Day 3A
Panel (linear)

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Advanced Econometrics
Bavarian Graduate Program in Economics

.

Based on A. Colin Cameron and Pravin K. Trivedi (2009, 2010),
Microeconometrics using Stata (MUS), Stata Press.
and A. Colin Cameron and Pravin K. Trivedi (2005),
Microeconometrics: Methods and Applications (MMA), C.U.P.

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1. Introduction

- Panel data are repeated measures on individuals (i) over time (t).
  - Regress y_{it} on $\mathbf{x}_{it}$ for $i = 1, ..., N$ and $t = 1, ..., T$.
- Complications compared to cross-section data:
  - **1.** Inference: correct (inflate) standard errors.
    This is because each additional year of data is not independent of previous years.
  - **2.** Modelling: richer models and estimation methods are possible with repeated measures.
    Fixed effects and dynamic models are examples.
  - **3.** Methodology: different areas of applied statistics may apply different methods to the same panel data set.

- Focus on panel methods most commonly used by microeconometricians.
- Three specializations to general panel methods:
  - **1.** Short panel: data on many individual units and few time periods.
    Then data viewed as clustered on the individual unit.
    Many panel methods also apply to clustered data such as cross-section individual-level surveys clustered at the village level.
  - **2.** Causation from observational data: use repeated measures to estimate key marginal effects that are causative rather than mere correlation.
    Fixed effects: assume time-invariant individual-specific effects.
    IV: use data from other periods as instruments.
  - **3.** Dynamic models: regressors include lagged dependent variables.

Outline

1. Introduction
2. Data example: wages
3. Linear models overview
4. Standard linear short panel estimators
5. Further topics

2. Data Example: Wages

- PSID wage data 1976-82 on 595 individuals. Balanced.
- Source: Baltagi and Khanti-Akom (1990).
  [Corrected version of Cornwell and Rupert (1998).]
- Goal: estimate causative effect of education on wages.
- Complication: education is time-invariant in these data.
  Rules out fixed effects estimation.
  Need to use IV methods (Hausman-Taylor).

- Commands `describe`, `summarize` and `tabulate` confound cross-section and time series variation.
- Instead use specialized panel commands after `xtset`:
  - `xtdescribe`: extent to which panel is unbalanced
  - `xtsum`: separate within (over time) and between (over individuals) variation
  - `xttab`: tabulations within and between for discrete data e.g. binary
  - `xttrans`: transition frequencies for discrete data
  - `xtline`: time series plot for each individual on one chart
  - `xtdata`: scatterplots for within and between variation.

Reading in panel data

- Data organization may be
  - long form: each observation is an individual-time (i, t) pair
  - wide form: each observation is data on i for all time periods
  - wide form: each observation is data on t for all individuals
- `xt` commands require data in long form
  - use `reshape long` command to convert from wide to long form.
- Data here are already in long form

```
.  * Read in data set
.  use mus08psidextract.dta, clear
(PSID wage data 1976-82 from Baltagi and Khanti-Akom
(1990))
```

Summarize data using non-panel commands

```
. * Describe dataset
. describe

Contains data from mus08psidextract.dta
  obs:         4,165                          PSID wage data 1976-82 from Baltagi and Khanti-Akom
 vars:            15                          16 Aug 2007 16:29
 size:       283,220 (97.5% of memory free)   (_dta has notes)
-----------------------------------------------------------------------------------------------------
              storage  display     value
variable name   type   format      label      variable label
-----------------------------------------------------------------------------------------------------
exp             float  %9.0g                  years of full-time work experience
wks             float  %9.0g                  weeks worked
occ             float  %9.0g                  occupation; occ==1 if in a blue-collar occupation
ind             float  %9.0g                  industry; ind==1 if working in a manufacturing indu
south           float  %9.0g                  residence; south==1 if in the South area
smsa            float  %9.0g                  smsa==1 if in the Standard metropolitan statistical
ms              float  %9.0g                  marital status
fem             float  %9.0g                  female or male
union           float  %9.0g                  if wage set be a union contract
ed              float  %9.0g                  years of education
blk             float  %9.0g                  black
lwage           float  %9.0g                  log wage
id              float  %9.0g
t               float  %9.0g
exp2            float  %9.0g
-----------------------------------------------------------------------------------------------------
```

