

## Another Crack at Dynamic Models in Chapter 8 (with STATA)

```
infile state year price pop popul6 cpi ndi c pimmn using c:/data/balagel/cigarettes.txt

tsset state year, yearly
gen cpc=(c*pop)/popul6
gen lpcp=L.cpc
gen lnc=log(cpc)
gen lnlc=log(lcpc)
gen lnlp=log(price/cpi)*100
gen lnlpn=log((pimmn/cpi)*100)
gen lnly=log(ndi/cpi)*100

* OLS (w/o time FE, following * p. 157)
reg lnlc lnlp lnlpn lnly

quietly tabulate year, gen(0)

* Within
* drop 2 year indicators, one for identification
* and the first year, b/c of the lagged dv on the RHS
xtreg lnlc lnlp lnlpn lnly (lnlc=lnlp lnlpn lnly) fe (state)

gen lnlp=L.lnp
gen lnlpn=L.lnpn
gen lnly=L.lnly

* 2SLS (w/o time FE, following * p. 157)
ivreg lnlc lnlp lnlpn lnly (lnlc=lnlp lnlpn lnly)

* Within 2SLS (with time FE)
xtivreg lnlc lnlp lnlpn lnly (lnlc=lnlp lnlpn lnly), fe (state)

* Arellano-Bond (with time FE)
* I got msize error at first, so added command immediately below
set msize 500

xtabond lnlc lnlp lnlpn lnly (3-130, lag(1) noconstant
* this should match p. 159
xtabond lnlc lnlp lnlpn lnly (3-130, lag(1) twostep noconstant
```

Wed Dec 7, 2005  
1

\* OLS (w/o time FE, following \* p. 157)  
 . reg Inc lnlc lnmp lnprn lnny

Source	SS	df	MS	Number of obs =
Model	64.3926449	4	16.0981612	1334
Residual	2.35376627	1329	.001771081	F(4, 1329) = 9089.46
Total	66.7464111	1333	.050072326	Prob > F = 0.0000
				R-squared = 0.9647
				Adj R-squared = 0.9646
				Root MSE = .04208

	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
Inc					
lnlc	.9694942	.0061489	157.67	0.000	.9574316 .9815569
lnmp	-.0901512	.0145795	-6.18	0.000	-.1187525 -.0615498
lnprn	.0240347	.0131562	1.83	0.068	-.0017746 .049844
lnny	-.0306788	.0060279	-5.09	0.000	-.0425041 -.0188535
_cons	.7240693	.0729962	9.92	0.000	.5808688 .8672697

✓ matches OLS row p. 157



```

. gen lnlp=L.lnp
(46 missing values generated)
. gen lnlpn=L.lnpn
(46 missing values generated)
. gen lnly=L.lny
(46 missing values generated)

```

```

. * 2SLS (w/o time FE, following * p. 157)
. ivreg lnc lnlp lnlpn lnly (lnlc=lnlp lnlpn lnly)
Instrumental variables (2SLS) regression

```

Source	SS	df	MS	Number of obs =
Model	63.7233971	4	15.9308493	1334
Residual	3.02301402	1329	.002274653	F( 4, 1329) = 2398.66
Total	66.7464111	1333	.050072326	Prob > F = 0.0000
				R-squared = 0.9547
				Adj R-squared = 0.9546
				Root MSE = .04769

lnc	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
lnlc	.8499651	.0335508	25.33	0.000	.7841468 .9157833
lnlp	-.2050105	.0356031	-5.76	0.000	-.2748548 -.1351662
lnlpn	.0523477	.0168147	3.11	0.002	.0193615 .085334
lnly	-.0169926	.0077967	-2.18	0.029	-.0322878 -.0016975
_cons	1.601765	.2547925	6.29	0.000	1.101926 2.101605

```

Instrumented: lnlc
Instruments: lnlp lnlpn lnly lnlp lnlpn lnly

```

✓ matches 2SLS row p. 157

```

. * Within 2SLS (with time FE)
. xtivreg lnc lnp lnpr lny t3-t30 (lnlc=lnlp lnpr lny), fe i(state)

Fixed-effects (within) IV regression
Group variable: state

R-sq: within = 0.9213
      between = 0.9369
      overall = 0.9230

Obs per group: min = 29
               avg  = 29.0
               max  = 29

Wald chi2(32) = 2.08e+07
Prob > chi2   = 0.0000

corr(u_i, Xb) = 0.4579

-----+-----
      lnc |      Coef.   Std. Err.      z    P>|z|      [95% Conf. Interval]
-----+-----
      lnlc |      .601629   .0353302    17.04   0.000   .5324384   .6708196
      lnpr |     -4956818   .0382645   -12.95   0.000   -5706788   -4206847
      lnprn |     -10159481   .0317401    -6.50   0.000   -10781575   -9462613
      lnprny |     .1893821   .0296233     6.39   0.000   .1313215   .2474427
      t3     |     .0165957   .0089228     1.86   0.063   -.0009029   .0340942
      t4     |     .004696    .0090059     0.52   0.602   -.0129553   .0223473
-----+-----
[SNRTP]

