14.170: Programming for Economists

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Lecture 2, Intermediate Stata

Warm-up and review

- Before going to new material, let's talk about the exercises …

  – exercise1a.do (privatization DD)
    - TMTOWTDI!
    - You had to get all of the different exp* variables into one variable. You had many different solutions, many of them very creative.
      – Replace missing values with 0, and then you added up all the exp* variables
      – You used the rsum() command in egen (this treats missing values as zeroes which is strange, but it works)
      – You "hard-coded" everything

Intermediate Stata overview slide

- Quick tour of other built-in commands: non-parametric estimation, quantile regression, etc.
  - If you're not sure it's in there, ask someone. And then consult reference manuals. And (maybe) e-mail around. Don't re-invent the wheel! If it's not too hard to do, it's likely that someone has already done it.
  - Examples:
    - Proportional hazard models (streg, stcox)
    - Generalized linear models (glm)
    - Kernel density (kdensity)
    - Conditional fixed-effects poisson (xtpoisson)
    - Arellano-Bond dynamic panel estimation (xtabond)
- But sometimes newer commands don't (yet) have exactly what you want, and you will need to implement it yourself
  - e.g. xtpoisson doesn't have clustered standard errors
- Monte carlo simulations in Stata
  - You should be able to do this based on what you learned last lecture (you know how to set variables and use control structures). Just need some matrix syntax.
- More with Stata matrix syntax
  - Precursor to Mata, Stata matrix languae has many useful built-in matrix algebra functions

“Intermediate” Stata commands

- Hazard models (streg, stcox)
- Generalized linear models (glm)
- Non-parametric estimation (kdensity)
- Quantile regression (qreg)
- Conditional fixed-effects poisson (xtpoisson)
- Arellano-Bond dynamic panel estimation (xtabond)

I have found these commands easy to use, but the econometrics behind them is not always simple. Make sure to understand what you are doing when you are running them. It’s easy to get results, but with many of these commands, the results are sometimes hard to interpret.

But first, a quick review and an easy warm-up …

Quick review, FE and IV

```
clear
set obs 10000
gen id = floor( (_n - 1) / 2000)
bys id: gen fe = invnorm(uniform()) if _n == 1
by  id: replace fe = fe[1]

gen spunk      = invnorm(uniform())
gen z          = invnorm(uniform())
gen schooling  = invnorm(uniform()) + z + spunk + fe
gen ability    = invnorm(uniform()) + spunk
gen e          = invnorm(uniform())
gen y = schooling + ability + e + 5*fe

reg y schooling

xtreg y schooling , i(id) fe
xi: reg y schooling i.id
xi i.id
reg y schooling _I*
areg y schooling, absorb(id)

ivreg y (schooling = z) _I*
xtivreg y (schooling = z), i(id)
xtivreg y (schooling = z), i(id) fe
```

Data check

```
.
. tab id
```

id	Freq.	Percent	Cum.
0	2,000	20.00	20.00
1	2,000	20.00	40.00
2	2,000	20.00	60.00
3	2,000	20.00	80.00
4	2,000	20.00	100.00
Total	10,000	100.00	

```
. list in 1/20
```

	id	fe	spunk	z	schooling	ability	e	y
1.	0	.5801376	-.2406844	-1.099788	-1.469551	-1.660281	-.3460338	-.5751783
2.	0	.5801376	1.726103	.0050004	1.268643	-.5901318	.1685174	3.747717
3.	0	.5801376	-.2909676	.5172438	1.350124	.4649253	.3624368	5.078174
4.	0	.5801376	-1.353611	1.395514	-1.227456	-.9913431	-2.209503	-1.527614
5.	0	.5801376	-.3666069	1.210201	1.267246	-.4916896	.9330731	4.609318
6.	0	.5801376	1.412722	-.9439728	1.550789	.8241584	-.6179897	4.657646
7.	0	.5801376	.6583463	-.2457964	.5150581	1.745985	-1.313493	3.848238
8.	0	.5801376	-.4458856	-.0946522	-.0027943	.6363754	-.9354327	2.598836
9.	0	.5801376	1.510083	1.064582	4.218287	1.383152	-.2734289	8.228698
10.	0	.5801376	-.433168	.8606828	-.5053311	1.581337	1.035773	5.012467
11.	0	.5801376	-.1699543	-.6866674	1.268839	2.474484	-.0743157	6.569695
12.	0	.5801376	.2398426	-.2654009	1.94654	.9611118	-.4235876	5.384752
13.	0	.5801376	.5992875	-.7492979	-.407327	1.009442	-.1929502	3.309853
14.	0	.5801376	-1.192293	.5730755	.2901712	-1.393483	-2.081219	-.2838426
15.	0	.5801376	-.7589176	.4376972	1.211469	-.1717598	-.3249905	3.615406
16.	0	.5801376	-1.283779	.3321107	-.2236305	-1.573899	-1.32857	-.2254121
17.	0	.5801376	.5506322	-.1371481	1.599051	.1497437	.4564812	5.105964
18.	0	.5801376	-2.214334	2.878901	3.165465	-2.988943	.0053362	3.082546
19.	0	.5801376	-1.386452	-.6435837	-1.856841	-3.562516	-2.277211	-4.79588
20.	0	.5801376	-.5060894	-1.114979	-1.821156	-.5424618	-1.334018	-.7969475

Results

```
.
. reg y schooling

      Source |       SS       df       MS              Number of obs =   10000
-------------+------------------------------           F(  1,  9998) =12539.25
       Model |  157778.58      1   157778.58           Prob > F      =  0.0000
    Residual | 125802.596   9998  12.5827761           R-squared     =  0.5564
-------------+------------------------------           Adj R-squared =  0.5563
       Total | 283581.176   9999  28.3609537           Root MSE      =  3.5472

------------------------------------------------------------------------------
           y |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   schooling |   2.121985   .0189499   111.98   0.000     2.084839     2.15913
       _cons |   .4353722   .0355205    12.26   0.000     .3657449    .5049994
------------------------------------------------------------------------------


.
. xtreg y schooling , i(id) fe

Fixed-effects (within) regression               Number of obs      =     10000
Group variable: id                              Number of groups   =         5

R-sq:  within  = 0.7538                         Obs per group: min =      2000
       between = 0.9997                                        avg =    2000.0
       overall = 0.5564                                        max =      2000

                                                F(1,9994)          =  30599.79
corr(u_i, Xb)  = 0.4070                         Prob > F           =    0.0000

------------------------------------------------------------------------------
           y |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   schooling |   1.337186   .0076442   174.93   0.000     1.322201     1.35217
       _cons |   .5120157   .0130914    39.11   0.000      .486354    .5376774
-------------+----------------------------------------------------------------
     sigma_u |  4.0359577
     sigma_e |  1.3070063
         rho |   .9050817   (fraction of variance due to u_i)
------------------------------------------------------------------------------
F test that all u_i=0:     F(4, 9994) = 15912.37             Prob > F = 0.0000
```