- Summary statistics combine variation over i and t.

```
. * Summarize dataset
. summarize
```

Variable	Obs	Mean	Std. Dev.	Min	Max
exp	4165	19.85378	10.96637	1	51
wks	4165	46.81152	5.129098	5	52
occ	4165	.5111645	.4999354	0	1
ind	4165	.3954382	.4890033	0	1
south	4165	.2902761	.4539442	0	1
smsa	4165	.6537815	.475821	0	1
ms	4165	.8144058	.3888256	0	1
fem	4165	.112605	.3161473	0	1
union	4165	.3639856	.4812023	0	1
ed	4165	12.84538	2.787995	4	17
blk	4165	.0722689	.2589637	0	1
lwage	4165	6.676346	.4615122	4.60517	8.537
id	4165	298	171.7821	1	595
t	4165	4	2.00024	1	7
exp2	4165	514.405	496.9962	1	2601

- Since 4165 $(= 7 \times 595)$ observations for all variables the dataset is balanced and complete.

- Listing the first few observations is useful

```
. * Organization of data set
. list id t exp wks occ in 1/3, clean

       id   t   exp   wks   occ
  1.    1   1     3    32     0
  2.    1   2     4    43     0
  3.    1   3     5    40     0
```

- Data are in long form, sorted by `id` and then by `t`

Summarize data using panel commands

- xtset command defines i and t.
  - Allows use of panel commands and some time series operators

```
.  * Declare individual identifier and time identifier
.  xtset id t
 panel variable:  id (strongly balanced)
 time variable:  t, 1 to 7
 delta:  1 unit
```

- `xtdescribe` command summarizes number of time periods each individual is observed.

```
. * Panel description of data set
. xtdescribe

      id:  1, 2, ..., 595                                      n =        595
       t:  1, 2, ..., 7                                        T =          7
           Delta(t) = 1 unit
           Span(t)  = 7 periods
           (id*t uniquely identifies each observation)

Distribution of T_i:   min      5%      25%       50%       75%     95%     max
                         7       7        7         7         7       7       7

     Freq.  Percent    Cum. |  Pattern
 ---------------------------+---------
      595    100.00  100.00 |  1111111
 ---------------------------+---------
      595    100.00         |  XXXXXXX
```

- Data are balanced with every individual i having 7 time periods of data.

- `xtsum` command splits overall variation into
  - between variation: variation in $\bar{x}_i = T_i^{-1} \sum_i x_{it}$ across individuals
  - within variation: variation in x_{it} around $\bar{x}_i$

```
. * Panel summary statistics: within and between variation
. xtsum lwage exp ed t
```

Variable		Mean	Std. Dev.	Min	Max	Observations
lwage	overall	6.676346	.4615122	4.60517	8.537	N = 4165
	between		.3942387	5.3364	7.813596	n = 595
	within		.2404023	4.781808	8.621092	T = 7
exp	overall	19.85378	10.96637	1	51	N = 4165
	between		10.79018	4	48	n = 595
	within		2.00024	16.85378	22.85378	T = 7
ed	overall	12.84538	2.787995	4	17	N = 4165
	between		2.790006	4	17	n = 595
	within		0	12.84538	12.84538	T = 7
t	overall	4	2.00024	1	7	N = 4165
	between		0	4	4	n = 595
	within		2.00024	1	7	T = 7

- For time-invariant variable `ed` the within variation is zero.
  For individual-invariant variable `t` the between variation is zero.
  For `lwage` the within variation $<$ between variation.