```

✓ matches Within-2SLS row p. 157

```

. * Arellano-Bond (with time FE)
. * I got matsize error at first, so added command immediately below
. set matsize 500

```

```

Current memory allocation

```

settable	current value	description	memory usage (1M = 1024k)
set maxvar	5000	max. variables allowed	1.733M
set memory	10M	max. data space	10.000M
set matsize	500	max. RHS vars in models	1.949M
			----- 13.682M

```

. xtabond lnc lnp lnpr lny t3-t30, lag(1) noconstant

```

```

Arellano-Bond dynamic panel-data estimation
Group variable (i): state

```

Number of obs	=	1288
Number of groups	=	46
Wald chi2(.)	=	.
Time variable (t): year		
Obs per group: min	=	28
avg	=	28
max	=	28

```

(↓ continued over ↓)

```

One-step results

	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
D.lnc					
LD:	.8428668	.0162092	52.00	0.000	.8110972 .8746363
lmp					
DL:	-.3772291	.0323381	-11.67	0.000	-.4406106 -.3138475
lmpn					
DL:	-.0161502	.0418921	-0.39	0.700	-.0982572 .0659568
lmy					
DL:	.1394493	.0364131	3.83	0.000	.0680808 .2108177
t3					
DL:	.028061	.0080258	3.50	0.000	.0123307 .0437912
t4					
t30					
DL:	.0149336	.0271575	0.55	0.582	-.0382941 .0681614

Sargan test of over-identifying restrictions:  
chi2(405) = 534.01 Prob > chi2 = 0.0000

Arellano-Bond test that average autocovariance in residuals of order 1 is 0:  
H0: no autocorrelation z = -16.23 Pr > z = 0.0000  
Arellano-Bond test that average autocovariance in residuals of order 2 is 0:  
H0: no autocorrelation z = 2.35 Pr > z = 0.0188

✓ matches GMM-one-step row p. 157

```

. * this should match p. 159
. xtabond Inc lnp lnpr lny t3-t30, lag(1) twostep noconstant
Arellano-Bond dynamic panel-data estimation
Group variable (i): state

```

```

Number of obs   = 1288
Number of groups = 46
Wald chi2(.)    = .
Obs per group:  min = 28
                  avg  = 28
                  max  = 28

```

Two-step results

	D.Inc	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
Inc		.8036634	.2200741	3.65	0.000	.372326 1.235001
LD.						
lnp		-.3786943	.0471325	-8.03	0.000	-.4710722 -.2863163
lnpr						
lny		-.0197169	.0495157	-0.40	0.690	-.1167659 .0773321
D1.		.2391497	.2778919	0.86	0.389	-.3055084 .7838078
lny						
D1.		.0238788	.0231137	1.03	0.302	-.0214232 .0691808
t3						
D1.		-.0062309	.0287669	-0.22	0.829	-.0626129 .0501512
t4						
D1.		.0050715	.0405765	0.12	0.901	-.074457 .0846
t5						
D1.		-.00913	.0468145	-0.20	0.845	-.1008847 .0826248
t6						
D1.		-.0198448	.0546753	-0.36	0.717	-.1270063 .0873167
t7						
D1.		-.0488936	.0621244	-0.79	0.431	-.170655 .0728679
t8						
D1.						



t27						
D1.	-1.1031526	.1812312	-0.57	0.569	-.4583591	.252054
t28						
D1.	-1.1002765	.1922681	-0.52	0.602	-.4771151	.2765621
t29						
D1.	-.0833889	.1990996	-0.42	0.675	-.4736169	.306839
t30						
D1.	-.0441254	.2174354	-0.20	0.839	-.470291	.3820401

Warning: Arellano and Bond recommend using one-step results for inference on coefficients

Sargan test of over-identifying restrictions:  
 chi2(405) = 15.40 Prob > chi2 = 1.0000

Arellano-Bond test that average autocovariance in residuals of order 1 is 0:  
 H0: no autocorrelation z = -3.53 Pr > z = 0.0004