Results, con't

```
. xi: reg y schooling i.id
i.id              _Iid_0-4            (naturally coded; _Iid_0 omitted)

      Source |       SS       df       MS              Number of obs =   10000
-------------+------------------------------           F(  5,  9994) =31202.27
       Model |  266508.771     5  53301.7541           Prob > F      =  0.0000
    Residual |  17072.4053  9994  1.70826549           R-squared     =  0.9398
-------------+------------------------------           Adj R-squared =  0.9398
       Total |  283581.176  9999  28.3609537           Root MSE      =   1.307

------------------------------------------------------------------------------
           y |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   schooling |   1.337186   .0076442   174.93   0.000     1.322201     1.35217
      _Iid_1 |   1.943564   .0414423    46.90   0.000     1.862329    2.024799
      _Iid_2 |   3.240114   .0416525    77.79   0.000     3.158467    3.321761
      _Iid_3 |   3.337538   .0416354    80.16   0.000     3.255924    3.419152
      _Iid_4 |   10.63719   .0447286   237.82   0.000     10.54951    10.72486
       _cons |  -3.319665   .0297053  -111.75   0.000    -3.377893   -3.261437
------------------------------------------------------------------------------

. xi i.id
i.id              _Iid_0-4            (naturally coded; _Iid_0 omitted)

. reg y schooling _I*

      Source |       SS       df       MS              Number of obs =   10000
-------------+------------------------------           F(  5,  9994) =31202.27
       Model |  266508.771     5  53301.7541           Prob > F      =  0.0000
    Residual |  17072.4053  9994  1.70826549           R-squared     =  0.9398
-------------+------------------------------           Adj R-squared =  0.9398
       Total |  283581.176  9999  28.3609537           Root MSE      =   1.307

------------------------------------------------------------------------------
           y |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   schooling |   1.337186   .0076442   174.93   0.000     1.322201     1.35217
      _Iid_1 |   1.943564   .0414423    46.90   0.000     1.862329    2.024799
      _Iid_2 |   3.240114   .0416525    77.79   0.000     3.158467    3.321761
      _Iid_3 |   3.337538   .0416354    80.16   0.000     3.255924    3.419152
      _Iid_4 |   10.63719   .0447286   237.82   0.000     10.54951    10.72486
       _cons |  -3.319665   .0297053  -111.75   0.000    -3.377893   -3.261437
------------------------------------------------------------------------------
```

Results, con't

```
. areg y schooling, absorb(id)

Linear regression, absorbing indicators               Number of obs =   10000
                                                       F(  1,  9994) =30599.79
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.9398
                                                       Adj R-squared =  0.9398
                                                       Root MSE      =   1.307

------------------------------------------------------------------------------
           y |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   schooling |   1.337186    .0076442   174.93   0.000     1.322201     1.35217
       _cons |   .5120157    .0130914    39.11   0.000      .486354    .5376774
-------------+----------------------------------------------------------------
          id |        F(4, 9994) =  15912.367   0.000           (5 categories)

.
. ivreg y (schooling = z) _I*

Instrumental variables (2SLS) regression

      Source |       SS       df       MS              Number of obs =   10000
-------------+------------------------------           F(  5,  9994) =21342.82
       Model |  262696.221     5  52539.2442           Prob > F      =  0.0000
    Residual |  20884.9547  9994  2.08974932           R-squared     =  0.9264
-------------+------------------------------           Adj R-squared =  0.9263
       Total |  283581.176  9999  28.3609537           Root MSE      =  1.4456

------------------------------------------------------------------------------
           y |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   schooling |   .9760564    .0150672    64.78   0.000     .9465216    1.005591
       _Iid_1 |   2.086821    .0461029    45.26   0.000     1.996451    2.177192
       _Iid_2 |    3.48405     .046833    74.39   0.000     3.392248    3.575852
       _Iid_3 |   3.574886    .0467741    76.43   0.000       3.4832    3.666573
       _Iid_4 |   11.44499     .056795   201.51   0.000     11.33366    11.55632
       _cons |  -3.570865    .0339812  -105.08   0.000    -3.637475   -3.504255
------------------------------------------------------------------------------
Instrumented:  schooling
Instruments:   _Iid_1 _Iid_2 _Iid_3 _Iid_4 z
------------------------------------------------------------------------------
```

Results, con’t

```
. xtivreg y (schooling = z), i(id)

G2SLS random-effects IV regression              Number of obs      =     10000
Group variable: id                              Number of groups   =         5

R-sq:  within  = 0.7538                         Obs per group: min =      2000
       between = 0.9997                                        avg =    2000.0
       overall = 0.5564                                        max =      2000

                                                Wald chi2(1)       =   2446.34
corr(u_i, X)       = 0 (assumed)                Prob > chi2        =    0.0000

------------------------------------------------------------------------------
           y |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   schooling |   .9703856   .0196194    49.46   0.000     .9319323    1.008839
       _cons |   .5478375   .0610966     8.97   0.000     .4280902    .6675847
-------------+----------------------------------------------------------------
     sigma_u |   .0998834
     sigma_e |  1.4455965
         rho |  .00475143   (fraction of variance due to u_i)
------------------------------------------------------------------------------
Instrumented:   schooling
Instruments:     z
------------------------------------------------------------------------------

. xtivreg y (schooling = z), i(id) fe

Fixed-effects (within) IV regression         Number of obs      =        10000
Group variable: id                           Number of groups   =            5

R-sq:  within  = 0.6988                      Obs per group: min =         2000
       between = 0.9997                                     avg =       2000.0
       overall = 0.5564                                     max =         2000

                                             Wald chi2(1)       =      6172.49
corr(u_i, Xb)  = 0.4070                      Prob > chi2        =       0.0000

------------------------------------------------------------------------------
           y |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   schooling |   .9760564   .0150672    64.78   0.000     .9465252    1.005588
       _cons |   .5472836   .0145307    37.66   0.000     .5188041    .5757632
-------------+----------------------------------------------------------------
     sigma_u |  4.3435356
     sigma_e |  1.4455965
         rho |  .90027943   (fraction of variance due to u_i)
------------------------------------------------------------------------------
F  test that all u_i=0:     F(4,9994) = 11075.25         Prob > F    = 0.0000
------------------------------------------------------------------------------
Instrumented:   schooling
Instruments:     z
------------------------------------------------------------------------------
```

