimator—perhaps a random effects estimator like **`xtreg ys k n, re robust`**.

See http://www.ats.ucla.edu/stat/Stata/faq/revsfe.htm for a simple take on the fixed-effects, between-effects, and random-effects estimators. For more, read a textbook by Wooldridge. Also note that if you ever run a random-effects model, you MUST run a Hausman test (see **`help hausman`**) to show that it is appropriate.

If you want to run a fixed-effects regression using pweights, use an equivalent command called **`areg`** (see **`help areg`** for the syntax). As of Stata 10, **`xtreg`** also allows pweights, but requires that they be constant within panel (**`areg`** does not).

```
areg ys k n, absorb(id) robust
```

More on clustering

In panel regressions, you should always cluster on the ID variable, or a higher (more inclusive) level if you can (i.e. you’ve got at least 50 units), since the cluster-robust variance estimator corrects for arbitrary serial correlation.

```
areg ys k n, absorb(id) robust
areg ys k n, absorb(id) cluster(id)
```

Some might hint that you should “always cluster your standard error on the same level on which you would use fixed effects” or somesuch, which is not the case. For example, if you observed individuals (who didn't move) over time, and you regressed their outcomes on county-level variables, you might want to include fixed effects for individual people, but cluster on the county level (accounting for the intra-county clustering of errors over time and people).

A useful treatment for the general case is “Robust Standard Error Estimation in Fixed-Effects Panel Models,” by Gábor Kézdi, originally published as a working paper in about 2001, and usually cited that way, but now with a publication date of 2004, and a ridiculously long URL, which shows that the cluster-robust estimator performs well even in the absence of clustering (i.e. there is no real danger when specifying the cluster option).

Another frequently cited source is Arellano (1987). "Computing robust standard errors for within-groups estimators." *Oxford Bulletin of Economics and Statistics*, 49(4): 431–434.

Quoting Mark Shaffer, "it's also worth adding that Stock and Watson, in an important little paper that appeared earlier this year, showed that the standard heteroskedasticity-robust estimator, available in Stata with the -robust- option, is inconsistent for the fixed effects estimator. Interestingly, the problem does not extend to the cluster-robust estimator, which is also heteroskedasticity-robust. Thus, if you are doing fixed effects and want your SEs to be robust to heteroskedasticity, you should avoid **`robust`** and use **`cluster()`** instead, and get SEs that are robust to both heteroskedasticity as well was intra-group correlation." The reference there is James H. Stock, Mark W. Watson (2006), "Heteroskedasticity-Robust Standard Errors for Fixed Effects Panel Data Regression", NBER Technical Working Paper No. 323. http://www.nber.org/papers/T0323

If you think clustering happens along more than one dimension, for example there is autocorrelation within panel (my error today is related to my error yesterday) and across panels at a point in time (my error today is related to my wife's error today), you can try out a two-way clustering approach by Cameron, Gelbach, and Miller:

http://www.nber.org/papers/t0327

http://glue.umd.edu/~gelbach/ado/cgmreg.ado

but this is an active research area, so you are unlikely to get much help if you run into trouble.

You can get nested clustering (households within counties within states, for example) using **`svy`** but my impression is that nested clustering makes little difference if you are able to cluster at the highest level (state in the example) and clusters are of roughly equal sizes.

Logit, Probit

You might also regress dropout on parent's marital status, but that is a bad idea whenever you have binary outcomes (two outcomes, usually 0 and 1 meaning false and true) since the linear probability model (LPM):

```
reg dropout pmarr, r
```

produces predicted probabilities that lie outside the [0,1] interval, among other reasons.

Instead, use a **`logit`** or **`probit`**. Which? Well, it makes little difference, usually, but a **`logit`** is usually faster and easier to interpret. You can get odds ratios by specifying the **`or`** option on **`logit`**, or using the logistic command.

```
logit dropout pmarr, r
logit dropout pmarr, r or
logistic dropout pmarr, r
```

You can get marginal effects for **`probit`** using the **`dprobit`** command, though you will probably want to use the **`mfx`** command to compute marginal effects for either **`logit`** or **`probit`**. The marginal effects will likely be wrong if you have any indicators (dummy variables) or interactions (see http://www.unc.edu/~enorton/NortonWangAi.pdf and its references for more details). Here's an old email on computing the marginal effect for a single indicator variable in a probit model:

To compute the marginal effect (change in probability) for a probit or logit, most will just calculate f(xbar beta) and multiply by the reported coef, but that is not right.