Arellano-Bond test that average autocovariance in residuals of order 2 is 0:  
 H0: no autocorrelation z = 1.63 Pr > z = 0.1027

✓ matches GMM-two-step row p. 157

## **SUNDRY COMMENTS ON (EVER-POPULAR) BECK AND KATZ METHOD**

- Beck and Katz suggest estimating models by OLS with PCSEs and lagged dependent variable
- PCSEs don't accommodate heterogeneity and require large T and small N (if N bigger than T, you get singular covariance matrix).
- Arellano already identified robust SEs long before (extension of White)—truly robust to heterogeneity in DGP
- large T and small N  $\rightarrow$  SURE with cross-equation restrictions, FE and RE are *very* similar in that situation and can be quite different from OLS
- Should focus on problem of unobserved heterogeneity that cause estimates to be biased

RE estimation is based on the structure of the variance-covariance matrix of the residuals (e.g.  $\varepsilon_{it} = \mu_i + \nu_{it}$  in the usual one-way case),  $\Omega_{NT \times NT}$  given the usual simplifying assumptions of homoscedasticity and no serial correlation, except as implied by the variance components themselves. In the one-way (spatial effects only) case,

$$E(uu') = \Omega = \sigma_\mu^2(I_N \otimes J_T) + \sigma_\nu^2(I_N \otimes I_T) \quad \text{with } \text{cov}(u_{it}, u_{js}) = \sigma_\mu^2 + \sigma_\nu^2 \text{ for } i=j, t=s \\ \text{and } = \sigma_\mu^2 \text{ (not 0) for } i=j, t \neq s$$

$$\text{In turn, } \rho = \text{corr}(u_{it}, u_{js}) = 1 \text{ for for } i=j, t=s \\ \text{and } = \sigma_\mu^2 / (\sigma_\mu^2 + \sigma_\nu^2) \text{ for } i=j, t \neq s$$

Devise weighting matrices based on  $\Omega^{-1}$  to transform the data matrices such that the transformed  $\Omega$  is spherical. Then, use estimates of the variance components  $\sigma_\mu^2$ ,  $\sigma_\lambda^2$ , and  $\sigma_\nu^2$  to do FGLS.

Dynamic-model estimators start with what  $\Omega$  should look like

e.g. simplest case,  $Y_{it}$  is a function of  $X_{it}$  and also  $Y_{it-1}$ , but not  $X_{it-1}$ ,  $Y_{it-2}$ , etc. and otherwise the usual simplifying assumptions about homoscedasticity and no-serial-correlation obtain

B&K (1995) targets the Parks (1967) method, which is essentially using OLS residuals to estimate  $\Omega$  and then estimating a model with FGLS. But the key problem with Parks's method is too many parameters.

assumptions:

- variation across units in residual variance component:  $E(u_{it}^2) = E(u_{is}^2) \forall t \neq s$
- contemporaneous (but not lagged) spatial correlation:  $E(u_{it}, u_{jt}) = \sigma_{ij} \forall i \neq j$   
 $= 0 \forall i \neq j, t \neq s$
- $E(u_{it}, u_{is}) = \rho$  or  $E(u_{it}, u_{is}) = \rho_i$

$$u_{it} = \rho_i u_{it-1} + v_{it} \quad w/v_{it} \sim IID(0, \sigma_v^2)$$

(with only T observations to estimate each  $\rho_i$ , it might be infeasible to allow rho to vary across units)

$$\Omega = \begin{bmatrix} \Sigma & 0 & \dots & 0 \\ 0 & \Sigma & & \\ \vdots & & \ddots & \\ 0 & \dots & \dots & \Sigma \end{bmatrix} = \Sigma \otimes \mathbf{I}_T \quad \text{with} \quad \Sigma = \begin{bmatrix} \sigma_1^2 & \sigma_{12} & \dots & \sigma_{1N} \\ \sigma_{12} & \sigma_2^2 & \dots & \sigma_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{1N} & \sigma_{2N} & \dots & \sigma_N^2 \end{bmatrix}$$

so  $N(N-1)/2$  off-diag. parameters to estimate

### **Gritiches (1999) on Maddala:**

“GS has an unassuming and quiet way. But he also has something that is close to perfect pitch in econometrics: when he sees work that is ‘off’, that somehow strikes the wrong note, it bothers him, and his irritation often produces pearls of papers. While much of his work is constructive, much is also critical of many current fads in econometrics.”

