

SOME SPECIFICATION TESTS

November 9, 2005

1. Poolability Tests for One-Way Fixed Effects

At the end of the “Analysis of Covariance” handout from October 19, I defined three F statistics to test “poolability,” that is, constraints applied to all of one or more categories of fixed effects. Unfortunately, the degrees of freedom were wrong—sorry! So let’s reconsider such tests, first in the fixed effects context, and then in the random effects context. Start with the most generic model, as in the beginning of Hsiao’s chapter 2:

$$y_{it} = \alpha_{it} + x'_{it}\beta_{it} + u_{it} \quad (1.1)$$

Here x_{it} and β_{it} are $k \times 1$ vectors. We previously noted that this model cannot be estimated (at least not while we regard effects as fixed), since it has more parameters ($NT(K+1)$) than degrees of freedom (NT). One way to impose identification restrictions is to assume that all the parameters are constant over time. (This is not the only way to proceed, of course. For instance, one could instead assume constancy over space (i.e. cross-sectional units) and then test time-constancy restrictions.)

These assumed constraints give us:

$$y_{it} = \alpha_i + x'_{it}\beta_i + u_{it} \quad (1.2)$$

Now we have only $N(k+1)$ parameters, which means the model can be estimated provided that $T > (k+1)$, in which case we have $N(T - (k+1))$ degrees of freedom for estimating this “unrestricted” model. The simplest, most natural tests for pooling involve restrictions of constancy across space for *all* of the intercepts, slopes, or both.

As in Section 3 of the ANCOVA handout, a null hypothesis is that both slopes and intercepts are constant:

$$H_0 : \alpha_1 = \alpha_2 = \dots = \alpha_N \text{ and } \beta_1 = \beta_2 = \dots = \beta_N.$$

That hypothesis corresponds to imposing $(N-1)(k+1)$ restrictions on (1.2), to give:

$$y_{it} = \alpha + x'_{it}\beta + u_{it} \quad (1.3)$$

Typeset by $\mathcal{A}\mathcal{M}\mathcal{S}\text{-}\mathcal{T}\mathcal{E}\mathcal{X}$

A first alternative hypothesis maintains only the assumption of constant slopes, while allowing intercepts to vary:

$$H_1 : \alpha_i \neq \alpha_j \text{ for some } i \text{ and } j \text{ and } \beta_1 = \beta_2 = \dots = \beta_N.$$

This hypothesis corresponds to imposing $(N-1)k$ restrictions on (1.2) to give:

$$y_{it} = \alpha_i + x'_{it}\beta + u_{it} \quad (1.4)$$

Or, equivalently, one can get (1.3) by imposing on (1.4) an additional $(N-1)$ restrictions representing equality of all the alphas.

A second alternative hypothesis is that slopes vary, but not intercepts:

$$H_2 : \alpha_1 = \alpha_2 = \dots = \alpha_N \text{ and } \beta_j \neq \beta_k \text{ for some } j, k.$$

This hypothesis corresponds to imposing $(N-1)k$ restrictions on (1.2) to give:

$$y_{it} = \alpha + x'_{it}\beta_i + u_{it} \quad (1.5)$$

Or, equivalently, by imposing an additional $(N-1)k$ restrictions on (1.5), that is, equality of all the betas, one can get (1.3). Hsiao ignores this possibility, and I cannot recall having seen an application in which this test seemed plausible.

Still another alternative hypothesis is that both intercepts and slopes vary across units:

$$H_3 : \alpha_i \neq \alpha_j \text{ and } \beta_k \neq \beta_l \text{ for some } i, j, k \text{ and } l.$$

This hypothesis, of course, corresponds to (1.2).

It will be assumed that the matrix of regressors is non-stochastic and of full column rank and that u_{it} is i.i.d. $N(0, \sigma^2)$.