For a probit with

$y^* = b^*X + g^*D + e$

$y = 1$ iff $y^*>0$

where X is a matrix of regressors, and D is a dummy variable representing treatment, the marginal effect of D is measured in a sample as

$E_i\,[y|D=1, X=E_i\,[X]]- E_i\,[y|D=0, X=E_i\,[X]]$

where the $E_i[.]$ operator denotes the sample mean. This is equivalent to

$E_i\,[\Phi\,(b^*X_i+g) - \Phi(b^*X_i\,)]$

where Φ (.) is the cumulative normal. For g small, this can be approximated as

$E_i\,[\phi\,(b^*X_i)\,]\,g$

but the quality of this approximation will vary with the size of g and the curvature of the function Φ (.) in the vicinity of b^*X_i or (b^*X_i+g). This quantity is sometimes approximated as

$\phi\,(E_i\,[b^*X_i\,])\,g$

the expression in my prior email (which I called f(xbar beta) multiplied by the reported coef), but this is a very rough approximation indeed. If b^*X_i is uniformly distributed on [-1,1] the expectation of $\phi\,(b^*X_i)$ is 0.68 and the normal density evaluated at $E_i\,[b^*X_i\,]$ is 0.4 (for other cases, e.g. a wider interval, the approximation might be substantially worse).

But g need not be small. If the coefficient on the dummy variable is 5 or 10, the first step of the approximation might be quite a poor one. If b^*X_i is tightly distributed around zero, and g is large, the true marginal effect will be close to one half. The first version of the approximation would give the marginal effect as 0.4 times g, so if g were 10 the marginal effect would be 4. In general, the first approximation might yield estimated marginal effects much greater than one, which are obviously poor estimates.

In short, **`predict`** probabilities and graph them, don't try to compute simplistic marginal effects at the mean.

If your dependent variable has multiple values, you might want **`mlogit`** (if the categories are not naturally ordered) or **`ologit`** (if they are), but see also **`gologit2`** (**`findit gologit2`**). If your model has binary outcomes measured multiple times for each unit, you may have panel data (see **`help xtlogit`**) or choice data (see http://stata.com/help.cgi?asclogit).

Poisson/GLM

Using **`poisson`** sounds odd to lots of folks, but the idea is this: if you have a nonnegative dependent variable that's mostly small, but has a few big values, you might be tempted to take the log and regress the log of y on X. But if there are any zeros, they are now missing. If you assume E[y|X]=exp(Xb) as you just did when taking the log, then you should run **`poisson`** regression, which does not drop zeros. The coefficients are interpreted just as if you had taken the log of y: a one-percent change in x is associated with a b/100 percent change in y.

You would not want to use **`tobit`** in this situation (though you will see it done a lot) since the assumptions are not satisfied: **`tobit`** is for the case when we don't observe the true value of y because it is censored, not because it is truly zero and we foolishly took the log of it.

The original idea of **poisson** is to model response variables that are counts (number of kids, number of cigarettes, number of doctor visits, how many dollars, etc.) but the model works well as long as E[y|X]=exp(Xb) which is true in a much broader class of problems. See Wooldridge 2002 (http://www.stata.com/bookstore/cspd.html) p.651 and surrounding text: "A nice property of the Poisson QMLE is that it retains some efficiency for certain departures from the Poisson assumption," etc.