### **Maddala (1999 *Pol Anal*) on Beck & Katz:**

“[SUR and the Parks method] involve the estimation of so many parameters that they have fallen into disrepute and are almost never used. The introduction of lagged dependent variables creates problems with OLS estimation if the errors are serially correlated. This is why instrumental variables estimation is the preferred method in the estimation of dynamic panel data models. This area is recent and is exploding, because there are many thorny problems to be tackled... The procedure of using OLS and reporting the ‘panel corrected’ standard errors is sweeping the problems under the rug... Their solution can also be categorized in ‘what not to do’ if there are lagged dependent variables.”

- B&K are right about problems w/ Parks & Kmenta methods, but OLS with LDV and PCSE is no magic bullet
- pay more attention to pooling and specification, don't use LDV w/o good reason

Wilson & Butler "A Lot More To Do: Promise and Peril of Panel Data" (2004 ms)

- 0. Static  $Y_t = \alpha + \beta_0 X_t + u_t$
- 1. AR(1)  $Y_t = \alpha + \beta_0 X_t + u_t$  ,  $u_t = \rho u_{t-1} + \epsilon_t$
- 2. DL(1)  $Y_t = \alpha + \beta_0 X_t + \beta_1 X_{t-1} + u_t$
- (BANK) 3. LQY  $Y_t = \alpha + \beta_0 X_t + \gamma_1 Y_{t-1} + u_t$
- 4. ARDL(1)  $Y_t = \alpha + \beta_0 X_t + \beta_1 X_{t-1} + \gamma_1 Y_{t-1} + u_t$
- 5. FD  $Y_t - Y_{t-1} = \beta_0 (X_t - X_{t-1}) + u_t$

Assuming 3 given DGP of 1 individuals bias

See Achen (2000) "Why Lagged Dep. Vars Can Suppress the Explanatory Power of Other Ind. Vars"

also see Green, Kim, and Yoon (2001 IO)

## Beck and Katz

```

. tset firm Year, Yearly
    panel variable:  firm, 1 to 10
    time variable:  year, 1935 to 1954

. xtprocse i f c

```

Linear regression, correlated panels corrected standard errors (PCSEs)

```

Group variable:  firm
Time variable:  year
Panels:         correlated (balanced)
Autocorrelation: no autocorrelation

Estimated covariances = 55
Estimated autocorrelations = 0
Estimated coefficients = 3

R-squared = 0.8124
Wald chi2(2) = 637.41
Prob > chi2 = 0.0000

```

		Panel-corrected		[95% Conf. Interval]	
	Coef.	Std. Err.	z	P> z	
F	.1155622	.0072124	16.02	0.000	.101426 .1296983
c	.2306785	.0278862	8.27	0.000	.1760225 .2853345
_cons	-42.71437	6.780965	-6.30	0.000	-56.00482 -29.42392

(also see page 399 of STATA 7 manual Su-Z for output above, and below)

```
. xtgls i f c, p(correlated)
```

```
Cross-sectional time-series FGLS regression
```

```
Coefficients: generalized least squares  
Panels: heteroskedastic with cross-sectional correlation  
Correlation: no autocorrelation
```

```
Estimated covariances = 55 Number of obs = 200  
Estimated autocorrelations = 0 Number of groups = 10  
Estimated coefficients = 3 Time periods = 20  
Wald chi2(2) = 3738.07  
Prob > chi2 = 0.0000
```

```
Log likelihood = -879.4274
```

i	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
f	.1127515	.0022364	50.42	0.000	.1083683 .1171347
c	.2231176	.0057363	38.90	0.000	.2118746 .2343605
_cons	-39.84382	1.717563	-23.20	0.000	-43.21018 -36.47746

```
. xtgls i f c, p(h)
```

```
Cross-sectional time-series FGLS regression
```

```
Coefficients: generalized least squares  
Panels: heteroskedastic  
Correlation: no autocorrelation
```

```
Estimated covariances = 10 Number of obs = 200  
Estimated autocorrelations = 0 Number of groups = 10  
Estimated coefficients = 3 Time periods = 20  
Wald chi2(2) = 669.69  
Prob > chi2 = -1037.152
```

```
Log likelihood = -1037.152
```

```

-----+-----
i | Coef. | Std. Err. | z | P>|z| | [95% Conf. Interval]
-----+-----
F | .1116328 | .0049823 | 22.41 | 0.000 | .1018676 .121398
C | .1537718 | .0125707 | 12.23 | 0.000 | .1291336 .17841
_cons | -21.44348 | 3.901219 | -5.50 | 0.000 | -29.08973 -13.79723
-----+-----

```

. xtgls i f c, p(het) corr(arr1)