Results, con't

```
. xtivreg y (schooling = z), i(id)

G2SLS random-effects IV regression              Number of obs      =     10000
Group variable: id                              Number of groups   =         5

R-sq:  within  = 0.7538                         Obs per group: min =      2000
       between = 0.9997                                        avg =    2000.0
       overall = 0.5564                                        max =      2000

                                                Wald chi2(1)       =   2446.34
corr(u_i, X)       = 0 (assumed)                Prob > chi2        =    0.0000

------------------------------------------------------------------------------
           y |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   schooling |   .9703856   .0196194    49.46   0.000     .9319323    1.008839
       _cons |   .5478375   .0610966     8.97   0.000     .4280902    .6675847
-------------+----------------------------------------------------------------
     sigma_u |   .0998834
     sigma_e |  1.4455965
         rho |  .00475143   (fraction of variance due to u_i)
------------------------------------------------------------------------------
Instrumented:   schooling
Instruments:     z
------------------------------------------------------------------------------

. xtivreg y (schooling = z), i(id) fe

Fixed-effects (within) IV regression         Number of obs      =        10000
Group variable: id                           Number of groups   =            5

R-sq:  within  = 0.6988                      Obs per group: min =         2000
       between = 0.9997                                     avg =       2000.0
       overall = 0.5564                                     max =         2000

                                             Wald chi2(1)       =      6172.49
corr(u_i, Xb)  = 0.4070                      Prob > chi2        =       0.0000

------------------------------------------------------------------------------
           y |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   schooling |   .9760564   .0150672    64.78   0.000     .9465252    1.005588
       _cons |   .5472836   .0145307    37.66   0.000     .5188041    .5757632
-------------+----------------------------------------------------------------
     sigma_u |  4.3435356
     sigma_e |  1.4455965
         rho |  .90027943   (fraction of variance due to u_i)
------------------------------------------------------------------------------
F  test that all u_i=0:     F(4,9994) = 11075.25          Prob > F    = 0.0000
------------------------------------------------------------------------------
Instrumented:   schooling
Instruments:     z
------------------------------------------------------------------------------
```

Fixed effects in Stata

- Many ways to do fixed effects in Stata. Which is best?
  - "xi: regress y x i.id" is almost always inefficient
  - "xi i.id" creates the fixed effects as variables (as "_Iid0", "_Iid1", etc.), so assuming you have the space this lets you re-use them for other commands (e.g. further estimation, tabulation, etc.)
  - "areg" is great for large data sets; it avoids creating the fixed effect variables because it demeans the data by group (i.e. it is purely a "within" estimator). But it is not straightforward to get the fixed effect estimates themselves ("**help areg postestimation**")
  - "xtreg" is an improved version of areg. It should probably be used instead (although requires panel id variable to be integer, can't have a string)
  - What if you want state-by-year FE in a large data set?

Generalized linear models (glm)

- E[y] = g(X*B) + e
- g() is called the “link function”. Stata’s “glm” command supports log, logit, probit, log-log, power, and negative binomial link functions
- Can also make distribution of “e” non-Gaussian and make a different parametric assumption on the error term (Bernoulli, binomial, Poisson, negative binomial, gamma are supported)
- Note that not all combinations make sense (i.e. can’t have Gaussian errors in a probit link function)
- This is implemented in Stata’s ML language (more on this next lecture)
- If link function or error distribution you want isn’t in there, it is very easy to write in Stata’s ML langauge (again, we will see this more next lecture)
- See Finkelstein (QJE 2007) for an example and discussion of this technique.

glm digression

Manning (1998) …

> *“In many analyses of expenditures on health care, the expenditures for users are subject to a log transform to reduce, if not eliminate, the skewness inherent in health expenditure data… In such cases, estimates based on logged models are often much more precise and robust than direct analysis of the unlogged original dependent variable. Although such estimates may be more precise and robust, no one is interested in log model results on the log scale per se.* ***Congress does not appropriate log dollars. First Bank will not cash a check for log dollars.*** *Instead, the log scale results must be retransformed to the original scale so that one can comment on the average or total response to a covariate x. There is a very real danger that the log scale results may provide a very misleading, incomplete, and biased estimate of the impact of covariates on the untransformed scale, which is usually the scale of ultimate interest.”*

glm

```
clear
set obs 100

gen x = invnormal(uniform())
gen e = invnormal(uniform())
gen y = exp(x) + e
gen log_y = log(y)

reg y x
reg log_y  x, robust
glm y x, link(log) family(gaussian)
```

glm, con’t

- Regression in levels produces coefficient that is too large, while regression in logs produces coefficient that is too low (which we expect since distribution of y is skewed)

```
.
. reg y x

      Source |       SS       df       MS              Number of obs =     100
-------------+------------------------------           F(  1,    98) =   74.59
       Model |  123.422594     1  123.422594           Prob > F      =  0.0000
    Residual |  162.168645    98  1.6547821            R-squared     =  0.4322
-------------+------------------------------           Adj R-squared =  0.4264
       Total |   285.59124    99    2.88476            Root MSE      =  1.2864

------------------------------------------------------------------------------
           y |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
           x |   1.263616   .1463147     8.64   0.000     .9732587    1.553972
       _cons |   1.468643   .1286384    11.42   0.000     1.213364    1.723922
------------------------------------------------------------------------------

. reg log_y  x, robust

Linear regression                                      Number of obs =      81
                                                       F(  1,    79) =   53.98
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.3531
                                                       Root MSE      =  .69725

------------------------------------------------------------------------------
             |               Robust
       log_y |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
           x |   .5638066   .0767411     7.35   0.000     .4110572     .716556
       _cons |   .3327507   .0811254     4.10   0.000     .1712746    .4942268
------------------------------------------------------------------------------

. glm y x, link(log) family(gaussian)

Iteration 0:   log likelihood = -167.96464
Iteration 1:   log likelihood = -151.97391
Iteration 2:   log likelihood = -148.17129
Iteration 3:   log likelihood = -148.16153
Iteration 4:   log likelihood = -148.16153

Generalized linear models                          No. of obs      =       100
Optimization     : ML                              Residual df     =        98
                                                   Scale parameter =  1.156683
Deviance         =  113.3549049                    (1/df) Deviance =  1.156683
Pearson          =  113.3549049                    (1/df) Pearson  =  1.156683

Variance function: V(u) = 1                        [Gaussian]
Link function    : g(u) = ln(u)                    [Log]

                                                   AIC             =  3.003231
Log likelihood   = -148.1615264                    BIC             = -337.9518

------------------------------------------------------------------------------
             |                 OIM
           y |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
           x |   1.028327   .0930878    11.05   0.000     .8458778    1.210775
       _cons |  -.0486902   .1295531    -0.38   0.707    -.3026095    .2052292
------------------------------------------------------------------------------
```