You can get the same answers as **poisson** (or **logit** or other related commands) using Generalized Linear Models via the command **glm**, which estimates

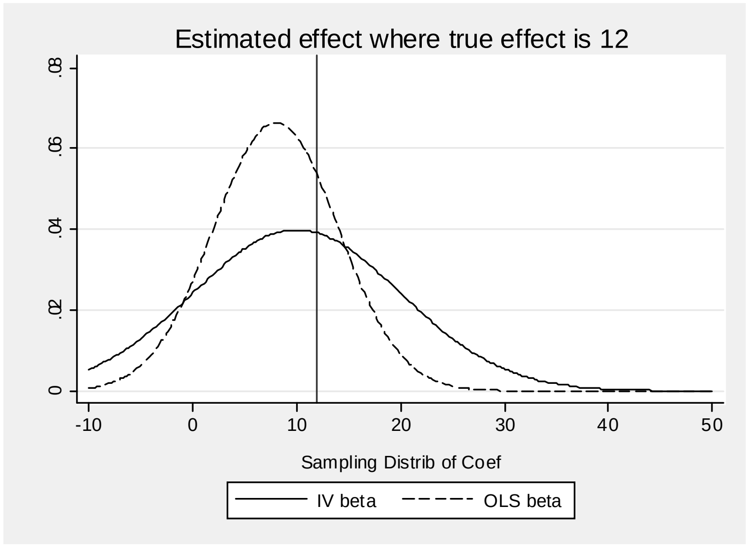
E(y)=F(Xb)
for a variety of different functions F() and error distributions. The key point is that there is a linear combination of x variables that F() is applied to.

When you have a bunch of zeros or variance substantially greater than the conditional mean, you may want models in which **`poisson`** may be nested, such as **`nbreg`** **`zip`** or **`ztp`**.

IV Regression

The thing that is wrong with most of the regressions you will run is that the RHS variables are endogenous. That is, they are correlated with the error term. Either you left an important variable out, or y and x are simultaneously determined (as part of a system of supply and demand, for example), or x is measured with error (that never happens, right?), or any of a large number of other plausible conditions are met where your coefficient on x is biased. What now? Well, you get $10 million to run a massive experiment, right? You want to do an experiment because an experiment gives an unbiased estimate, but experiments are not only costly, they can also be downright infeasible, so we turn to quasi-experimental methods (see http://www.urban.org/toolkit/data-methods/quasi-experimental.cfm).

The most frequently used is instrumental variables (IV) regression, where you find something that moves x around, but has no direct effect on y. This is your excluded instrument. If you can find a few, you can conduct an **`overid`** test to see if they are any good at all (see http://fmwww.bc.edu/ec-p/WP545.pdf for more details, and other tests you should run). Good instruments are hard to come by, and even once you've got one, it may be weak (see http://www.stata.com/meeting/5nasug/wiv.pdf for more). Note that the official Stata 9 command **`ivreg`** does not offer the full range of diagnostics for IV regression—type **`findit ivreg2`** to get the good one, based on **`ivreg`** but augmented (Stata 10 has **`ivregress`** which offers weak instrument diagnostics but still does not offer the full range of stuff that **`ivreg2`** can). Even if you can conclude you don't have weak instruments, your estimates are still biased (though consistent now), just a bit less than they were before, and the price you've paid is a large increase in variability.



The upside is, as you add more data, you will get closer to the true answer, which won't happen in the standard regression, and your inference will be approximately correct, if low-powered, whereas tests after the standard regression may be way off.

There are also panel versions of the IV estimator—type **`findit xtivreg2`** to get the good one for fixed effects.

```
use http://fmwww.bc.edu/ec-p/data/macro/abdata.dta
xtivreg2 ys k (n=l2.n l3.n), fe small first cluster(id)
```

Dummy endogenous variables (endogenous indicator variables) are not a problem for the consistency of IV though you can get improved efficiency using Procedure 18.1 of Wooldridge 2002 (http://www.stata.com/bookstore/cspd.html), pp.621-625. If you have a single endogenous indicator variable and a binary outcome, you may want **`treatreg`** instead. If your outcome variable is bounded or discrete, you may want the GLM equivalent of IV which is estimated by **`qvf`** as described in Stata Journal Volume 3, Number 4 and at http://www.stata.com/merror/. Try not to use **`ivtobit`**.