With each hypothesis, one can associate an error sum of squares:

$$SSE_j = \sum_{i=1}^N \sum_{j=1}^T \hat{u}_{it(j)}^2 \quad (j = 0, 1, 2, 3)$$

where $\hat{u}_{it(j)}$ is the least squares residual obtained by imposing H_j :

$$\hat{u}_{it(j)} = y_{it} - \hat{\alpha}_{i(j)} - x'_{it}\hat{\beta}_{i(j)}$$

Consider first H_0 . To obtain $\hat{u}_{(0)}$, regress y on X and a constant, then use Proposition 1 from the ANCOVA handout (i.e. the two-step estimation result):

$$\hat{\beta}_{i(0)} = \left(\sum_{i=1}^N \sum_{t=1}^T (x_{it} - \bar{x}_{..})(x_{it} - \bar{x}_{..})' \right)^{-1} (x_{it} - \bar{x}_{..})y_{it} \equiv \hat{\beta}_{(0)}$$

$$\hat{\alpha}_{i(0)} = \bar{y}_{..} - \bar{x}'_{..}\hat{\beta}_{(0)}$$

It follows that:

$$\hat{u}_{it(0)} = (y_{it} - \bar{y}_{..}) - (x_{it} - \bar{x}_{..})' \hat{\beta}_{(0)} \quad (1.6)$$

Next, under H_1 , Proposition 2 gives $\hat{\beta}_{i(1)} = \beta_W$ and $\hat{\alpha}_{i(1)} = \bar{y}_i - \bar{x}'_i \hat{\beta}_W$, so:

$$\hat{u}_{it(1)} = (y_{it} - \bar{y}_i) - (x_{it} - \bar{x}_i)' \hat{\beta}_W = \tilde{y}_{it} - \tilde{x}'_{it} \hat{\beta}_W \quad (1.7)$$

which are the residuals from the within-groups regression.

The coefficients in the unrestricted regression (1.2) can be estimated by applying least squares separately to each of the N sets of T observations, yielding:

$$\hat{\beta}_{i(3)} = \left(\sum_{t=1}^T (x_{it} - \bar{x}_i)(x_{it} - \bar{x}_i)' \right)^{-1} \sum_{t=1}^T (x_{it} - \bar{x}_i)(y_{it} - \bar{y}_i)$$

$$\hat{\alpha}_{i(3)} = \bar{y}_i - \bar{x}'_i \hat{\beta}_{i(3)}$$

Upon substitution:

$$\hat{u}_{it(2)} = (y_{it} - \bar{y}_i) - (x_{it} - \bar{x}_i)' \hat{\beta}_{i(2)} \quad (1.8)$$

The residual sums of squares can be computed using (1.6), (1.7), and (1.8). In turn, we can form an F statistic to test H_0 against H_3 as follows:

$$F_3 = \frac{(SSE_0 - SSE_3)/((N-1)(k+1))}{SSE_3/(N(T-(k+1)))}$$

where we make use of the fact that under H_0 , F_3 follows an F distribution with $(N-1)(k+1)$ numerator d.f. and $NT - Nk - N$ denominator d.f. (This is Hsiao's F_3 , but what I'm labelling SSE_0 is his S_3 , my SSE_3 is his S_1 , and my H_0 is his H_3 .)

To test H_1 against H_3 , form:

$$F_1 = \frac{(SSE_1 - SSE_3)/((N-1)k)}{SSE_3/(N(T-(k+1)))}$$

where we make use of the fact that under H_1 , F_1 follows an F distribution with $(N-1)k$ numerator d.f. and $NT - Nk - N$ denominator d.f. (This is Hsiao's F_1 , and this time our H_1 s agree (but my notation for F statistics was inconsistent.))

At the outset, we assumed, without testing, constancy over time. We could instead have assumed constancy across units, and then tested for constant parameters over time. For instance, we could have found the SSE from running 20 different OLS models each having 10 observations and 3 parameters (and thus only 7 degrees of freedom). Then we could then have computed a test statistic that would be distributed as $F(57, 140)$, to test the 57 restrictions imposed on these models to yield a single OLS regression for the whole sample. In this case, the dimensions of the panel weakly favour the opposite approach, since $T > N$. With very small N or T , one approach or the other is likely to be infeasible.