- xttab command provides more detail for discrete-valued variable.

```
. * Panel tabulation for a variable
. xttab south

                  Overall             Between            Within
    south |    Freq.  Percent      Freq.  Percent       Percent
----------+-----------------------------------------------------
        0 |    2956     70.97        428    71.93         98.66
        1 |    1209     29.03        182    30.59         94.90
----------+-----------------------------------------------------
    Total |    4165    100.00        610   102.52         97.54
                                 (n = 595)
```

- 29.03% on average were in the south.
  30.59% were ever in the south.
  94.9% of those ever in the south were always in the south.

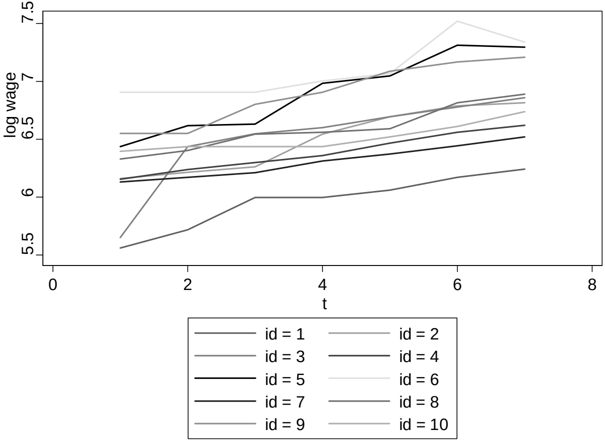
- `xttab` provides transition probabilities for discrete-valued variable.

```
. * Transition probabilities for a variable
. xttrans south, freq
```

residence; south==1 if in the South area	residence; south==1 if in the South area 0	1	Total
0	2,527 99.68	8 0.32	2,535 100.00
1	8 0.77	1,027 99.23	1,035 100.00
Total	2,535 71.01	1,035 28.99	3,570 100.00

- For the 28.99% of the sample ever in the south, 99.23% remained in the south the next period.

```
. * Time series plots of log wage for first 10 individuals
. xtline lwage if id<=10, overlay
```



- Much autocorrelation in each person's wage.

- Can compute autocorrelations for a variable.

```
. * First-order autocorrelation in a variable
. sort id t

. correlate lwage L.lwage L2.lwage L3.lwage L4.lwage L5.lwage L6.lwage
(obs=595)
```

	lwage	L. lwage	L2. lwage	L3. lwage	L4. lwage	L5. lwage	L6. lwage
lwage							
--.	1.0000						
L1.	0.9238	1.0000					
L2.	0.9083	0.9271	1.0000				
L3.	0.8753	0.8843	0.9067	1.0000			
L4.	0.8471	0.8551	0.8833	0.8990	1.0000		
L5.	0.8261	0.8347	0.8721	0.8641	0.8667	1.0000	
L6.	0.8033	0.8163	0.8518	0.8465	0.8594	0.9418	1.0000

- High serial correlation: $\text{Cor}[y_t, y_{t-6}] = 0.80$.
- Note that estimated autocorrelations without imposing stationarity.

Pooled OLS

- Pooled OLS is regular OLS of y_{it} on $\mathbf{x}_{it}$.

```
. * Pooled OLS with incorrect default standard errors
. regress lwage exp exp2 wks ed, noheader
```

lwage	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
exp	.044675	.0023929	18.67	0.000	.0399838	.0493663
exp2	-.0007156	.0000528	-13.56	0.000	-.0008191	-.0006121
wks	.005827	.0011827	4.93	0.000	.0035084	.0081456
ed	.0760407	.0022266	34.15	0.000	.0716754	.080406
_cons	4.907961	.0673297	72.89	0.000	4.775959	5.039963

- The default standard errors erroneously assume errors are independent over i for given t.
  - Reason: Assumes more information content from data then is the case.