Matching and RDD

For more quasi-experimental methods, see **`findit psmatch2`** (see also http://www.stata.com/statalist/archive/2007-06/msg01026.html) and **`findit nnmatch`** (see also http://www.stata.com/statalist/archive/2007-04/msg00011.html and http://www.stata.com/meeting/5nasug/Imbens_stata_06july.pdf) for matching methods, and see http://www.urban.org/toolkit/data-methods/regression.cfm and http://nber.org/papers/t0334 and http://www.nber.org/papers/t0337 for more on regression discontinuity methods.

Mixed models

Mixed models have a mixture of fixed and random effects, and are often called multi-level models or hierarchical models (the software HLM is designed to just do these; UI has two copies of this software, but they are not on the network). The command **`xtmixed`** is for multi-level linear models, and has a more flexible but slower user-written analog **`gllamm`** (**`findit gllamm`** and http://www.gllamm.org/) that will also do nonlinear models. There are a few books on using these methods in Stata, including http://www.stata-press.com/books/mlmus.html, and a full discussion would be another multi-day class. Stata 10 now offers some nonlinear mixed models—see http://www.stata.com/help.cgi?xtmelogit, http://www.stata.com/help.cgi?xtmepoisson

5. Manual Bootstrap Estimates and Monte-Carlo Simulation

6. Mata Programming

Introduced with Stata 9, Mata is a separate programming language within Stata that is compiled, and runs with speed comparable to C and other high-level languages. Its syntax is similar to C, and it offers a library of convenient matrix functions. As of 25 June 2007, Stata 10 offers a general optimize command in Mata, which is useful in a variety of ways. The entire three-volume set of Mata manuals is online; just type help mata to get started. However, the help files do not have many helpful examples. Below are two simple examples, demonstrating a small fraction of Mata's tremendous capacities: (1) writing out a GMM estimator, and (2) solving a complicated function.

Mata is fast, because functions are compiled, rather than interpreted. I.e. if you look at what Stata sees in the pre-Mata "ado language" version of a program, you see code like the text on the left; if you look at what Stata sees in a Mata function, you see bytecode like on the right (zeros and ones, really, but easier to read in this formatted hexadecimal way).

```
forvalues j = 1/`p' {
          tempvar x`j'
          qui gen double `x`j'' = .
          local xs `xs' `x`j''
}
qui gen double `arg' = .
qui gen double `karg' = .
forvalues i = 1/`n' {
          qui replace `arg'=(`x'-`xgrid'[`i'])/`h' if `touse'
qui replace `karg' = .
if "`kern'" == "biweight" {
          local con1 = .9375
          qui replace `karg' = `con1'*(1-(`arg')^2)^2 /*
                    */ if `touse' & abs(round(`arg',1e-8))<1
}
```

```
2220 7b0d 0a09 0971 7569 2072 6570 6c61
6365 2060 6b61 7267 2720 3d20 302e 3520
6966 2061 6273 2872 6f75 6e64 2860 6172
6727 2c31 652d 3829 293c 3120 2620 6074

6f75 7365 270d 0a09 7d0d 0a09 656c 7365
207b 2009 0909 092f 2f20 6570 616e 6563
686e 696b 6f76 0d0a 0909 6c6f 6361 6c20
636f 6e31 203d 2033 2f28 342a 7371 7274
```

Of course there is a readable version of the Mata code, before it is compiled into "bytecode" that is optimized for the computer to read. You write Mata in the readable version, and then Stata compiles into the bytecode before running it. The first time you run your newly written programs, there may be no speed advantage, but every subsequent time, it will run about 2 to 10 times faster.

The syntax of Mata is quite different from Stata's "ado language" but still fairly easy, especially if you have used C or C++ before.

Interactive Use

You can enter Mata in several ways; essentially type `mata` and then type Mata commands until you're done in Mata, then type `end`.

For example, to multiply two matrices, you could type in Stata:

```
matrix a=(1,2,3)
matrix aa=a'*a
matrix list aa
```

or you could type:

```
mata
a=(1,2,3)
a'a
end
```

to get the same output from Mata. Note that to get the output of some calculation, you can just type the calculation. To assign it to some named object, just type name=result. We could have also typed:

```
mata
a=(1,2,3)
aa=a'a
aa
end
```

where we first assign the result to a named entity, then get Mata to display the named entity by simply typing its name (the simplest form of calculation, if you will, is just the identity function).