Non-parametric estimation

- Stata has built-in support for kernel densities. Often a useful descriptive tool to display “smoothed” distributions of data
- Can also non-parametrically estimate probability density functions of interest.
- Example: Guerre, Perrigne & Vuong (EMA, 2000) estimation of first-price auctions with risk-neutral bidders and iid private values:
  - Estimate distribution of bids non-parametrically
  - Use observed bids and this estimated distribution to construct distribution of values
  - Assume values are distributed according to following CDF:

$$F(v) = 1 - e^{-v}$$

  - Then you can derive the following bidding function for *N*=3 bidders

$$b = \frac{(v+0.5)e^{-2v} - 2(1+v)e^{-v} + 1.5}{1 - 2e^{-v} + e^{-2v}}$$

  - QUESTION: Do bidders “shade” their bids for all values?

GPV with kdensity

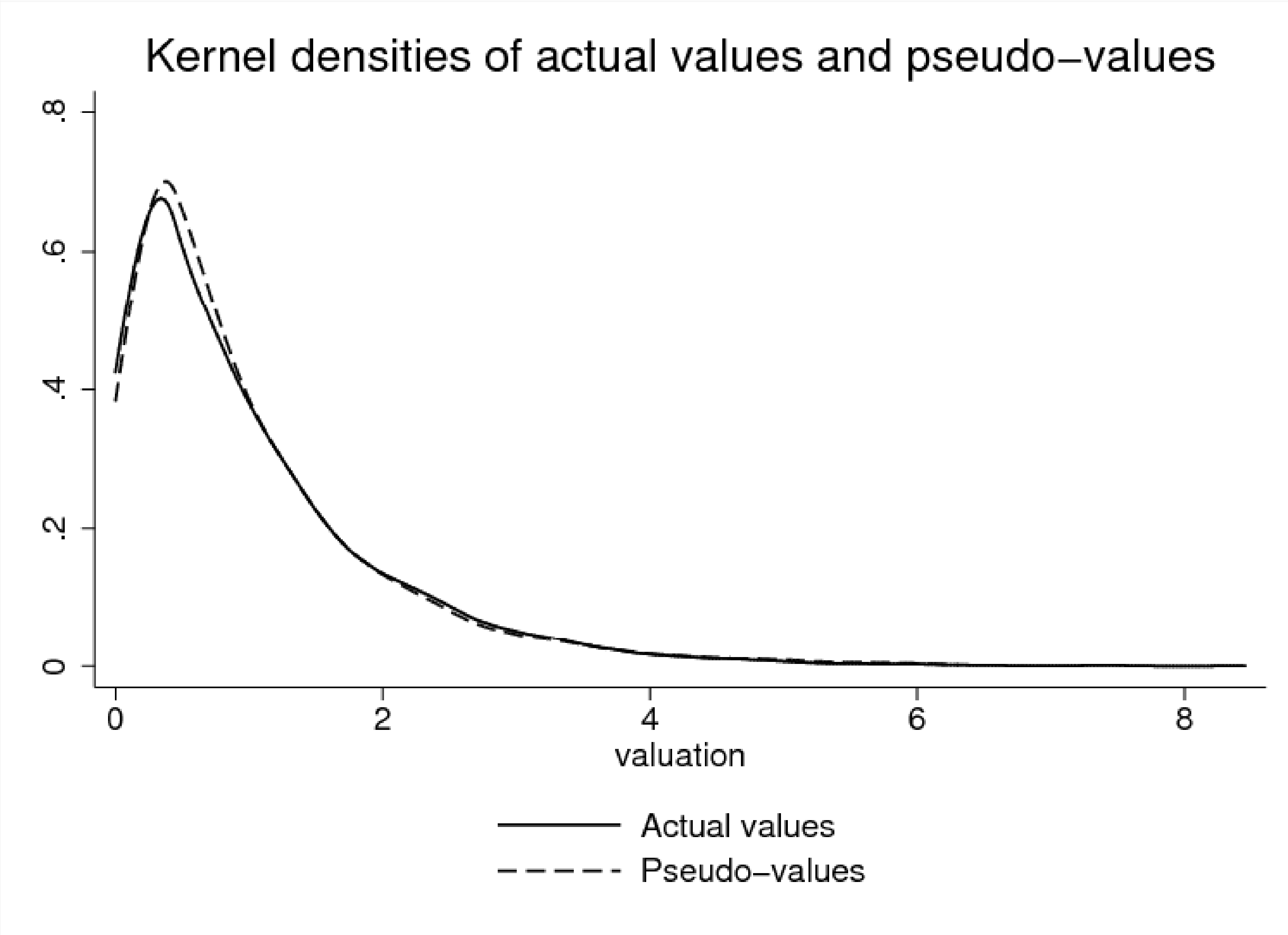
```
clear
set mem 100m
set seed 14170
set obs 5000

local N = 3
gen value = -log(1-uniform())
gen bid = ( (value+0.5)*exp(-2*value)-2*(1+value)*exp(-value)+1.5 ) ///
   / (1-2*exp(-value)+exp(-2*value))
sort bid
gen cdf_G = _n / _N
kdensity bid, width(0.2) generate(b pdf_g) at(bid)

** pseudo-value backed-out from bid distribution
gen pseudo_v = bid + (1/(`N'-1))*cdf_G/pdf_g

twoway  (kdensity value, width(0.2) ) (kdensity pseudo_v, width(0.2) ), ///
       title("Kernel densities of actual values and pseudo-values") ///
       scheme(s2mono) ylabel(, nogrid) graphregion(fcolor(white)) ///
       legend(region(style(none))) ///
       legend(label(1 "Actual values")) ///
       legend(label(2 "Pseudo-values")) ///
       legend(cols(1)) ///
       xtitle("valuation")
graph export gpv.eps, replace
```

GPV with kdensity



Quantile regression (qreg)

```
qreg log_wage age female edhsg edclg black other _I*, quantile(.1)
matrix temp_betas = e(b)
matrix betas = (nullmat(betas) \ temp_betas)

qreg log_wage age female edhsg edclg black other _I*, quantile(.5)
matrix temp_betas = e(b)
matrix betas = (nullmat(betas) \ temp_betas)

qreg log_wage age female edhsg edclg black other _I*, quantile(.9)
matrix temp_betas = e(b)
matrix betas = (nullmat(betas) \ temp_betas)
```

QUESTIONS:

- What does it mean if the coefficient on “edclg” differs by quantile?
- What are we learning when the coefficients are different? (HINT: What does it tell us if the coefficient is nearly the same in every regression)
- What can you do if education is endogenous?