2. Poolability in Two-Way Fixed Effects Extending the F tests in section 1 to two-way models is fairly simple, since the difference between one-way and two-way fixed effects models is simply a set of restrictions on parameters exactly like the restrictions we were just testing. Thus, given a two-way model with constant parameters:

$$y_{it} = \alpha_i + \eta_t + x'_{it}\beta + u_{it} \quad (2.1)$$

one can test the T restrictions that generate the one-way model:

$$y_{it} = \alpha_i + x'_{it}\beta + u_{it} \quad (2.2)$$

with an F test based on SSE of the unrestricted (2.1) and the restricted (2.2). A difficulty—which is generic to specification tests, not unique to the panel data context—is that there are huge numbers of possible restrictions, that can be nested in huge numbers of ways. Thus far, for simplicity, we have considered only tests that restrict whole sets of parameters simultaneously. Suppose that we start with:

$$y_{it} = \alpha_i + \eta_t + x'_{it}\beta_t + u_{it} \quad (2.3)$$

and assume that we want to test for change points, which multiple runs of β s that are equal. Even if we know that we expect only one change point, there are $T - 2$ restricted models to examine (fewer if we set a minimum number of observations per “regime”). If we don’t allow for an unknown number of change points, the number of possible restricted models grows exponentially, even before we bring in possible restrictions on the fixed effects.

There is a very large literature on change points, some of which can be adapted to the panel data context, but we will not wade into this topic in our remaining weeks. Obviously, between the extremes of estimating all parameters for the model separately by spatial unit (or time unit) and estimating a pooled model with no time or space effects, there are many intermediate assumptions. In chapter 6, Hsiao discusses a variety of varying-coefficient models. Baltagi doesn’t really try to include the topic.

2. Poolability Tests for Random Effects Perhaps surprisingly, the same basic framework as in Section 1 works to test poolability under the random effects, or error components, perspective as well. The key step in generating random effects estimates was estimating the variance components, and then using those to construct weights such that WLS would give the GLS estimates we sought. Since the estimation, after weighting, is just by OLS, the procedure from Section 1 carries over. Skipping the technical details, the F test is a special case of a procedure outlined by Roy and Zellner, so the random effects version of the F test described above is called the “Roy-Zellner test” for poolability. Since Ω and Σ are not actually known, but estimated, the test statistic only approximately follows an F distribution.

These F tests are not the last word on pooling. In particular, there might be reason to trade off lower variance for some bias, in which case some other criterion like MSE would be necessary. As usual, there’s a not-small, rather technical literature to explore, but we’ll not wade into it right now.

Grunfeld Data: one-way model poolability (F) tests

$H_0: \alpha_i = \alpha_j, \beta_k = \beta_l$ for all $i, j; k, l$ vs.
 $H_3: \alpha_i \neq \alpha_j, \beta_k \neq \beta_l$ for some $i, j; k, l$

[unrestricted estimates — estimate coefficients for each firm in separate model]

. reg i f c if (firm==1)

Source	SS	df	MS	Number of obs =
Model	1677686.65	2	838843.326	F(2, 17) = 99.58
Residual	143205.85	17	8423.87352	Prob > F = 0.0000
				R-squared = 0.9214
Total	1820892.5	19	95836.4475	Adj R-squared = 0.9121
				Root MSE = 91.782

i	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
f	.1192808	.0258342	4.62	0.000	.0647755 .1737861
c	.3714448	.0370728	10.02	0.000	.293228 .4496616
_cons	-149.7824	105.8421	-1.42	0.175	-373.0897 73.52493

. reg i f c if (firm==2)