Or we could type:

```
mata
a=(1,2,3)
aa=a'a
st_matrix("A", aa)
end
matrix list A
```

where we create a matrix A in Stata (from the Mata matrix aa), exit Mata, and then display the resulting calculation in Stata. This suggests the basic procedure for most interactions—do all the calculations you can in Mata, to improve speed, then return them in Stata.

Mata has all the matrix functions of Stata, plus a lot more. Importantly, there is no limit on the size of matrices, and matrices can contain strings or real/complex numbers.

Defining New Mata Functions and Type Declarations

You make a new function in Mata like so:

```
type name(arguments)
  {
    contents
  }
```

where `type` is the type of entity the function returns, such as a matrix, or the special type `void`, meaning the function returns nothing. The type of a Mata variable has two pieces: the element type and organizational type (choose any one from each column):

```
eltype                orgtype
------------          ----------
transmorphic          matrix
numeric               vector
real                  rowvector
complex               colvector
string                scalar
pointer               ----------
------------
```

The default is the most general type: a transmorphic matrix, where transmorphic means that the matrix can be real, complex, string, or pointer; and matrix means that the organization is to be r X c, r ≥ 0 and c ≥ 0. Here's an example function that swaps rows in a matrix:

```
real matrix swaprows(real matrix A, real scalar i1, real scalar i2)
        {
                B = A
                v = B[i1, .]
                B[i1, .] = B[i2, .]
                B[i2, .] = v
                return(B)
        }
```

but all those type declarations are optional, so you could also write:

```
swaprows(A, i1, i2)
        {
                B = A
                v = B[i1, .]
                B[i1, .] = B[i2, .]
                B[i2, .] = v
                return(B)
        }
```

All of those variables created within a Mata function can also be declared to have a particular type. See `help m2_declarations` for more info.

Every variable created within a Mata function is "private" meaning its scope is just within the function, like a local macro. You can also declare variables to be global by using the **external** declaration, which is a useful but dangerous way of passing info back and forth between programs. Useful because you don't have to pass arguments, dangerous because if you accidentally modify a global variable, it's gone. For example, in a complex program, if you create two globals with the same name, you will be replacing the first with the wrong values (the values of the second), and may get some errors that are hard to track down to their source.

Void Functions

One common type of function is the void function, which returns nothing. For example,

```
void iv_pois(todo,b,crit,g,H)
 {
  external y,X,Z,W
  m=((1/rows(Z)):*Z'((y:*exp(-X*b') :- 1)))'
  crit=(m*W*m')
 }
```

declares that the function iv_pois has five arguments (two of which are used inside the function, but all must be well-defined for the function to operate without spitting out an error message). Then it says there are four globals it's going to use, does some calculations to modify some variable crit, and that's it.

That particular function calculates the value of a Generalized Method of Moments objective function, also called a criterion function.

GMM Estimation Using Mata

The Generalized Method of Moments (GMM), briefly, supposes that there are some population moments that we can try to match in our sample by a good choice of some parameter vector, e.g. in OLS where the population model is

$$E(y) = X\beta$$

or with a mean-zero error term

$$y = X\beta + \varepsilon$$

the usual assumption is that $E(X'\varepsilon) = 0$ in the population. So we can try to make the sample analog true via a good choice of b in an equation

$$y = Xb + e$$

i.e. we try to make the mean of the vector $m = X'e$ as close to zero as possible. The justification for this approach is given by Hansen (1982)[1].

1 Hansen, Lars Peter. 1982. "Large sample properties of generalized method of moments estimators." Econometrica 50(3): 1029-1054. See also for more accessible discussions Hansen, Bruce E. 2000. "Econometrics. 1st ed." Madison, WI: [http://www.ssc.wisc.edu/bhansen/notes/notes.htm] and Baum, C.F., M.E. Schaffer, and S. Stillman. 2002. "Instrumental variables and GMM: Estimation and testing." [http://fmwww.bc.edu/ec-p/wp545.pdf] and 2007. "Enhanced routines for instrumental variables/GMM estimation and testing." [http://fmwww.bc.edu/ec-p/wp667.pdf], both published in the Stata Journal.