Non-linear least squares (NLLS)

```
clear
set obs 50

global alpha = 0.65
gen k=exp(invnormal(uniform()))
gen l=exp(invnormal(uniform()))
gen e=invnormal(uniform())
gen y=2.0*(k^($alpha)*l^(1-$alpha))+e
nl (y = {b0} * l^{b2} * k^{b3})
```

```
.
. nl (y = {b0} * l^{b2} * k^{b3})
(obs = 50)

Iteration 0:  residual SS =  350.2076
Iteration 1:  residual SS =  126.9884
Iteration 2:  residual SS =  63.38518
Iteration 3:  residual SS =  59.83852
Iteration 4:  residual SS =  59.83428
Iteration 5:  residual SS =  59.83427

      Source |       SS       df       MS            Number of obs =        50
-------------+------------------------------         F(  3,    47) =     76.03
       Model |   290.37331     3  96.7911034         Prob > F      =    0.0000
    Residual |  59.8342736    47  1.27306965         R-squared     =    0.8291
-------------+------------------------------         Adj R-squared =    0.8182
       Total |  350.207584    50  7.00415168         Root MSE      =  1.128304
                                                     Res. dev.     =  150.8716

------------------------------------------------------------------------------
           y |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
          b0 |   2.021732   .1762746    11.47   0.000     1.667113     2.37635
          b2 |   .3486468   .0621272     5.61   0.000     .2236629    .4736306
          b3 |   .6559907   .1146375     5.72   0.000     .4253699    .8866116
------------------------------------------------------------------------------
  (SEs, P values, CIs, and correlations are asymptotic approximations)
```

Non-linear least squares (NLLS)

- NLLS: minimize the sum of squared residuals to get parameter estimates
  - QUESTION: How are the standard errors calculated?
- The “nl” method provides built-in support for NLLS minimization, and also provides robust and clustered standard errors.
- The syntax allows for many types of nonlinear functions of data and parameters
- Will see examples of NLLS in Stata ML later

More NLLS (CES)

$$Y = A\left((1-d)K^{n} + (d)L^{n}\right)^{1/n}$$

```
clear
set obs 100
set seed 14170

global d = 0.6
global n = 4.0
global A = 2.0
gen k = exp(invnormal(uniform()))
gen l = exp(invnormal(uniform()))
gen e = 0.1 * invnormal(uniform())

** CES production function
gen y = ///
 $A*( (1-$d)*k^($n) + $d*l^($n) )^(1/$n) + e

nl (y = {b0}*( (1-{b1})*k^({b2}) + ///
                  {b1}*l^({b2})  )^(1/{b2}) ), ///
 init(b0 1 b1 0.5 b2 1.5) robust
```

More NLLS

```
.
. ** CES production function
. gen y = ///
>  $A*( (1-$d)*k^($n) + $d*l^($n) )^(1/$n) + e

.
. nl (y = {b0}*( (1-{b1})*k^({b2}) + ///
>                      {b1}*l^({b2})  )^(1/{b2}) ), ///
>  init(b0 1 b1 0.5 b2 1.5) robust
(obs = 100)

Iteration 0:  residual SS =  1138.476
Iteration 1:  residual SS =  3.220384
Iteration 2:  residual SS =  1.023647
Iteration 3:  residual SS =  1.017296
Iteration 4:  residual SS =  1.017295

Nonlinear regression with robust standard errors     Number of obs =        100
                                                     F(  3,    97) = 180829.75
                                                     Prob > F      =    0.0000
                                                     R-squared     =    0.9997
                                                     Root MSE      =  .1024089
                                                     Res. dev.     = -175.0146

------------------------------------------------------------------------------
             |               Robust
           y |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
          b0 |    1.99775   .0189951   105.17   0.000      1.96005     2.03545
          b1 |    .595155   .0063743    93.37   0.000     .5825038    .6078061
          b2 |   3.955974   .2414426    16.38   0.000     3.476777     4.43517
------------------------------------------------------------------------------
 (SEs, P values, CIs, and correlations are asymptotic approximations)
```

Conditional FE Poisson (xtpoisson)

- Useful for strongly skewed <u>count</u> data (e.g. days absent), especially when there are a lot of zeroes (since otherwise a log transformation would probably be fine in practice)
- “xtpoisson” provides support for fixed and random effects

```
xtpoisson days_absent gender math reading, i(id) fe
```

- See Acemoglu-Linn (QJE 2004) for a use of this technique (using number of approved drugs as the “count” dependent variable)
- Note that they report clustered standard errors, which are NOT built into Stata
- NOTE: this command is implemented in Stata’s ML language

Arellano-Bond estimator (xtabond)

- Dynamic panel data estimator using GMM
- Specification is lagged dependent variable and use excluded lags as instruments for the other lags
- Example of a GMM implementation in Stata
- Syntax:

```
tsset state year
xtabond log_payroll miningXoilprice _I*, lags(2)
```

- “tsset” is standard command to tell Stata you have a time-series data set (the panel variable is optional for some commands, but for xtabond it is required)

Other important commands

- The following commands are commonly used and you should be aware of them (since they are all ML estimators, we will see some of them tomorrow)
  - probit
  - tobit
  - logit
  - clogit
  - ivprobit
  - ivtobit
- I will also not be discussing these useful commands:
  - heckman
  - cnsreg
  - mlogit
  - mprobit
  - ologit
  - oprobit
- You should look these up on your own, especially after Lecture 3

Stata matrix language

- Before Mata (Lecture 4), Stata had built-in matrix language. Still useful even with Mata because Mata syntax is somewhat cumbersome

- When to use Stata matrix language:
  - Adding standard errors to existing estimators
  - Writing new estimators from scratch (when such estimators are naturally implemented using matrix algebra)
  - Storing bootstrapping and Monte Carlo results (simulations)

Monte Carlo in Stata

- There is a “simulate” command that is supposed to make your life easier. I don’t think it does, but you should decide for yourself. (“help simulate”)

- Monte Carlo simulations can clarify intuition when the math isn’t obvious.

