

LPO 9951: More Dataset Manipulation

PURPOSE

Today we'll continue to work on dataset manipulation. We'll focus on more complicated merges as well as reshaping.

Downloading ado files, setting globals, and loading data

```
. capture log close // closes any logs, should they be open
. log using "more_dataset_manipulation.log", replace // open new log
-----
name: <unnamed>
log: /Users/doylewr/lpo_prac/lessons/sl-05-more_dataset_manipulation/more_dataset_manipulation.log
log type: text
opened on: 23 Sep 2020, 10:41:25

. clear all // clear memory

. set more off // turn off annoying "__more__" feature

. global urldata "https://stats.idre.ucla.edu/stat/stata/seminars/svy_stata_intro/apipop"

. ssc install mdesc
checking mdesc consistency and verifying not already installed...
all files already exist and are up to date.

. ssc install onewayplot
checking onewayplot consistency and verifying not already installed...
all files already exist and are up to date.

. net install dm91, from ("http://www.stata.com/stb/stb61")
checking dm91 consistency and verifying not already installed...
all files already exist and are up to date.

. use $urldata, clear

. save api, replace
file api.dta saved

. preserve

. collapse (mean) api99, by(cnum)

. drawnorm county_inc, means(30) sds(5)

. sort cnum

. save county_data, replace
file county_data.dta saved

. restore

. preserve

. collapse (mean) api99, by(dnum)

. rename api99 api99c

. gen edd = rbinomial(1,.3)

. save district_data, replace
file district_data.dta saved

. restore
```

Many-to-one match merging

Many times we'd like to add information about a unit that is the same across a grouping of units. For instance, we may want to add some county data to our already existing school-level data. This really isn't much different than the merging we've done before, except we need to make certain that the variables are sorted correctly.

Let's say we have county level data that we'd like to import into our school level dataset. Remember that we sorted the county data by the county number (its unique id) when we created the dataset. We do the same for the district data. Finally we merge the two together:

```
. sort cnum

. merge m:1 cnum using county_data
(note: variable api99 was int, now float to accommodate using data's values)

      Result                # of obs.
-----
not matched                    0
matched                      6,194  (_merge==3)

. tab _merge

      _merge |      Freq.      Percent      Cum.
-----+-----
      matched (3) |      6,194      100.00      100.00
-----+-----
              Total |      6,194      100.00

. list cnum api99 county_inc if _n < 10

      +-----+
      | cnum | api99 | county-c |
      +-----+
1.   | 1 | 693 | 37.266 |
2.   | 1 | 589 | 37.266 |
3.   | 1 | 572 | 37.266 |
4.   | 1 | 732 | 37.266 |
5.   | 1 | 784 | 37.266 |
6.   | 1 | 725 | 37.266 |
7.   | 1 | 765 | 37.266 |
8.   | 1 | 667 | 37.266 |
9.   | 1 | 792 | 37.266 |
      +-----+

. onewayplot api99, by(county_inc) stack ms(oh) msize(*.1) width(1) name(api99_ow)

. graph export ${plotdir}api99_ow.eps, name(api99_ow) replace
(file api99_ow.eps written in EPS format)
```

Quick Exercise

Create a (fake) county level variable for average educational spending. It should be normally distributed and have a mean of 8000 and a standard deviation of 1000. Add this variable to a county-level dataset and merge this new dataset into the api dataset.

One-to-many match merging

One to many match merging is the reverse of many to one, and isn't really recommended. If you have to, here's how to do it:

Let's say we have some district data on whether or not the principal has an EdD. We can open this up and merge the api data with it, matching on district number. It's generally better to have the *finer-grained* dataset open in memory, and then to match the *coarser* data to that one, doing a many-to-one match merge. But should you need to complete a one-to-many match merge, here's an example:

```
. use api, clear
. sort dnum
. save api, replace
file api.dta saved

. use district_data, clear
. sort dnum
. merge 1:m dnum using api

Result-----# of obs.-----
not matched          0
matched             6,194  (_merge==3)

. tab _merge

      _merge |      Freq.      Percent      Cum.
-----+-----
      matched (3) |      6,194      100.00     100.00
-----+-----
             Total |      6,194      100.00

. list dnum api99 edd if _n < 10

      +-----+
      | dnum  api99  edd |
      +-----+
1.    |    1    734    0  |
2.    |    2    802    1  |
3.    |    3    760    0  |
4.    |    4    737    1  |
5.    |    5    464    0  |
      +-----+
6.    |    6    651    0  |
7.    |    7    836    1  |
8.    |   10    399    0  |
9.    |   12    782    0  |
      +-----+
```

Quick Exercise

Create a (fake) district level variable for average teacher salary. It should have a mean of 40 and a standard deviation of 5. Merge the api data into this dataset.

Many-to-many match merging

Nope.