Source	SS	df	MS	Number of obs =
Model	140682.043	2	70341.0214	F(2, 17) = 7.56
Residual	158093.277	17	9299.60455	Prob > F = 0.0045
				R-squared = 0.4709
Total	298775.32	19	15725.0168	Adj R-squared = 0.4086
				Root MSE = 96.434

i	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
f	.174856	.0741981	2.36	0.031	.0183118 .3314002
c	.3896419	.1423669	2.74	0.014	.089274 .6900097
_cons	-49.19831	148.0754	-0.33	0.744	-361.61 263.2134

[etc. through (firm==10)]

. reg i f c if(firm==10)

Source	SS	df	MS	Number of obs =
Model	36.0953645	2	18.0476822	20
Residual	20.026731	17	1.178043	F(2, 17) = 15.32
Total	56.1220955	19	2.9537945	Prob > F = 0.0002
				R-squared = 0.6432
				Adj R-squared = 0.6012
				Root MSE = 1.0854

i	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
f	.0045734	.0271608	0.17	0.868	-.0527308 .0618777
c	.4373692	.0795889	5.50	0.000	.2694513 .6052871
_cons	.1615187	2.065564	0.08	0.939	-4.196441 4.519478

yields $SSE_3 = 143,205.85 + 158,093.28 + 13,216.59 + 2,997.44 + 1,396.84 + 1,110.53 + 1,507.40 + 1,773.23 + 1,407.36 + 20.026731 = 324,728.55$

H₁: $\alpha_i = \alpha_j, \beta_k \neq \beta_l$ for all i, j ; for some k, l vs.
H₃: $\alpha_i \neq \alpha_j, \beta_k \neq \beta_l$ for some $i, j; k, l$

```
. anova i f c firm, continuous(f c)
Number of obs = 200      R-squared = 0.9441
Root MSE = 52.768      Adj R-squared = 0.9408
```

Source	Partial SS	df	MS	F	Prob > F

Model	8836465.8	11	803315.073	288.50	0.0000
f	240201.566	1	240201.566	86.27	0.0000
c	88838.4	1	88838.4	319.21	0.0000
firm	1232372.32	9	136930.258	49.18	0.0000
Residual	523478.114	188	2784.45805		

Total	9359943.92	199	47034.8941		

Note that default ANCOVA table F-tests from STATA also test hypotheses on $\beta=0$ so they aren't equivalent to the F we defined to evaluate poolability of slopes allowing for variable intercepts. Instead, form:

$$F_1 = \frac{[SSE_1 - SSE_3 / (N-1)k]}{[SSE_3 / (N(T-(k+1)))]}$$

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

a smaller F, but still $\mathbf{p=0.000}$, so we can reject poolability of slopes with varying intercepts

p. 58 “Note that one could have tested poolability across time. The Chow test gives an observed value of 1.12 which is distributed as $F(57,140)$. This does not reject poolability across time...”

```
.gen urss=0
.foreach y of numlist 1935/1954 {
2. reg i f c if[year==`y']
3. replace urss=urss+e(rss)
4. }
```

Source	SS	df	MS	Number of obs = 10	
Model	84964.8462	2	42482.4231	F(2, 7) =	22.48
Residual	13230.6643	7	1890.0949	Prob > F	= 0.0009
				R-squared	= 0.8653
Total	98195.5105	9	10910.6123	Adj R-squared	= 0.8268
				Root MSE	= 43.475

i	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
f	.1024979	.0157931	6.49	0.000	.0651532 .1398425
c	-.0019948	.2148591	-0.01	0.993	-.5100557 .5060662
_cons	.3560334	23.82794	0.01	0.988	-55.98808 56.70015

(200 real changes made)
(ETC.)

```
. list urss in 1
+-----+
|      urss      |
+-----+
1. | 1205818 |
+-----+
F=((1,755,850.43 - 1,205,818)/57)/(1,205,818/140) = 1.12 (p=0.29)
```

In a random effects context, we can perform exactly the same tests, but with WLS instead of OLS, with the weights determined by estimates of the error components. I previously demonstrated calculation of thetas (the weighting parameters) and then FGLS estimation using these thetas.