Cross-sectional time-series FGLS regression

Coefficients: generalized least squares  
 Panels: heteroskedastic

Correlation: common AR(1) coefficient for all panels (0.9261)

```

Estimated covariances = 10 Number of obs = 200
Estimated autocorrelations = 1 Number of groups = 10
Estimated coefficients = 3 Time periods = 20
Wald chi2(2) = 107.43
Prob > chi2 = 0.0000
Log likelihood = -856.2668

```

```

-----+-----
i | Coef. | Std. Err. | z | P>|z| | [95% Conf. Interval]
-----+-----
f | .0715306 | .0087269 | 8.20 | 0.000 | .0544262 .088635
c | .1405652 | .0314945 | 4.46 | 0.000 | .0788371 .2022933
_cons | -1.979683 | 6.781349 | -0.29 | 0.770 | -15.27088 11.31152
-----+-----

```

. xtgee i f c, robust

Iteration 1: tolerance = .33946478  
Iteration 2: tolerance = .00362671  
Iteration 3: tolerance = .00001665  
Iteration 4: tolerance = 7.455e-08

GEE population-averaged model  
Group variable: firm  
Link: identity  
Family: Gaussian  
Correlation: exchangeable  
Scale parameter: 9203.121  
Wald chi2(2) = 71.77  
Prob > chi2 = 0.0000

(standard errors adjusted for clustering on firm)

i	Coef.	Semi-robust Std. Err.	z	P> z	[95% Conf. Interval]
f	.1097626	.0136213	8.06	0.000	.0830655 .1364598
c	.307942	.0548629	5.61	0.000	.2004128 .4154712
_cons	-57.7672	24.55615	-2.35	0.019	-105.8964 -9.638037

Grunfeld Again and Again, Part 1

	<b>OLS</b>	<b>avg(10xOLS) unweighted</b>	<b>Between</b>	<b>Within (oneway)</b>	<b>R.E. (Am) (oneway)</b>
f (market value)	0.116 (0.006)	0.091 (0.042)	0.135 (0.029)	.110 (0.012)	0.110 (0.010)
c (capital stock)	0.231 (0.025)	0.205 (0.067)	0.032 (0.191)	0.310 (0.017)	0.308 (0.017)
constant	-42.7 (9.5)	-21.4 (58.9)	-8.53 (47.5)	-58.7 (12.5)	-7.92 (4.00)
firm indicators	--	--	--	Yes	--
year indicators	--	--	--	--	--
i_(t-1) lagged investment	--	--	--	--	--

Grunfeld Again and Again, Part 2

	<b>OLS</b>	<b>B&amp;K PCSE</b>	<b>FE PCSE</b>	<b>GLS (robust)</b>	<b>FGLS het,AR(1)</b>
f (market value)	0.116 (0.006)	0.116 (0.007)	0.110 (0.018)	0.110 (0.014)	0.072 (0.009)
c (capital stock)	0.231 (0.025)	0.231 (0.028)	0.310 (0.025)	0.308 (0.055)	0.141 (0.031)
constant	-42.7 (9.5)	-42.7 (6.8)	--	-57.8 (24.6)	-2.00 (6.8)
firm indicators	--	--	yes	--	--
year indicators	--	--		--	--
i <sub>t</sub> (t-1) lagged investment	--	--		--	--

Grunfeld Again and Again, Part 3

	<b>ArBond robust</b>	<b>A&amp;H FDIV</b>	<b>B&amp;K PCSE</b>	<b>Within-2</b>	<b>R.E. (Am) two-way</b>
f (market value)	0.106 (0.013)	0.092 (0.014)	0.117 (0.008)	0.118 (0.014)	0.112 (0.011)
c (capital stock)	0.139 (0.031)	0.671 (0.511)	0.220 (0.037)	0.358 (0.023)	0.325 (0.019)
constant	-1.53 (1.36)	0	0	0	-8.00 (3.87)
firm indicators	--	--	--	yes	--
year indicators	--	yes	yes	yes	--
i <sub>t</sub> (t-1) lagged investment	0.668 (0.080)	-0.601 (0.916)	--	--	--

**Pooled Intercept, Varying Slopes**

```

reg i f _fifrf_2 _fifrf_3 _fifrf_4 _fifrf_5 _fifrf_6 _fifrf_7 _fifrf_8 _fifrf_9
_fifrf_10 c _I
> _fifrc_2 _fifrc_3 _fifrc_4 _fifrc_5 _fifrc_6 _fifrc_7 _fifrc_8 _fifrc_9
_fifrc_10