- Should instead use cluster-robust standard errors

```
. * Pooled OLS with cluster-robust standard errors
. regress lwage exp exp2 wks ed, noheader vce(cluster id)
                                 (Std. Err. adjusted for 595 clusters in id)
```

lwage	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
exp	.044675	.0054385	8.21	0.000	.0339941	.055356
exp2	-.0007156	.0001285	-5.57	0.000	-.0009679	-.0004633
wks	.005827	.0019284	3.02	0.003	.0020396	.0096144
ed	.0760407	.0052122	14.59	0.000	.0658042	.0862772
_cons	4.907961	.1399887	35.06	0.000	4.633028	5.182894

- Cluster-robust standard errors are twice as large as default!
  Cluster-robust t-statistics are half as large as default!
- Typical result. Need to use cluster-robust se's if use pooled OLS.

3. Linear panel models: Basic considerations

1. Regular time intervals assumed.
2. Unbalanced panel okay (`xt` commands handle unbalanced data). [Should then rule out selection/attrition bias].
3. Short panel assumed, with T small and $N \rightarrow \infty$. [Versus long panels, with $T \rightarrow \infty$ and N small or $N \rightarrow \infty$.]
4. Errors are correlated. [For short panel: correlated over t for given i, but not over i.]
5. Parameters may vary over individuals or time. Intercept: Individual-specific effects model (fixed or random effects). Slopes: Pooling and random coefficients models.
6. Regressors: time-invariant, individual-invariant, or vary over both.
7. Prediction: ignored. [Not always possible even if marginal effects computed.]
8. Dynamic models: possible. [Usually static models are estimated.]

Basic linear panel models

- Pooled model (or population-averaged)

$$y_{it} = \alpha + \mathbf{x}_{it}'\boldsymbol{\beta} + u_{it}. \tag{1}$$

- Two-way effects model allows intercept to vary over i and t

$$y_{it} = \alpha_i + \gamma_t + \mathbf{x}_{it}'\boldsymbol{\beta} + \varepsilon_{it}. \tag{2}$$

- Individual-specific effects model

$$y_{it} = \alpha_i + \mathbf{x}_{it}'\boldsymbol{\beta} + \varepsilon_{it}, \tag{3}$$

  where α_i may be fixed effect or random effect.
- Mixed model or random coefficients model allows slopes to vary over i

$$y_{it} = \alpha_i + \mathbf{x}_{it}'\boldsymbol{\beta}_i + \varepsilon_{it}. \tag{4}$$

Fixed effects versus random effects model

- Individual-specific effects model:

$$y_{it} = \mathbf{x}_{it}'\boldsymbol{\beta} + (\alpha_i + \varepsilon_{it}).$$

- Fixed effects (FE):
  - α_i is a random variable possibly correlated with $\mathbf{x}_{it}$
  - so regressor $\mathbf{x}_{it}$ may be endogenous (wrt to α_i but not ε_{it})
    e.g. education is correlated with time-invariant ability
  - pooled OLS, pooled GLS, RE are inconsistent for $\boldsymbol{\beta}$
  - within (FE) and first difference estimators are consistent.
- Random effects (RE) or population-averaged (PA):
  - α_i is purely random (usually iid $(0, \sigma_\alpha^2)$) unrelated to $\mathbf{x}_{it}$
  - so regressor $\mathbf{x}_{it}$ is exogenous
  - all estimators are consistent for $\boldsymbol{\beta}$
- Fundamental divide: microeconometricians FE versus others RE.

4. Linear panel estimators: cluster-robust inference

- There are many different panel estimators - detailed below.
- Many methods assume ε_{it} and α_i (if present) are iid.
  - This yields wrong standard errors if heteroskedastic or if errors are not equicorrelated over time for a given individual.
- Instead, for a short panel can relax assumptions and use cluster-robust inference.
  - This allows heteroskedasticity and general correlation over time for given i.
  - Independence over i is still assumed.
- In Stata
  - For `xtreg` use option `vce(robust)` does cluster-robust
  - For some other `xt` commands use option `vce(cluster)`
  - And for some other `xt` commands there is no option, but may be able to do a cluster bootstrap.