[canned random effects (Swamy-Arora) does not output SSE]

```

. xtreg i f c, i(firm) sa
Random-effects GLS regression
Group variable (i): firm
Number of obs = 200
Number of groups = 10

R-sq:  within = 0.7668
      between = 0.8196
      overall = 0.8061

Random effects u_i ~ Gaussian
corr(u_i, X) = 0 (assumed)
Wald chi2(2) = 657.67
Prob > chi2 = 0.0000

-----+-----
i |      Coef.   Std. Err.      z    P>|z|    [95% Conf. Interval]
-----+-----
f |      .1097811   .0104927    10.46   0.000   .0892159   .1303464
c |      .308113   .0171805    17.93   0.000   .2744399   .3417861
_cons |     -57.83441   28.89893    -2.00   0.045   -114.4753  -1.193537
-----+-----
sigma_u |      84.20095
sigma_e |     52.767964
rho     |     .71800838   (fraction of variance due to u_i)
-----+-----

```

[we could generate SSE or we could just run WLS, given θ]

[for Swamy-Arora, estimated $\theta=0.861224$ (2nd ed. and p. 22, 3rd ed.)]

```
. gen isw=(i-0.861224*ib)
. gen csw=(c-0.861224*cb)
. gen fsw=(f-0.861224*fb)
. reg isw fsw csw
```

Source	SS	df	MS		Number of obs =
Model	1832485.78	2	916242.888		200
Residual	548903.934	197	2786.31439		F(2, 197) = 328.84
Total	2381389.71	199	11966.7825		Prob > F = 0.0000
					R-squared = 0.7695
					Adj R-squared = 0.7672
					Root MSE = 52.786

isw	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
fsw	.1097811	.0104927	10.46	0.000	.0890888 .1304735
csw	.308113	.0171805	17.93	0.000	.2742318 .3419942
_cons	-8.026028	4.010488	-2.00	0.047	-15.93503 -.1170292

So $F = [SSE_0 - SSE_3 / (N-1)(k+1)] / [SSE_3 / (N(T-(k+1)))]$

$$= (548,903.93 - 324,728.55) / 27 / (324,728.55 / 170) = \mathbf{4.35}$$

```
. display F(27,170,4.35)
```

So we reject poolability of all coefficients even when allowing for one-way error component disturbances. [Compare Baltagi 3rd ed., page 58, 'Roy-Zellner']

Two-Way or One-Way Fixed Effects?

. anova i f c firm year, continuous(f c) reg nocons

Source	SS	df	MS	Number of obs =
Model	131168559	31	424792.227	F(31, 169) = 158.78
Residual	452147.043	169	2675.42629	Prob > F = 0.0000
				R-squared = 0.9668
				Adj R-squared = 0.9607
Total	13620706.1	200	68103.5304	Root MSE = 51.725

	i	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
f		.1177158	.0137513	8.56	0.000	.0905694 .1448623
c		.3579163	.022719	15.75	0.000	.3130667 .4027659
firm						
	1	-180.4264	65.00055	-2.78	0.006	-308.744 -52.10879
	2	26.62781	36.91653	0.72	0.472	-46.24913 99.50474
	3	-315.6572	37.07073	-8.51	0.000	-388.8386 -242.4759
	4	-85.0726	25.05781	-3.40	0.001	-134.5392 -35.60598
	5	-185.865	27.22086	-6.83	0.000	-239.6018 -132.1283
	6	-77.53781	23.48448	-3.30	0.001	-123.8985 -31.17708
	7	-128.9598	24.81305	-5.20	0.000	-177.9433 -79.97639
	8	-112.9359	24.70425	-4.57	0.000	-161.7046 -64.16725
	9	-150.2089	24.9983	-6.01	0.000	-199.558 -100.8597
	10	-53.58933	21.59303	-2.48	0.014	-96.21613 -10.96253
year						
	1	93.52622	27.10786	3.45	0.001	40.01258 147.0399
	2	74.32881	26.28383	2.83	0.005	22.4419 126.2157
	3	52.83621	26.07413	2.03	0.044	1.363259 104.3092
	4	54.29982	26.0657	2.08	0.039	2.843504 105.7561
	5	24.05593	25.52497	0.94	0.347	-26.33292 74.44478
	6	49.29115	25.45668	1.94	0.055	-9.9631395 99.54543
	7	74.72176	25.33737	2.95	0.004	24.70324 124.7403
	8	72.38643	25.49756	2.84	0.005	22.05169 122.7212
	9	50.5486	25.17805	2.01	0.046	.8446089 100.2526