- EXAMPLE: We will use a simulation to demonstrate the importance of using a robust variance-covariance matrix in the presence of heteroskedasticity.

Monte Carlo in Stata, con't

```
clear
set more off
set mem 100m
set matsize 1000
local B = 1000
matrix Bvals = J(`B', 1, 0)
matrix pvals = J(`B', 2, 0)
forvalues b = 1/`B' {
 drop _all
 quietly set obs 200
 gen cons = 1
 gen x = invnormal(uniform())
 gen e = x*x*invnormal(uniform())
 gen y = 0*x + e

 qui regress y x cons, nocons
 matrix betas = e(b)
 matrix Bvals[`b',1] = betas[1,1]
 qui testparm x
 matrix pvals[`b',1] = r(p)

 qui regress y x cons , robust nocons
 qui testparm x
 matrix pvals[`b',2] = r(p)
}
drop _all
svmat Bvals
svmat pvals
summ *, det
```

Monte Carlo in Stata, con’t

set more off	*On UNIX, this will keep the buffer from “locking”*
set matsize 1000	*Sets default matrix size*
matrix Bvals = J(`B', 1, 0)	*Creates `B’-by-1 matrix*
drop _all	*Unlike “clear”, this only drops the data (NOT matrices!)*
quietly set obs 200	*Suppresses output*
qui regress y x cons, **nocons**	*“qui” is abbreviation; nocons means constant not included*
matrix betas = **e(b)**	*e() stores the return values from regression; e(b) is betas*
matrix Bvals[`b',1] = betas[1,1]	*syntax to set matrix values*
qui **testparm x**	*performs a Wald test to see if “x” is statistically significant*
qui regress y x cons , **robust** nocons	*uses “robust” standard errors*
svmat Bvals	*writes out matrix as a data column*

Monte Carlo in Stata, con't

```
. summ *, det

                           Bvals1
-------------------------------------------------------------
      Percentiles      Smallest
 1%    -.7108901      -.867761
 5%    -.4510751     -.8387734
10%    -.3548669     -.8244087       Obs                1000
25%    -.1722884     -.7698361       Sum of Wgt.        1000

50%     .0038993                     Mean           -.0046056
                        Largest      Std. Dev.       .2693386
75%     .1797461      .6604921
90%     .3240661      .7583284       Variance        .0725433
95%     .4148443       .816509       Skewness       -.1505003
99%      .605374      .9324661       Kurtosis        3.210481

                           pvals1
-------------------------------------------------------------
      Percentiles      Smallest
 1%     6.92e-07      2.28e-11
 5%     .0000421      9.73e-10
10%     .0003121      1.40e-08       Obs                1000
25%     .0123931      1.59e-08       Sum of Wgt.        1000

50%     .1238899                     Mean            .2603048
                        Largest      Std. Dev.       .2998066
75%     .4540875      .9949121
90%     .7795787      .9956778       Variance         .089884
95%     .9047533      .9977634       Skewness        1.036197
99%     .9803216      .9999624       Kurtosis        2.771922

                           pvals2
-------------------------------------------------------------
      Percentiles      Smallest
 1%     .0083116      .0009476
 5%     .0529822      .0011581
10%     .0896799       .002251       Obs                1000
25%     .2348141      .0027212       Sum of Wgt.        1000

50%     .4535128                     Mean            .4742613
                        Largest      Std. Dev.       .2868344
75%     .7167521      .9971678
90%     .8921935      .9980425       Variance         .082274
95%     .9535336      .9989994       Skewness        .1459861
99%     .9904989      .9999799       Kurtosis        1.861137
```

OLS “by hand”

$$\beta = (X'X)^{-1}X'y$$

```
clear
set obs 10
set seed 14170
gen x1 = invnorm(uniform())
gen x2 = invnorm(uniform())
gen y = 1 + x1 + x2 + 0.1 * invnorm(uniform())

gen cons = 1
mkmat x1 x2 cons, matrix(X)
mkmat y, matrix(y)
matrix list X
matrix list y

matrix beta_ols = invsym(X'*X) * (X'*y)
matrix e_hat = y - X * beta_ols
matrix V = (e_hat' * e_hat) * invsym(X'*X) / (rowsof(X) - colsof(X))
matrix beta_se = (vecdiag(V))'
local rows = rowsof(V)
forvalues i = 1/`rows' {
 matrix beta_se[`i',1] = sqrt(beta_se[`i',1])
}
matrix ols_results = [beta_ols, beta_se]
matrix list ols_results
reg y x1 x2
```

```
. matrix list X

X[10,3]
             x1          x2        cons
 r1  -1.5950224   .20092869           1
 r2  -.64034598  -.60358792           1
 r3  -.40134595    2.359099           1
 r4  -.60476729   .11293815           1
 r5  -.26287592  -.71784865           1
 r6  -.36271503  -1.9359163           1
 r7   1.7407799   1.1414781           1
 r8  -.03460691   2.2267994           1
 r9   1.4960149   1.4628167           1
r10   .48152901  -1.2280046           1

. matrix list y

y[10,1]
              y
 r1  -.51445416
 r2  -.36395637
 r3   2.8763379
 r4   .46112738
 r5  -.05183486
 r6  -1.1868566
 r7   3.9082622
 r8   3.0423635
 r9    4.094496
r10   .25329242
```

```
.
. matrix ols_results = [beta_ols, beta_se]

. matrix list ols_results

ols_results[3,2]
               y          r1
  x1   1.0719562   .02491212
  x2   .97005487   .01720588
cons   .97870197   .02363347

.
. reg y x1 x2

      Source |       SS       df       MS              Number of obs =      10
-------------+------------------------------           F(  2,     7) = 3390.36
       Model |  35.9448584     2  17.9724292           Prob > F      =  0.0000
    Residual |  .03710729      7  .005301041           R-squared     =  0.9990
-------------+------------------------------           Adj R-squared =  0.9987
       Total |  35.9819657     9  3.99799619           Root MSE      =  .07281

------------------------------------------------------------------------------
           y |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
          x1 |   1.071956   .0249121    43.03   0.000     1.013048    1.130864
          x2 |   .9700549   .0172059    56.38   0.000     .9293694     1.01074
       _cons |    .978702   .0236335    41.41   0.000     .9228177    1.034586
------------------------------------------------------------------------------
```