Fixed effects estimator

- Mean-differencing eliminates α_i

$$\begin{array}{rrcl} & y_{it} & = & \alpha_i + \mathbf{x}_{it}'\boldsymbol{\beta} + \varepsilon_{it} \\ \Rightarrow & \bar{y}_i & = & \alpha_i + \bar{\mathbf{x}}_i'\boldsymbol{\beta} + \bar{\varepsilon}_i \\ \Rightarrow & (y_{it} - \bar{y}_i) & = & (\mathbf{x}_{it} - \bar{\mathbf{x}}_i)'\boldsymbol{\beta} + (\varepsilon_{it} - \bar{\varepsilon}_i) \end{array}$$

- The within or fixed effects estimator is OLS of $(y_{it} - \bar{y}_i)$ on $(\mathbf{x}_{it} - \bar{\mathbf{x}}_i)$
  - Efficiency loss as use only within variation
  - Coefficient of any time-invariant regressor is not identified $(x_{it} = \bar{x}_i)$
  - Use cluster-robust standard errors
  - Stata command `xtreg, fe`
- This can be shown to be same as OLS of y_{it} on N individual dummies and $\mathbf{x}_{it}$
  - least squares dummy variable (LSDV) estimator.

- Within or FE estimates:

```
. * Within or FE estimator with cluster-robust standard errors
. xtreg lwage exp exp2 wks ed, fe vce(robust)

Fixed-effects (within) regression               Number of obs      =      4165
Group variable: id                              Number of groups   =       595

R-sq:  within  = 0.6566                         Obs per group: min =         7
       between = 0.0276                                        avg =       7.0
       overall = 0.0476                                        max =         7

                                                F(3,594)           =   1059.72
corr(u_i, Xb)  = -0.9107                        Prob > F           =    0.0000

                                 (Std. Err. adjusted for 595 clusters in id)
------------------------------------------------------------------------------
             |               Robust
       lwage |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         exp |   .1137879   .0040289    28.24   0.000     .1058753    .1217004
        exp2 |  -.0004244   .0000822    -5.16   0.000    -.0005858   -.0002629
         wks |   .0008359   .0008697     0.96   0.337    -.0008721    .0025439
          ed |  (dropped)
       _cons |   4.596396   .0600887    76.49   0.000     4.478384    4.714408
-------------+----------------------------------------------------------------
     sigma_u |  1.0362039
     sigma_e |  .15220316
         rho |  .97888036   (fraction of variance due to u_i)
------------------------------------------------------------------------------
```

- Variable ed is not identified as time-invariant regressor in this dataset.

Random effects estimator

- Random effects estimator is FGLS estimator for the RE model

$$\begin{aligned} y_{it} &= \alpha_i + \mathbf{x}_{it}'\boldsymbol{\beta} + \varepsilon_{it} \\ \alpha_i &\sim \text{i.i.d.}[0, \sigma_\alpha^2] \\ \varepsilon_{it} &\sim \text{i.i.d.}[0, \sigma_\varepsilon^2] \end{aligned}$$

- This can be shown to equal OLS in the transformed model

$$(y_{it} - \widehat{\theta}_i \bar{y}_i) = (\mathbf{x}_{it} - \widehat{\theta}_i \bar{\mathbf{x}}_i)'\boldsymbol{\beta} + error,$$

where $\widehat{\theta}_i$ is a consistent estimate of $\theta_i = 1 - \sqrt{\sigma_\varepsilon^2 / (T_i \sigma_\alpha^2 + \sigma_\varepsilon^2)}$.