It's not always possible to make a vector equal to zero, so instead we try to make the sum of squared deviations from zero as small as possible, i.e. instead of choosing b to set m=0 we choose b to minimize (m'Wm) where W is some weight matrix. Each W defines a different GMM estimator. Choosing a weight matrix to be the inverse variance estimate leads to the most efficient GMM estimator.

The instrumental variables (IV) version is a population model

$$y = X\beta + \varepsilon$$

plus the assumption that $E(Z'\varepsilon) = 0$ in the population. We can try to make the sample analog true via a good choice of b in an equation

$$y = Xb + e$$

i.e. we try to make the mean of m = Z'e = Z'(y-Xb) as close to zero as possible by minimizing the real-valued function m'Wm with our choice of b.

As another example, consider the population model

$$E(y) = \exp(X\beta)$$

which is the assumption in Poisson regression (like regressing the log of y on X, but y=0 is not a problem). Usually we specify an error term with mean 1 like so:

$$y = \exp(X\beta)\varepsilon$$

Note that if $\nu=\exp(\varepsilon)$ then $y = \exp(X\beta)\exp(\nu) =\exp(X\beta + \nu)$ so $\ln(y) = X\beta + \nu$ if y>0, which is why I say Poisson regression is like regressing the log of y on X.

The assumption for an IV version of Poisson regression is that $E(Z'\upsilon) = 0$ in the population, where υ is the mean-zero error $y/\exp(X\beta)-1$. So we can try to make the sample analog true via a good choice of b in the equation

$$y = \exp(Xb)e$$

i.e. we try to make the mean of m = Z'u = Z'(y/exp(Xb)-1) as close to zero as possible. Using a weight matrix $W = (Z'Z)^{-1}$, we minimize the real-valued function m'Wm by choosing b.

It turns out to be pretty easy in Mata to minimize or maximize some arbitrary function. Having already defined a function iv_pois that takes a parameter b and calculates the real valued function crit=(m'Wm) given b, we just need to tell Mata that we want to minimize crit with our choice of b.

We need Z and X and y matrices: these are matrices of data, which we can form from the variables on a Stata dataset like so:

```
clear all
use http://fmwww.bc.edu/ec-p/data/wooldridge/card
g tousename=!mi(wage,educ,nearc4)
mata
y = st_data(., "wage", "tousename")
X1 = st_data(., "educ", "tousename")
Z1 = st_data(., "nearc4", "tousename")
```

Then we can add a constant term to both the X and Z matrices like so:

```
cons=J(rows(X1),1,1)
X = X1, cons
```

```
Z = Z1, cons
```
and calculate the weight matrix W:
```
W=rows(Z)*cholinv(Z'Z)
```
Then pick some arbitrary starting vector, say a vector of zeros:
```
init=J(1,cols(X),0)
```
where the only real limitation on a starting vector in numerical optimization is that the objective function has to be defined in a neighborhood of that starting value, and that is always true in this problem for a zero vector, since exp(Xb)=1 for b=0 and exp(Xb) is smooth in b at b=0.

Then we declare a new variable to hold our optimization problem, and call a few functions to set up the type of optimization we want. Then the function optimize() finds the optimum and returns the vector b that optimizes the function. Let's just assign that to a new variable p. We can report the result by just typing p in Mata.
```
S=optimize_init()
optimize_init_evaluator(S, &iv_pois())
optimize_init_which(S,"min")
optimize_init_evaluatortype(S,"d0")
optimize_init_params(S,init)
p=optimize(S)
```
The evaluator is designated as iv_pois in the second line, and we specify minimization in the third line. The fourth line is more interesting. "d" type evaluators max/minimize a real-valued function, and "v" type evaluators a vector-valued function.
```
evaluatortype   Description
------------------------------------------------------------
"d0"            function() returns scalar value
"d1"            same as "d0" and returns gradient rowvector
"d2"            same as "d1" and returns Hessian matrix
"v0"            function() returns colvector value
"v1"            same as "v0" and returns score matrix
"v2"            same as "v1" and returns Hessian matrix
```
In some statistical applications, "v" type evaluators are more convenient to code than "d" type, particularly since one tends to think of a dataset of values arranged in matrix X, the rows of which are observations. A function h(p, X[i,.]) of a parameter p can be calculated for each row i separately, as with a log likelihood, and it is the sum of those resulting values that forms the function f(p) that is to be maximized or minimized. All of Stata's maximum likelihood routines are being rewritten in this way.