OLS “by hand”

```
clear
set obs 100000
set seed 14170
gen x1 = invnorm(uniform())
gen x2 = invnorm(uniform())
gen y = 1 + x1 + x2 + 0.1 * invnorm(uniform())

gen cons = 1
mkmat x1 x2 cons, matrix(X)
mkmat y, matrix(y)
matrix list X
matrix list y

matrix beta_ols = invsym(X'*X) * (X'*y)
matrix e_hat = y - X * beta_ols
matrix V = (e_hat' * e_hat) * invsym(X'*X) /
   (rowsof(X) - colsof(X))
matrix beta_se = (vecdiag(V))'
local rows = rowsof(V)
forvalues i = 1/`rows' {
 matrix beta_se[`i',1] = sqrt(beta_se[`i',1])
}
matrix ols_results = [beta_ols, beta_se]
matrix list ols_results
reg y x1 x2
```

```
. clear

. set obs 100000
obs was 0, now 100000

. set seed 14170

. gen x1 = invnorm(uniform())

. gen x2 = invnorm(uniform())

. gen y = 1 + x1 + x2 + 0.1 * invnorm(uniform())

.
. gen cons = 1

. mkmat x1 x2 cons, matrix(X)
matsize too small to create a [100000,3] matrix
r(908);

end of do-file

r(908);
```

("help set matsize"; maximum matrix size is 11,000 on Stata/SE and Stata/MP)

OLS “by hand” v2.0

```
clear
set obs 100000
set seed 14170
gen x1 = invnorm(uniform())
gen x2 = invnorm(uniform())
gen y = 1 + x1 + x2 + 100 * invnorm(uniform())

global xlist = "x1 x2"
matrix accum XpX = $xlist
matrix vecaccum Xpy = y $xlist
matrix beta_ols = invsym(XpX) * Xpy'
matrix list beta_ols
gen e_hat = y
local i = 1
foreach var of varlist $xlist {
 replace e_hat = e_hat - beta_ols[`i',1] * `var'
 local i = `i' + 1
}
** constant term!
replace e_hat = e_hat - beta_ols[`i',1]
matrix accum e2 = e_hat, noconstant
matrix V = invsym(XpX) * e2[1,1] / (_N - colsof(XpX))
matrix beta_se = (vecdiag(V))'
local rows = rowsof(V)
forvalues i = 1/`rows' {
 matrix beta_se[`i',1] = sqrt(beta_se[`i',1])
}
matrix ols_results = [beta_ols, beta_se]
matrix list ols_results
reg y x1 x2
```

```
ols_results[3,2]
               y          r1
   x1  1.0141917   .31550833
   x2  1.0507246   .31459431
_cons  .86855402   .31548979

. reg y x1 x2

      Source |       SS       df       MS              Number of obs =  100000
-------------+------------------------------           F(  2, 99997) =   10.72
       Model |  213407.047     2  106703.523           Prob > F      =  0.0000
    Residual |   995296663 99997  9953.26523           R-squared     =  0.0002
-------------+------------------------------           Adj R-squared =  0.0002
       Total |   995510070 99999  9955.20025           Root MSE      =  99.766

------------------------------------------------------------------------------
           y |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
          x1 |   1.014192   .3155003     3.21   0.001     .3957993    1.632504
          x2 |   1.050725   .3145943     3.34   0.001     .4341236    1.667326
       _cons |    .868554   .3154898     2.75   0.006     .2501979     1.48691
------------------------------------------------------------------------------
```

“helper” programs

```
clear
set obs 1000
program drop _all
program add_stat, eclass
 ereturn scalar `1' = `2'
end

gen z = invnorm(uniform())
gen v = invnorm(uniform())
gen x = .1*invnorm(uniform()) + 2.0*z + 10.0*v
gen y = 3.0*x + (10.0*v + .1*invnorm(uniform()))
reg y x
estimates store ols
reg x z
test z
return list
add_stat "F_stat" r(F)
estimates store fs
reg y z
estimates store rf
ivreg y (x = z)
estimates store iv
estout * using baseline.txt, drop(_cons) ///
 stats(F_stat r2 N, fmt(%9.3f %9.3f %9.0f)) modelwidth(15) ///
 cells(b( fmt(%9.3f)) se(par fmt(%9.3f)) p(par([ ]) fmt(%9.3f)) ) ///
 style(tab) replace notype mlabels(, numbers )
```

“helper” programs

```
.
. reg x z

      Source |       SS       df       MS              Number of obs =    1000
-------------+------------------------------           F(  1,   998) =   43.91
       Model |  4328.58096     1  4328.58096           Prob > F      =  0.0000
    Residual |  98388.7101   998  98.5858819           R-squared     =  0.0421
-------------+------------------------------           Adj R-squared =  0.0412
       Total |  102717.291   999  102.820111           Root MSE      =   9.929

------------------------------------------------------------------------------
           x |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
           z |   2.077355   .3135057     6.63   0.000     1.462149    2.692561
       _cons |   .1735656   .3139839     0.55   0.581    -.4425789      .78971
------------------------------------------------------------------------------

. test z

 ( 1)  z = 0

       F(  1,   998) =   43.91
            Prob > F =    0.0000

. return list

scalars:
              r(drop) =  0
              r(df_r) =  998
                 r(F) =  43.90670219895473
                r(df) =  1
                 r(p) =  5.62473556326e-11

. add_stat "F_stat" r(F)

. estimates store fs
```

“helper” programs

```
[noto@afink2 ~/14.170]$ more baseline.txt
                    (1) ols           (2) fs           (3) rf           (4) iv
                    b/se/p            b/se/p           b/se/p           b/se/p
x                    3.959                                               3.034
                   (0.006)                                             (0.146)
                   [0.000]                                             [0.000]
z                                      2.077            6.303
                                     (0.314)          (1.254)
                                     [0.000]          [0.000]
F_stat                                43.907
r2                   0.998             0.042            0.025            0.943
N                     1000              1000             1000             1000
```

ADO files in Stata

```
**
** Monte Carlo to investigate heteroskedasticity-robust s.e.'s
**
clear
set more off
set seed 14170
local count = 0

global B = 1000
forvalues i = 1(1)$B {
quietly {
 clear
 set obs 2000
 gen x = invnorm(uniform())
 gen y = 0*x + abs(0.1*x)*invnorm(uniform())
 regress y x
 test x
 if (r(p) < 0.05) {
  local count = `count' + 1
 }
}
}
local rate = `count' / $B
di "Rejection rate (at alpha=0.05): `rate'"
```