	SS	df	MS	F(12, 188)	Prob > F	R-squared	Adj R-squared	Root MSE
10	50.42746	25.13577	2.01	0.046				
11	37.84319	24.95347	1.52	0.131				
12	62.35694	24.80931	2.51	0.013				
13	54.13398	24.7417	2.19	0.030				
14	49.80971	24.63549	2.02	0.045				
15	20.03112	24.43391	0.82	0.413				
16	17.63011	24.19119	0.73	0.467				
17	31.04532	23.67891	1.31	0.192				
18	28.89389	23.43739	1.23	0.219				
19	25.80826	23.22233	1.11	0.268				
20	(dropped)							

. anova i f c firm, continuous(f c) reg nocons

Source	SS	df	MS	F(12, 188)	Prob > F	R-squared	Adj R-squared	Root MSE
Model	13097228	12	1091435.66					
Residual	523478.114	188	2784.45805					
Total	13620706.1	200	68103.5304					

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
firm					
1	-70.29669	49.70796	-1.41	0.159	-168.3537 27.76034
2	101.9058	24.93832	4.09	0.000	52.71093 151.1007
3	-235.5718	24.43162	-9.64	0.000	-283.7672 -187.3765
4	-27.80929	14.07775	-1.98	0.050	-55.57995 -.038631
5	-114.6168	14.16543	-8.09	0.000	-142.5604 -86.67319
6	-23.16129	12.66874	-1.83	0.069	-48.15244 1.829856
7	-66.55347	12.84297	-5.18	0.000	-91.88833 -41.21862
8	-57.54565	13.99315	-4.11	0.000	-85.14941 -29.9419

9	-87.22227	12.89189	-6.77	0.000	-112.6536	-61.79091
10	-6.567843	11.82689	-0.56	0.579	-29.89831	16.76262

```

F = (SSER - SSEU/T-1) / (SSEU / (NT-N-k-T+1))
= ((523,478.11-452,147.04) / 19) / (452,147.04/179) = 1.49
. display F(19,179,1.49)
.9065414

```

So we do not reject the restriction of no time fixed effects, given space fixed effects.

Table 2

$$Y_{it} = \alpha_i + \eta_t + X_{it}\beta$$

incumbency indicator
test possible
if $\beta \neq 0$

Estimated Incumbency Effects on Conservative Percentage of Vote, 1950-59
(vote percentages; standard errors in parentheses; n=2424)

	Models (continued below)...				
	(1)	(2)	(3)	(4)	(5)
Conservative Incumbents					
General, Same	1.43 (0.38)	1.45 (0.38)	1.00 (0.36)	}	}
General, New	-0.05 (0.49)	-0.13 (0.48)			
By-, Same	0.85 (0.73)	0.99 (0.64)	0.95 (0.64)	}	}
By-, New	1.37 (1.16)				
General or By-, Same				1.35 (0.37)	0.99 (0.35)
General or By-, New				0.08 (0.47)	
Labour Incumbents					
General, Same	-0.73 (0.42)	-0.67 (0.42)	-0.97 (0.41)	}	}
General, New	-1.66 (0.51)	-1.70 (0.50)			
By-, Same	-1.61 (0.73)	-1.04 (0.55)	-0.82 (0.55)	}	}
By-, New	-0.49 (0.71)				
General or By-, Same				-0.74 (0.41)	-0.93 (0.40)
General or By-, New				-1.40 (0.48)	
Liberal (all)	-4.19 (1.84)	-4.12 (1.84)	-4.41 (1.84)	-4.10 (1.84)	-4.40 (1.84)
R^2	0.958	0.957	0.957	0.957	0.957
F_1		1.18	5.64	2.56	3.78
p value		0.307	0.000	0.037	0.001
...Models (continued from above)					
	...	(6)	(7)	(8)	(9)
Conserv. (+) or Labour (-) Inc.s					
General, Same		1.05 (0.21)	0.98 (0.21)	}	}
General, New		0.88 (0.28)			
By-, Same		1.19 (0.48)	0.87 (0.36)	}	}
By-, New		0.42 (0.54)			
General or By-, Same				1.02 (0.21)	0.97 (0.20)
General or By-, New				0.79 (0.26)	
Liberal (all)		-4.38 (1.82)	-4.45 (1.82)	-4.43 (1.81)	-4.42 (1.81)
R^2		0.957	0.957	0.957	0.957
F_1		4.97	3.76	3.48	3.24
p value		0.001	0.001	0.002	0.002