```

Source	SS	df	MS
Model	9017883.96	20	450894.198
Residual	342059.957	179	1910.94948
Total	9359943.92	199	47034.8941

Number of obs = 200  
F( 20, 179) = 235.95  
Prob > F = 0.0000  
R-squared = 0.9635  
Adj R-squared = 0.9594  
Root MSE = 43.714

	1	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
_fifrf_2	f	.0872213	.0046097	18.92	0.000	.0781249 .0963177
_fifrf_3	f	.0703704	.0116173	6.06	0.000	.047446 .0932949
_fifrf_4	f	-.0593291	.0103507	-5.73	0.000	-.0797542 -.0389039
_fifrf_5	f	.0000671	.026621	0.00	0.998	-.0524643 .0525984
_fifrf_6	f	.2429773	.233709	1.04	0.300	-.218202 .7041566
_fifrf_7	f	.0634017	.1377529	0.46	0.646	-.2084268 .3352301
_fifrf_8	f	.0421774	.167553	0.25	0.802	-.2884559 .3728107
_fifrf_9	f	-.0132334	.03838	-0.34	0.731	-.0889688 .062502
_fifrf_10	f	.0007175	.1243338	0.01	0.995	-.2446311 .2460661
c	c	.0831719	.3224964	0.26	0.797	-.553212 .7195557
_fifrc_2	c	.3825272	.0172113	22.23	0.000	.3485641 .4164903
_fifrc_3	c	.0020079	.0641753	0.03	0.976	-.1285762 .132592
_fifrc_4	c	-.2303208	.0430791	-5.35	0.000	-.315329 -.1453126
_fifrc_5	c	-.0676998	.0962194	-0.70	0.483	-.2575702 .1221705
_fifrc_6	c	-.3924791	.1066863	-3.68	0.000	-.6030038 -.1819544
_fifrc_7	c	-.3404627	.4978163	-0.68	0.495	-1.322806 .6418809
_fifrc_8	c	-.2529759	.07327	-3.45	0.001	-.3975599 -.1083918
_fifrc_9	c	-.3226458	.2256228	-1.43	0.154	-.7678685 .1225769
_fifrc_10	c	-.2979863	.1340945	-2.22	0.028	-.5625958 -.0333768

._firxc_10	.2402446	2.985162	0.08	0.936	-5.650392	6.130881
_cons	-12.8802	12.96132	-0.99	0.322	-38.45684	12.69644

**Pooled Slopes, Varying Intercepts**  
 . reg i f c f1 f2 f3 f4 f5 f6 f7 f8 f9 f10, nocons

Source	SS	df	MS	Number of obs =	200
Model	13097228	12	1091435.66	F (12, 188) =	391.97
Residual	523478.114	188	2784.45805	Prob > F =	0.0000
Total	13620706.1	200	68103.5304	R-squared =	0.9616
				Adj R-squared =	0.9591
				Root MSE =	52.768

i	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
F	.1101238	.0118567	9.29	0.000	.0867345 .1335131
C	.3100653	.0173545	17.87	0.000	.2758308 .3442999
f1	-.70.29669	49.70796	-1.41	0.159	-168.3537 27.76034
f2	101.9058	24.93832	4.09	0.000	52.71093 151.1007
f3	-.235.5718	24.43162	-9.64	0.000	-283.7672 -187.3765
f4	-.27.80929	14.07775	-1.98	0.050	-55.57995 -.038631
f5	-.114.6168	14.16543	-8.09	0.000	-142.5604 -86.67319
f6	-.23.16129	12.66874	-1.83	0.069	-48.15244 1.829856
f7	-.66.55347	12.84297	-5.18	0.000	-91.88833 -41.21862
f8	-.57.54565	13.99315	-4.11	0.000	-85.14941 -29.9419
f9	-.87.22227	12.89189	-6.77	0.000	-112.6536 -61.79091
f10	-.6.567843	11.82689	-0.56	0.579	-29.89831 16.76262

**Pooled Slopes & Intercept**  
 . reg i f c

Source	SS	df	MS	Number of obs =	200
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Model1	7604093.48	2	3802046.74			F ( 2, 197) =	426.58		
Residual	1755850.43	197	8912.94636			Prob > F	= 0.0000		
						R-squared	= 0.8124		
						Adj R-squared	= 0.8105		
Total	9359943.92	199	47034.8941			Root MSE	= 94.408		

i	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
f	.1155622	.0058357	19.80	0.000	.1040537 .1270706
c	.2306785	.0254758	9.05	0.000	.1804382 .2809188
_cons	-42.71437	9.511676	-4.49	0.000	-61.47215 -23.95659