The previous optimization problem can all be wrapped in a function that can be called from within Stata like so:

```
    void i_pois(string scalar depvar, string scalar x, string scalar z, string
scalar tousename, string scalar beta)
     {
      external y,X,Z,W
      y = st_data(., tokens(depvar), tousename)
      X1 = st_data(., tokens(x), tousename)
      Z1 = st_data(., tokens(z), tousename)
      cons=J(rows(X1),1,1)
      X = X1, cons
      Z = Z1, cons
      W=rows(Z)*cholinv(Z'Z)
      init=J(1,cols(X),0)
      b=init
      S=optimize_init()
      optimize_init_evaluator(S, &iv_pois())
      optimize_init_which(S,"min")
      optimize_init_evaluatortype(S,"d0")
      optimize_init_params(S,init)
      p=optimize(S)
      st_replacematrix(beta,p)
     }
```

where now we pass to the function i_pois the list of variables that form X, Z, and y, and an indicator for which observations we want to include (tousename), then once the optimization is done, we store the parameter vector in the Stata matrix designated "beta" (the name of which we also passed as an argument to the function i_pois).

The above is most of the SSC program **`ivpois`** (**`ssc install ivpois`**). The remainder is a matter of parsing options, error-checking, and returning results.

So a new GMM estimator that you read about in the econometrics literature is a matter of a few hours to program, once you get the hang of the most common elements of the language (i.e. the first program might take a matter of a day or two to write, but the second an hour or two).

Solving Functions

The foregoing GMM discussion also suggests a way to solve some complicated function, e.g.

$$f(p) = g(q)$$

where f and g are real-valued functions of row vectors p and q, writing

$$h(r) = f(p) - g(q) = 0$$

where r = (p,q), and then we can find solutions (or near-solutions for insoluble problems) by minimizing

$$h(r)^2$$

with our choice of r.

Here's a silly example to calculate the solution to ln(r)=0

```
void obj(todo,b,crit,g,H)
 {
  crit=ln(b)^2
  }
init=5
S=optimize_init()
optimize_init_evaluator(S, &obj())
optimize_init_which(S,"min")
optimize_init_evaluatortype(S,"d0")
optimize_init_params(S,init)
optimize(S)
```

Note in the above that if you started at 0 you would get an error in this case, since ln(0) is undefined. Everything would look fine until the last command, when you would see:

```
: optimize(S)
initial values not feasible
r(1400);
```

In general, of course, there is no guarantee that an optimum is unique, so if it is possible that there are multiple solutions to h(r) = 0 you would have to start the optimization at many appropriately chosen starting points to see if the optimizer finds different optimal parameter vectors.

Suppose you wanted to find the zeros in

$$y = x^2 - 5x + 4$$

and you were too lazy to use the quadratic formula (I chose this problem, of course, because its analytic solution is so easy, whereas the numerical methods are trickier). You could just type

```
void q(todo,b,crit,g,H)
 {
  crit=(b^2-5*b+4)^2
 }
sol=J(1,0,0)
void grid(n1,n2)
 {
  external sol, p
  for (i=n1; i<=n2; i++) {
   init=i
   S=optimize_init()
   optimize_init_evaluator(S, &q())
   optimize_init_which(S,"min")
   optimize_init_evaluatortype(S,"d0")
   optimize_init_params(S,init)
   p=round(optimize(S),10e-4)
   if (!anyof(sol, p)) {
    sol=(sol,p)
   }
  }
  sol
 }
grid(-10,10)
```

The above code does the optimization for every starting value on a grid over the integers -10 to 10 (and saves any solutions that are new to a Mata variable **sol**, then reports its values). A function that took a vector as an argument would be no harder to specify (though the appropriate grid search might be harder to specify).