- Random effects estimates:

```
. * Random effects estimator with cluster-robust standard errors
. xtreg lwage exp exp2 wks ed, re vce(robust) theta

Random-effects GLS regression                   Number of obs      =      4165
Group variable: id                              Number of groups   =       595

R-sq:  within  = 0.6340                         Obs per group: min =         7
       between = 0.1716                                        avg =       7.0
       overall = 0.1830                                        max =         7

Random effects u_i ~ Gaussian                   Wald chi2(5)       = 175914.07
corr(u_i, X)       = 0 (assumed)                Prob > chi2        =    0.0000
theta              = .82280511

                                  (Std. Err. adjusted for clustering on id)
------------------------------------------------------------------------------
             |               Robust
       lwage |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         exp |   .0888609   .0028515    31.16   0.000     .0832721    .0944497
        exp2 |  -.0007726   .0000623   -12.40   0.000    -.0008946   -.0006505
         wks |   .0009658   .0009286     1.04   0.298    -.0008542    .0027857
          ed |   .1117099   .0063256    17.66   0.000      .099312    .1241079
       _cons |   3.829366   .1039432    36.84   0.000     3.625641    4.033091
-------------+----------------------------------------------------------------
     sigma_u |  .31951859
     sigma_e |  .15220316
         rho |  .81505521   (fraction of variance due to u_i)
------------------------------------------------------------------------------
```

- Option theta gives $\widehat{\theta} = 0.82 = 1 - \sqrt{0.152^2/(7 \times 0.319^2 + 0.152^2)}$.

Fixed effects versus random effects estimators

- RE has advantages that can estimate all parameters and may be more efficient.
  - But RE is inconsistent if fixed effects present.
- Use Hausman test to discriminate between FE and RE.
  - This tests difference between FE and RE estimates is statistically significantly different from zero.
- Do not use `hausman` command as it requires RE estimator fully efficient.
- Do use a panel bootstrap of the Hausman test.
- Or use the Wooldridge (2002) robust version of Hausman test.
  - Test $H_0 : \gamma = \mathbf{0}$ in the auxiliary OLS regression

$$(y_{it} - \widehat{\theta}\bar{y}_i) = (1 - \widehat{\theta})\alpha + (\mathbf{x}_{it} - \widehat{\theta}\bar{\mathbf{x}}_i)'\boldsymbol{\beta} + (\mathbf{x}_{1it} - \bar{\mathbf{x}}_{1i})'\gamma + v_{it},$$

    where $\mathbf{x}_1$ denotes time-varying regressors only.
  - Use cluster-robust standard errors for this test.

Other panel estimators

- Population-averaged or pooled GLS estimator
  - Regress y_{it} on $\mathbf{x}_{it}$ using feasible GLS as error u_{it} is not iid.
  - Example is to assume that u_{it} is an AR(2) error.
    - `xtgee lwage exp exp2 wks ed, corr(ar 2) vce(robust)`
- Between estimator
  - OLS regression of $\bar{y}_i$ on $\bar{\mathbf{x}}_i$, i.e. use each individual's averages.
  - Uses only between variation in the data.
    - `xtreg lwage exp exp2 wks ed, be`
- First differences estimator
  - OLS regression of $(y_{it} - y_{i,t-1})$ on $(\mathbf{x}_{it} - \mathbf{x}_{i,t-1})$, i.e. use first differences.
  - First-differencing eliminates α_i in $y_{it} = \alpha_i + \mathbf{x}'_{it}\boldsymbol{\beta} + \varepsilon_{it}$
  - So like within it is consistent in FE model
    - `regress D.(lwage $xlist), vce(cluster id)`

Summary of standard linear panel estimators

- Pooled OLS (command `regress`)
- Pooled GLS (command `xtgee`)
- Between estimator (command `xtreg, be`)
- Within or FE estimator (command `xtreg, fe`)
- Random effects estimator (command `xtreg, re`)
- First differences estimator (command `regress` with `d.y` and `d.x`)