Messy merge

Many merge procedures are quite messy. To simulate this, let's eliminate a couple of variables from the `api` dataset and remove 10% of the observations. We'll put this into a file we're pretending is the `api99` file. Next, we'll drop some data from the `api00` file. Finally, we'll merge the resulting two files together.□

```
. use api, clear
. preserve
. drop api00 ell mobility
. sample 90
(619 observations deleted)
. save api_99, replace
file api_99.dta saved

. restore
. drop api99
. sample 90
(619 observations deleted)
. save api_00, replace
file api_00.dta saved

. merge snum using api_99, sort
(note: you are using old merge syntax; see [D] merge for new syntax)
(label stype already defined)
(label sch_wide already defined)
(label comp_imp already defined)
(label both already defined)
(label awards already defined)
(label yr_rnd already defined)

. tab _merge

      _merge |      Freq.      Percent      Cum.
-----+-----
           1 |      562         9.16         9.16
           2 |      562         9.16        18.32
           3 |     5,013        81.68       100.00
-----+-----
             Total |      6,137       100.00

. inspect api99
```

```

api99:
-----
      #           Negative
      #           Zero
      # #         Positive
      # # #
      # # # #
      # # # # #
-----
Total      5,575
Integers   5,575
Nonintegers
-----
302          966
(More than 99 unique values)
6,137

. inspect api99

api99:
-----
      #           Negative
      #           Zero
      # #         Positive
      # # #
      # # # #
      # # # # #
      # # # # #
-----
Total      5,575
Integers   5,575
Nonintegers
-----
346          969
(More than 99 unique values)
6,137

. mdesc api99 api99
-----
Variable | Missing | Total | Percent Missing
-----
api99    | 562     | 6,137 | 9.16
api99    | 562     | 6,137 | 9.16
-----

. mvpatterns api99 api99 ell mobility
Variable | type | obs | mv | variable | label
-----
api99    | int  | 5575 | 562 |           |
api99    | int  | 5575 | 562 |           |
ell       | byte | 5575 | 562 | english language learners
mobility  | byte | 5573 | 564 | pct 1st year in school
-----

Patterns of missing values
-----
+-----+
|_pattern|_mv|_freq|
+-----+
|+++|0|5011|
|,+++|1|562|
|+...|3|562|
|+++|1|2|
+-----+

```

These combined files are likely to have lots of missing data. Let's take a look at some of the patterns of missing data. The first command to use is called `inspect`. The results from the `inspect` command look like this:

This gives you a nice quick glance at the variable in question. You can also use the `mdesc` command, the output of which looks like this:

Why do we care so much about missing values? Because the missingness of variable values is unlikely to be random across all observations. Instead, observations with missing values for covariate X may have different average values for covariate Z than those who don't have missing values. These differences can greatly skew inferences we might hope to make with our analyses, so it is important that we have an understanding of the missingness of our data.

Later in the year we'll go over different approaches for dealing with missing data. For now it's important that we understand the prevalence of missing data and its relationship with other variables.

Here is a graphical example of the differences in `api99` scores between districts with `ell` data and those without:

```

. gen ell_flag = ell == .

. kdensity api99 if ell_flag == 1, ///
  name(api99_kdens) ///
  addplot(kdensity api99 if ell_flag == 0) ///
  legend(label(1 "Not Missing ELL") label(2 "Missing ELL")) ///
  note("") ///
  title("")

. graph export api99_kdens.eps, name(api99_kdens) replace
(file api99_kdens.eps written in EPS format)

```

Quick Exercise

Create a new dataset by dropping the meals and emergency credentials variables. Eliminate half of the data. Next create another dataset, dropping the parental education variables, and again get rid of half of the data. Merge the remaining two datasets together, then describe the patterns of missing data.

Reshaping data

Wide to long

The last major type of data manipulation is known as `reshaping`. Many datasets have multiple observations per unit. One way to store this type of data is in a wide format, meaning each additional observation is another variable. Here's some data from the Bureau of Economic Analysis on quarterly income growth that's in wide format:

```

. insheet using income.csv, comma clear
(35 vars, 60 obs)

. sort fips

```

We want to have this data in long format, meaning that there will be multiple lines per unit, each one identifying a year and a quarter. The command for this is `reshape long <stub>, i(<index>) j(<time var>)`. As you can see after the command, each unit/year now has its own line, and income is a single variable.

```

. reshape long inc_, i(fips) j(year_quarter, string)

```

```
(note: j = 2001q1 2001q2 2001q3 2001q4 2002q1 2002q2 2002q3 2002q4 2003q1 2003q2 2003q3 2003q4 2004q1 2004q2 2004q3 2004q4 2005q1 2005q2 2005q3 2005q4 2006)
```

	Data	wide	->	long
Number of obs.	60	->	1980	
Number of variables	35	->	4	
j variable (33 values)		->	year_quarter	
xij variables:				
	inc_2001q1 inc_2001q2 ... inc_2009q1	->	inc_	

```

. gen date = quarterly(year_quarter, "YQ")
. format date %tq
. list if _n < 10

