

## 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

To start, we need to create some example datasets so that we can use them for merging.

```
. 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 to aid in merge
. sort cnum

. // merge many-to-one
. 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)

Inspecting the merge:

```
. 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	27.79561
2.	1	589	27.79561
3.	1	572	27.79561
4.	1	732	27.79561
5.	1	784	27.79561
6.	1	725	27.79561
7.	1	765	27.79561
8.	1	667	27.79561
9.	1	792	27.79561

```
. // plot and save
. 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 to aid in merge
. sort dnum

. // save newly sorted dataset
. save api, replace
file api.dta saved

. // load example data
. use district_data, clear

. // sort to aid in merge
. sort dnum

. // merge one-to-many
. merge 1:m dnum using api
```

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

```
. // inspect one-to-many merge
. 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	491	1
2.	2	856	0
3.	3	760	1
4.	4	717	0
5.	5	669	1
6.	6	667	0
7.	7	857	1
8.	10	411	0
9.	12	782	0

```
. // messy merge
. 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 datasets
. 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)

```

### 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.

### 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 datasets
. 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)

. // inspect messy merge
. 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	

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:

```

. // command: inspect
. inspect api99

```

api99:				Number of Observations		
				Total	Integers	Nonintegers
	#		Negative	-	-	-
	#		Zero	-	-	-
	#	#	Positive	5575	5575	-
	#	#		----	----	----

```

|      #      #      #      Total      5575      5575      -
|      #      #      #      #      Missing      562
+-----+-----+
302                      966                      6137
(More than 99 unique values)

. inspect api00

api00:
-----
|      #      #      #      Negative      Total      Integers      Nonintegers
|      #      #      #      Zero      -      -      -
|      #      #      #      Positive      5575      5575      -
|      #      #      #      -----
|      #      #      #      Total      5575      5575      -
|      #      #      #      #      Missing      562
+-----+-----+
346                      969                      6137
(More than 99 unique values)

```

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:

```

. mdesc api99 api00

Variable |      Missing      Total      Percent Missing
-----+-----
api99 |      562      6,137      9.16
api00 |      562      6,137      9.16
-----+-----

```

This is helpful in giving you a sense of how much missing data you have. Last, you can also use the `mvpatterns` command, which gives you a sense of the patterns of missing data in your dataset:

```

. mvpatterns api99 api00 ell mobility
Variable | type      obs      mv      variable label
-----+-----
api99    | int      5575      562
api00    | int      5575      562
ell      | byte     5575      562      english language learners
mobility | byte     5571      566      pct 1st year in school
-----+-----

```

### Patterns of missing values

+-----+			
_pattern	_mv	_freq	
+-----+			
	++++	0	5009
	.+++	1	562
	+...	3	562
	+++.	1	4
+-----+			

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.

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

```
. gen ell_flag = ell == .

. // plot kernel density of api99 of observations missing 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:

```
. // read in data and sort
. insheet using income.csv, comma clear
(35 vars, 60 obs)

. sort fips

. // reshape long
```

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 2003q
> 2 2003q3 2003q4 2004q1 2004q2 2004q3 2004q4 2005q1 2005q2 2005q3 2005q4 2006q
> 1 2006q2 2006q3 2006q4 2007q1 2007q2 2007q3 2007q4 2008q1 2008q2 2008q3 2008q
> 4 2009q1)
```

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_

```
. // create date that stata understands
. gen date = quarterly(year_quarter, "YQ")

. // format date so we understand it
. format date %tq
```

```
. // list few rows
. 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 non-states
. drop if fips < 1 | fips > 56
(297 observations deleted)

. // graph
. 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 that we added (no longer needed)
. drop date
```