**Varying Slopes & Intercept**

```
. reg i f _Ifixf_2 _Ifixf_3 _Ifixf_4 _Ifixf_5 _Ifixf_6 _Ifixf_7 _Ifixf_8 _Ifixf_9
_Ifixf_10 c _I
> fixc_2 _Ifixc_3 _Ifixc_4 _Ifixc_5 _Ifixc_6 _Ifixc_7 _Ifixc_8 _Ifixc_9
_Ifixc_10 f1 f2 f3 f4 f5
> f6 f7 f8 f9 f10, nocons
```

Source	SS	df	MS	Number of obs =	200
Model1	13295977.5	30	443199.251	F ( 30, 170) =	232.02
Residual	324728.552	170	1910.16795	Prob > F	= 0.0000
				R-squared	= 0.9762
				Adj R-squared	= 0.9720
Total	13620706.1	200	68103.5304	Root MSE	= 43.705

i	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
f	.1192808	.012302	9.70	0.000	.0949965 .1435651
_Ifixf_2	.0555752	.0358072	1.55	0.123	-.0151088 .1262592
_Ifixf_3	-.0927296	.0273253	-3.39	0.001	-.1466703 -.038789
_Ifixf_4	-.041333	.0668818	-0.62	0.537	-.1733589 .0906928

__FfrrXF_5	.0430969	.2752797	0.16	0.876	-.5003098	.5865035
__FfrrXF_6	.012174	.1690119	0.07	0.943	-.3214583	.3458064
__FfrrXF_7	-.0317536	.304842	-0.10	0.917	-.6335169	.5700096
__FfrrXF_8	-.0663867	.0683301	-0.097	0.333	-.2012714	.068498
__FfrrXF_9	-.0438929	.163553	-0.27	0.789	-.3667492	.2789634
__FfrrXF_10	-.1147074	1.093767	-0.10	0.917	-2.273823	2.044408
__C	.3714448	.0176537	21.04	0.000	.3365961	.4062935
__FfrrXC_2	.0181971	.0668942	0.27	0.786	-.1138532	.1502473
__FfrrXC_3	-.2197509	.0439884	-5.00	0.000	-.3065847	-.1329171
__FfrrXC_4	-.0557266	.0964656	-0.58	0.564	-.2461514	.1346982
__FfrrXC_5	-.3683431	.1073683	-3.43	0.001	-.5802899	-.1563962
__FfrrXC_6	-.2860706	.5426892	-0.53	0.599	-1.357348	.7852069
__FfrrXC_7	-.2476634	.0811476	-3.05	0.003	-.4078501	-.0874767
__FfrrXC_8	-.2790383	.240715	-1.16	0.248	-.7542138	.1961372
__FfrrXC_9	-.2893412	.1356119	-2.13	0.034	-.5570415	-.021641
__FfrrXC_10	.0659244	3.204899	0.02	0.984	-6.260599	6.392448
F1	.149.7824	50.40091	-2.97	0.003	-249.2746	-50.29017
F2	-.49.19831	67.10986	-0.73	0.465	-181.6743	83.27768
F3	-9.956308	49.17834	-0.20	0.840	-107.0352	87.12256
F4	-6.189955	44.45563	-0.14	0.889	-93.94611	81.5662
F5	22.70711	33.13412	0.69	0.494	-42.70019	88.11442
F6	-8.685544	24.57788	-0.35	0.724	-57.20269	39.8316
F7	-4.499533	52.39817	-0.09	0.932	-107.9344	98.93533
F8	-.5093876	34.30018	-0.01	0.988	-68.21852	67.19974
F9	-7.72284	44.95757	-0.17	0.864	-96.46984	81.02416
F10	.1615187	83.1752	0.00	0.998	-164.0277	164.3508

**Ad hoc restrictions for some varying slopes & intercepts**

. reg i f \_IfirXF\_3 c \_IfirXC\_3 \_IfirXC\_5 \_IfirXC\_7 \_IfirXC\_9 f1 f2 f4 f6 f8, nocons

Source	SS	df	MS	Number of obs =
Model	13262843.4	12	1105236.95	200
Residual	357862.678	188	1903.52488	F(12, 188) = 580.63
Total	13620706.1	200	68103.5304	Prob > F = 0.0000
				R-squared = 0.9737
				Adj R-squared = 0.9720
				Root MSE = 43.629