```

	fips	year_q-r	areaname	inc_	date
1.	0	2001q1	United States	8681021	2001q1
2.	0	2001q2	United States	8713764	2001q2
3.	0	2001q3	United States	8726357	2001q3
4.	0	2001q4	United States	8746826	2001q4
5.	0	2002q1	United States	8802758	2002q1
6.	0	2002q2	United States	8876427	2002q2
7.	0	2002q3	United States	8888413	2002q3
8.	0	2002q4	United States	8923886	2002q4
9.	0	2003q1	United States	8985759	2003q1

We can now more easily set the date in a format Stata understands and take advantage of graphing commands such as `xtline`:

```

. xtset fips date, quarterly
    panel variable: fips (strongly balanced)
    time variable: date, 2001q1 to 2009q1
    delta: 1 quarter

. drop if fips < 1 | fips > 56
(297 observations deleted)

. xtline inc_, i(areaname) t(date) name(xtline_fipsinc)

. graph export $(plotdir)xtline_fipsinc.eps, name(xtline_fipsinc) replace
(file xtline_fipsinc.eps written in EPS format)

```

Long to wide

The reverse of the above is reshaping from long to wide. To shift the above dataset back, use the same command, but substitute `wide` for `long`:

```

. drop date
. reshape wide inc_, i(fips) j(year_quarter, string)
(note: j = 2001q1 2001q2 2001q3 2001q4 2002q1 2002q2 2002q3 2002q4 2003q1 2003q2 2003q3 2003q4 2004q1 2004q2 2004q3 2004q4 2005q1 2005q2 2005q3 2005q4 2006)

```

	Data	long	->	wide
Number of obs.	1683	->	51	
Number of variables	4	->	35	
j variable (33 values)	year_quarter	->	(dropped)	
xij variables:				
	inc_	->	inc_2001q1 inc_2001q2 ... inc_2009q1	

```

. list if _n < 4

```

	fips	inc_-1q1	inc_-1q2	inc_-1q3	inc_-1q4	inc_-2q1	inc_-2q2	inc_-2q3	inc_-2q4	inc_-3q1
1.	1	109274	110408	110688	111313	112368	113461	114291	115220	116690
	inc_-3q2	inc_-3q3	inc_-3q4	inc_-4q1	inc_-4q2	inc_-4q3	inc_-4q4	inc_-5q1	inc_-5q2	inc_-5q3
	117483	118720	120532	122976	125119	126811	130174	130665	132880	133344
	inc_-5q4	inc_-6q1	inc_-6q2	inc_-6q3	inc_-6q4	inc_-7q1	inc_-7q2	inc_-7q3	inc_-7q4	inc_-8q1
	137933	138491	140760	142824	144444	147643	149042	150891	152389	153897
	inc_-8q2	inc_-8q3	inc_-8q4	inc_-9q1	areaname					
	158468	157344	156638	156690	Alabama					
2.	2	19620	20092	20146	20341	20462	20642	20779	21006	20783
	inc_-3q2	inc_-3q3	inc_-3q4	inc_-4q1	inc_-4q2	inc_-4q3	inc_-4q4	inc_-5q1	inc_-5q2	inc_-5q3
	21155	21251	21550	21979	22189	22555	23015	23607	23854	24346
	inc_-5q4	inc_-6q1	inc_-6q2	inc_-6q3	inc_-6q4	inc_-7q1	inc_-7q2	inc_-7q3	inc_-7q4	inc_-8q1
	24700	25294	25815	26085	26535	26882	27180	27367	27662	29105
	inc_-8q2	inc_-8q3	inc_-8q4	inc_-9q1	areaname					
	29712	30091	30335	29371	Alaska					
3.	4	137195	138552	139826	139842	142595	143408	144410	146108	147196
	inc_-3q2	inc_-3q3	inc_-3q4	inc_-4q1	inc_-4q2	inc_-4q3	inc_-4q4	inc_-5q1	inc_-5q2	inc_-5q3
	149424	151205	154504	159779	163073	165946	170893	175472	180311	185625
	inc_-5q4	inc_-6q1	inc_-6q2	inc_-6q3	inc_-6q4	inc_-7q1	inc_-7q2	inc_-7q3	inc_-7q4	inc_-8q1
	188724	194543	197373	201417	204527	205774	207079	210275	211284	212797
	inc_-8q2	inc_-8q3	inc_-8q4	inc_-9q1	areaname					
	215657	214590	212970	211477	Arizona					

Quick Exercise

Download data on personal per capita income from 1950 to the present for all 50 states from the [Bureau of Economic Analysis](#). Create a plot using the `xtline` command.

```
. log close // close log
```

```
name: <unnamed>  
log: /Users/doylewr/lpo_prac/lessons/s1-05-more_dataset_manipulation/more_dataset_manipulation.log  
log type: text  
closed on: 23 Sep 2020, 10:41:56
```

```
. exit                                // exit script
```