```
. // long to wide
. reshape wide inc_, i(fips) j(year_quarter, string)
(note: j = 2001q1 2001q2 2001q3 2001q4 2002q1 2002q2 2002q3 2002q4 2003q1 2003q
> 2 2003q3 2003q4 2004q1 2004q2 2004q3 2004q4 2005q1 2005q2 2005q3 2005q4 2006q
> 1 2006q2 2006q3 2006q4 2007q1 2007q2 2007q3 2007q4 2008q1 2008q2 2008q3 2008q
> 4 2009q1)
```

```
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_20
> 09q1
-----
```

```
. // list first rows
. list if _n < 4
```

```
+-----+
1. | fips | inc_~1q1 | inc_~1q2 | inc_~1q3 | inc_~1q4 | inc_~2q1 | inc_~2q2 |
   |    1 |   109274 |   110408 |   110688 |   111313 |   112368 |   113461 |
   +-----+
   | inc_~2q3 | inc_~2q4 | inc_~3q1 | inc_~3q2 | inc_~3q3 | inc_~3q4 |
   |   114291 |   115220 |   116690 |   117483 |   118720 |   120532 |
   +-----+
   | inc_~4q1 | inc_~4q2 | inc_~4q3 | inc_~4q4 | inc_~5q1 | inc_~5q2 |
   |   122976 |   125119 |   126811 |   130174 |   130665 |   132880 |
   +-----+
   | inc_~5q3 | inc_~5q4 | inc_~6q1 | inc_~6q2 | inc_~6q3 | inc_~6q4 |
   |   133344 |   137933 |   138491 |   140760 |   142824 |   144444 |
   +-----+
   | inc_~7q1 | inc_~7q2 | inc_~7q3 | inc_~7q4 | inc_~8q1 | inc_~8q2 |
   |   147643 |   149042 |   150891 |   152389 |   153897 |   158468 |
   +-----+
   |      inc_~8q3      |      inc_~8q4      |      inc_~9q1      |      areaname      |
   |      157344      |      156638      |      156690      |      Alabama      |
   +-----+
```

```
+-----+
2. | fips | inc_~1q1 | inc_~1q2 | inc_~1q3 | inc_~1q4 | inc_~2q1 | inc_~2q2 |
   |    2 |   19620 |   20092 |   20146 |   20341 |   20462 |   20642 |
   +-----+
   | inc_~2q3 | inc_~2q4 | inc_~3q1 | inc_~3q2 | inc_~3q3 | inc_~3q4 |
   |   20779 |   21006 |   20783 |   21155 |   21251 |   21550 |
   +-----+
```

inc_~4q1	inc_~4q2	inc_~4q3	inc_~4q4	inc_~5q1	inc_~5q2
21979	22189	22555	23015	23607	23854
inc_~5q3	inc_~5q4	inc_~6q1	inc_~6q2	inc_~6q3	inc_~6q4
24346	24700	25294	25815	26085	26535
inc_~7q1	inc_~7q2	inc_~7q3	inc_~7q4	inc_~8q1	inc_~8q2
26882	27180	27367	27662	29105	29712
inc_~8q3	inc_~8q4	inc_~9q1	areaname		
30091	30335	29371	Alaska		

3.	fips	inc_~1q1	inc_~1q2	inc_~1q3	inc_~1q4	inc_~2q1	inc_~2q2
	4	137195	138552	139826	139842	142595	143488
	inc_~2q3	inc_~2q4	inc_~3q1	inc_~3q2	inc_~3q3	inc_~3q4	
	144410	146108	147196	149424	151205	154504	
	inc_~4q1	inc_~4q2	inc_~4q3	inc_~4q4	inc_~5q1	inc_~5q2	
	159779	163073	165946	170893	175472	180311	
	inc_~5q3	inc_~5q4	inc_~6q1	inc_~6q2	inc_~6q3	inc_~6q4	
	185625	188724	194543	197373	201417	204527	
	inc_~7q1	inc_~7q2	inc_~7q3	inc_~7q4	inc_~8q1	inc_~8q2	
	205774	207079	210275	211284	212797	215657	
	inc_~8q3	inc_~8q4	inc_~9q1	areaname			
	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.

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