0.236 ☹

ADO files in Stata

```
**
** Monte Carlo to investigate heteroskedasticity-robust s.e.'s
**
clear
set more off
set seed 14170
local count = 0

global B = 1000
forvalues i = 1(1)$B {
quietly {
 clear
 set obs 2000
 gen x = invnorm(uniform())
 gen y = 0*x + abs(0.1*x)*invnorm(uniform())
 regress y x, robust
 test x
 if (r(p) < 0.05) {
  local count = `count' + 1
 }
}
}
local rate = `count' / $B
di "Rejection rate (at alpha=0.05): `rate'"
```

0.048 ☺

ADO files in Stata

(robust_regress.ado file)

```
program define robust_regress, eclass
   syntax varlist
gettoken depvar varlist: varlist

quietly regress `depvar' `varlist'
predict resid, residuals
gen esample = e(sample)
local obs = e(N)
matrix betas = e(b)

matrix accum XpX = `varlist'
gen all = _n
sort all
matrix opaccum W = `varlist', opvar(resid) group(all)
matrix V = invsym(XpX) * W * invsym(XpX)

ereturn post betas V, dep(`depvar') o(`obs') esample(esample)
ereturn display
end
```

$$V_{robust} = (X'X)^{-1} * \left(\sum_{i=1}^{N} (\hat{\varepsilon}_i x_i)'(\hat{\varepsilon}_i x_i) \right) * (X'X)^{-1}$$

ADO files in Stata

```
**
** Monte Carlo to investigate heteroskedasticity-robust s.e.'s
**
clear
set more off
set seed 14170
local count = 0

global B = 1000
forvalues i = 1(1)$B {
quietly {
 clear
 set obs 2000
 gen x = invnorm(uniform())
 gen y = 0*x + abs(0.1*x)*invnorm(uniform())
 robust_regress y x
 test x
 if (r(p) < 0.05) {
  local count = `count' + 1
 }
}
}
local rate = `count' / $B
di "Rejection rate (at alpha=0.05): `rate'"
```

0.049 😐

ADO files in Stata

```
clear
set obs 2000
gen x = invnorm(uniform())
gen y = 0*x + abs(0.1*x)*invnorm(uniform())
robust_regress y x
regress y x, robust
```

```
. robust_regress y x
(obs=2000)
------------------------------------------------------------------------------
           y |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
           x |  -.0001554   .0035848    -0.04   0.965    -.0071815    .0068707
       _cons |  -.0013051    .002211    -0.59   0.555    -.0056385    .0030283
------------------------------------------------------------------------------

. regress y x, robust

Linear regression                                      Number of obs =    2000
                                                       F(  1,  1998) =    0.00
                                                       Prob > F      =  0.9655
                                                       R-squared     =  0.0000
                                                       Root MSE      =  .09897

------------------------------------------------------------------------------
             |               Robust
           y |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
           x |  -.0001554   .0035866    -0.04   0.965    -.0071892    .0068785
       _cons |  -.0013051   .0022121    -0.59   0.555    -.0056433    .0030331
------------------------------------------------------------------------------
```

ADO files in Stata

(robust_regress.ado file)

```
program define robust_regress, eclass
   syntax varlist
gettoken depvar varlist: varlist

quietly reg `depvar' `varlist', robust
predict resid, residuals
gen esample = e(sample)
local obs = e(N)
matrix betas = e(b)

matrix accum XpX = `varlist'
gen all = _n
sort all
matrix opaccum W = `varlist', opvar(resid) group(all)
matrix V = (_N/(_N-colsof(XpX))) * invsym(XpX) * W * invsym(XpX)

ereturn post betas V, dep(`depvar') o(`obs') esample(esample)
ereturn display
end
```

$$V_{robust} = \frac{N}{N-K} * (X'X)^{-1} * \left(\sum_{i=1}^{N} (\hat{\varepsilon}_i x_i)'(\hat{\varepsilon}_i x_i) \right) * (X'X)^{-1}$$

“Reflections on Trusting Trust”

- Ken Thompson Turing Award speech:

(http://www.ece.cmu.edu/~ganger/712.fall02/papers/p761-thompson.pdf)

“You can't trust code that you did not totally create yourself. (Especially code from companies that employ people like me).”

(an aside) More on “trusting trust”

```
clear
set obs 2000
set seed 14170
gen x = invnorm(uniform())
gen id = 1+floor((_n - 1)/50)
gen y = x + ///
 abs(x)*invnorm(uniform())+id
areg y x, ///
 cluster(id) absorb(id)
```

```
. areg y x, cluster(id) absorb(id)

Linear regression, absorbing indicators                Number of obs =    2000
                                                       F(  1,    39) =  823.46
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.9928
                                                       Adj R-squared =  0.9927
                                                       Root MSE      =  .99208

                                  (Std. Err. adjusted for 40 clusters in id)
------------------------------------------------------------------------------
             |               Robust
           y |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
           x |    .982857   .0342507    28.70   0.000     .9135785    1.052136
       _cons |   20.49485   .0003223        .   0.000      20.4942     20.4955
-------------+----------------------------------------------------------------
          id |   absorbed                                        (40 categories)
```

```
. areg y x, cluster(id) absorb(id)

Linear regression, absorbing indicators                Number of obs =    2000
                                                       F(  1,    39) =  839.85
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.9928
                                                       Adj R-squared =  0.9928
                                                       Root MSE      =  .99208

                                  (Std. Err. adjusted for 40 clusters in id)
------------------------------------------------------------------------------
             |               Robust
           y |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
           x |    .982857   .0339147    28.98   0.000     .9142579    1.051456
       _cons |   20.49485   .0003191        .   0.000     20.49421     20.4955
-------------+----------------------------------------------------------------
          id |   absorbed                                        (40 categories)
```

STATA v9.1

STATA v10.0

Exercises

- Go to following URL:
  http://web.mit.edu/econ-gea/14.170/exercises/

- Download each DO file
  - No DTA files! All data files loaded from the web (see "help webuse")

- 1 exercise (increasing difficulty)
  A. Monte carlo test of OLS/GLS with serially correlated data
  B. Heckman two-step with bootstrapped standard errors
  C. Correcting for measurement error of known form