	1	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
f		.11374	.0107487	10.58	0.000	.0925363 .1349436
_IfirXF_3		-.0917551	.0142069	-6.46	0.000	-.1197805 -.0637297
c		.368109	.0165488	22.24	0.000	.3354638 .4007542
_IfirXC_3		-.2181603	.0426321	-5.12	0.000	-.302259 -.1340616
_IfirXC_5		-.3021013	.0240904	-12.54	0.000	-.3496234 -.2545791
_IfirXC_7		-.267541	.0326215	-8.20	0.000	-.3318922 -.2031899
_IfirXC_9		-.3506112	.0350371	-10.01	0.000	-.4197276 -.2814948
f1		-123.6061	44.31642	-2.79	0.006	-211.0275 -36.18476
f2		77.66093	21.95567	3.54	0.001	34.3498 120.9721
f4		-37.35355	11.92762	-3.13	0.002	-60.88272 -13.82439
f6		-30.73267	10.58462	-2.90	0.004	-51.61256 -9.852785
f8		-64.94263	11.8607	-5.48	0.000	-88.33979 -41.54547

F = ((357, 862-324, 729) / 18) / ((324, 728 / 170)) = 0.9

$$F = \frac{(SSR_R - SSR_U) / r}{SSR_U / df}$$

$SSR_0 = 342,059.957$	$(k=21)$	$\alpha, \beta_i$	
$SSR_1 = 523,478.114$	$(k=12)$	$\alpha_i, \beta$	FE
$SSR_2 = 324,728.552$	$(k=30)$	$\alpha_i, \beta_i$	10x OLS
$SSR_3 = 1,755,850.43$	$(k=3)$	$\alpha, \beta$	OLS

$$F_1 = \frac{(1,755,850.43 - 324,728.55) / 27}{324,728.55 / 170} = 27.8 \checkmark$$

$$F_2 = \frac{(342,059.96 - 324,728.55) / 9}{324,728.55 / 170} = 1.01 \checkmark$$

$$F_3 = \frac{(523,478.11 - 324,728.55) / 18}{324,728.55 / 170} = 5.78 \checkmark$$

$$F_4 = \frac{(357,862.68 - 324,728.55) / 18}{324,728.55 / 170} = 0.9 \quad (\text{ad hoc inductive model})$$

## WHAT ARE THE ISSUES IN ESTIMATING PD MODELS?

### A. Dynamic or Static?

include lagged d.v. on right? if so, how?  
guide: theory, ideally  
tests: unsettled

TS rule of thumb: you need ~50 observations

PD with smallish T contain multiple instances of TS,  
so more variation to exploit than size of T suggests  
BUT ability to lag and difference is limited by small T  
and ability to test rival forms of dynamics (AR, DL, MA,...) is  
limited

### B. 1. Serial correlation?

This is not the same question as whether the data-generating process is dynamic, though serially correlated errors are a form of dynamics. MC studies show that

if the Data Generating Process has equation dynamics and the models do not, there are spurious error dynamics. The converse is true as well.

### B.2.Heteroscedasticity?

In cross-sectional models, “robust std errors” have caught on in a huge way. Poli-sci seems to be moving towards a norm that one should always compute robust SEs, without any explanation of why they are necessary. Though it is true that WLS is a lot of trouble (comparatively) in the XS world, when it is the SEs that we are worried about, robust SEs don’t always make sense. Extension of the robust idea to PD models is not always straight-forward (though STATA allows the “robust” option on some of the `xt` procedures).

### C. Poolability

of intercepts...  
over time? over space?  
of slopes...  
over time? over space?

We can't test all of the above (at once). We impose some constraints by theory or according to panel dimensions. OLS on the whole NT sample is the ultimate pool (almost always rejected by data).

tests: depends on whether effects assumed to be random or fixed  
(and complicated by dynamic specification)

Ongoing debate (especially in dynamic models) whether heterogeneous coefficients are necessary.

#### D. Balance

Lack of balance in the panel at minimum complicates computations.

Severe imbalance wreaks havoc—known results for balanced panels do not carry over to unbalanced panels.

Asymptotics complicated by variation in T across units (or in N across waves).

There are a variety of measures of balance to do quick checks on whether the unbalance is “severe” or not.

#### E. Specification

Not uniquely a PD problem, but a generic issue that is probably the most fundamental problem for most of our problems much of the time, whatever the data structure.

#### F. Spatial auto-correlation

New rapidly growing area—very complicated likelihood functions, but software emerging.

“Finally, it should be noted that although panel data offer many advantages, they are not panacea. The power of panel data analysis depends critically on the compatibility of the assumptions of statistical tools with the data generating process. Otherwise, misleading inference will follow.”

(Cheng Hsiao)