Estimator comparison

```
. * Compare various estimators (with cluster-robust se's)
. global xlist exp exp2 wks ed
. quietly regress lwage $xlist, vce(cluster id)
. estimates store OLS
. quietly xtgee lwage exp exp2 wks ed, corr(ar 2)
   vce(robust)
. estimates store PFGLS
. quietly xtreg lwage $xlist, be
. estimates store BE
. quietly xtreg lwage $xlist, re vce(robust)
. estimates store RE
. quietly xtreg lwage $xlist, fe vce(robust)
. estimates store FE
. estimates table OLS PFGLS BE RE FE, b(%9.4f) se stats(N)
```

Variable	OLS	PFGLS	BE	RE	FE
exp	0.0447	0.0719	0.0382	0.0889	0.1138
	0.0054	0.0040	0.0057	0.0029	0.0040
exp2	-0.0007	-0.0009	-0.0006	-0.0008	-0.0004
	0.0001	0.0001	0.0001	0.0001	0.0001
wks	0.0058	0.0003	0.0131	0.0010	0.0008
	0.0019	0.0011	0.0041	0.0009	0.0009
ed	0.0760	0.0905	0.0738	0.1117	0.0000
	0.0052	0.0060	0.0049	0.0063	0.0000
_cons	4.9080	4.5264	4.6830	3.8294	4.5964
	0.1400	0.1057	0.2101	0.1039	0.0601
N	4165.0000	4165.0000	4165.0000	4165.0000	4165.0000

legend: b/se

- Coefficients vary considerably across OLS, RE, FE and RE estimators.
  - FE and RE similar as $\widehat{\theta} = 0.82 \simeq 1$.
- Not shown is that even for FE and RE cluster-robust changes se's.
- Coefficient of `ed` not identified for FE as time-invariant regressor!

5. Further Topics

- Long panels not covered here
  - Asymptotics are in $T \to \infty$ with N fixed or $N \to \infty$
- Instrumental variables
  - Estimators include panel IV and Hausman-Taylor
- Dynamic short panels $y_{it} = \alpha_i + \rho y_{i,t-1} + \mathbf{x}_{it}'\boldsymbol{\beta} + u_{it}$
  - Usual FE and FD estimates are inconsistent
  - Instead use Arellano-Bond (panel IV in FD model with lagged $y_{i,t-k}$ as instruments)
- Random coefficients
  - mixed linear models
- Nonlinear panel models
  - cannot always eliminate fixed effects α_i (only in Poisson, logit, negative binomial)
  - leads to alternatives such as correlated random effects.

6. Stata Commands

- Linear panel estimators

Panel summary	`xtset; xtdescribe; xtsum; xtdata;` `xtline; xttab; xttran`
Pooled OLS	`regress`
Feasible GLS	`xtgee, family(gaussian)` `xtgls; xtpcse`
Random effects	`xtreg, re; xtregar, re`
Fixed effects	`xtreg, fe; xtregar, fe`
Random slopes	`xtmixed; quadchk; xtrc`
First differences	`regress` (with differenced data)
Static IV	`xtivreg; xthtaylor`
Dynamic IV	`xtabond; xtdpdsys; xtdpd`

- Nonlinear panel estimators

Estimator	**Count data**	**Binary data**
Pooled	`poisson`	`logit`
	`nbreg`	`probit`
GEE (PA)	xtgee,family(poisson)	xtgee,family(binomial) link(
	xtgee,family(nbinomial)	xtgee,family(poisson) link(
RE	`xtpoisson, re`	`xtlogit, re`
	`xtnbreg, fe`	`xtprobit, re`
Random slopes	`xtmepoisson`	`xtmelogit`
FE	`xtpoisson, fe`	`xtlogit, fe`
	`xtnbreg, fe`	

- Also `tobit` and `xttobit` for Tobit models
  - `xttobit` is for RE only (same for `xtprobit`).