The Breusch-Pagan LM Test

In the one-way model, if $\text{var}(\mu_i) = \sigma_\mu^2 = 0$ then the RE are superfluous. So BP devised an LM test for $H_0: \sigma_\mu^2 = 0$. In the two-way model, the RE are superfluous if both $\sigma_\mu^2 = 0$ and $\sigma_\lambda^2 = 0$.

Derivation of the statistic is quite involved (to begin with, it is formulated in terms of the MLE estimator of the variance components, which we have (thus far) skipped), so I won't attempt to work through the math. But the key results are that:

$$LM_1 = \frac{NT}{2(T-1)} \left[1 - \frac{\tilde{u}'(I_N \otimes J_T)\tilde{u}}{\tilde{u}'\tilde{u}} \right]^2, \quad LM_2 = \frac{NT}{2(N-1)} \left[1 - \frac{\tilde{u}'(J_N \otimes I_T)\tilde{u}}{\tilde{u}'\tilde{u}} \right]^2$$

and $LM = LM_1 + LM_2$ where the u-tildes are the OLS residuals

Under H_0 , $LM \sim \chi_2^2$

However, BP uses two-sided alternative even though variances must be positive. Honda suggests:

$$HO = \sqrt{\frac{NT}{2(T-1)}} \left[\frac{\tilde{u}'(I_N \otimes J_T)\tilde{u}}{\tilde{u}'\tilde{u}} - 1 \right] \xrightarrow{H_0} N(0,1)$$

Breusch-Pagan LM Test on Grunfeld data

one-way random effects (space), $H_0: \sigma_u=0$

```
. xtreg i f c, i(firm) re
Random-effects GLS regression
Group variable (i): firm
Number of obs = 200
Number of groups = 10
R-sq: within = 0.7668
between = 0.8196
overall = 0.8061
Obs per group: min = 20
avg = 20.0
max = 20
Random effects u_i ~ Gaussian
corr(u_i, X) = 0 (assumed)
Wald chi2(2) = 657.67
Prob > chi2 = 0.0000
```

```
-----+-----
```

i	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
f	.1097811	.0104927	10.46	0.000	.0892159 .1303464
c	.308113	.0171805	17.93	0.000	.2744399 .3417861
_cons	-57.83441	28.89893	-2.00	0.045	-114.4753 -1.193537
sigma_u	84.20095				
sigma_e	52.767964				
rho	.71800838				

```
-----+-----
(fraction of variance due to u_i)
```

```
. xttest0
Breusch and Pagan Lagrangian multiplier test for random effects:
i[[firm,t]] = Xb + u[[firm]] + e[[firm,t]]
```


[For kicks, let's use R to check up on STATA's canned routines]

```
> grun <- read.csv("c:/documents/teaching/493Panel/grfldat.csv")
> y <- grun[,3]
> f <- grun[,4]
> c <- grun[,5]
> X <- grun[,4:5]
> X<- cbind(1,X)
>
> lm.OLS<-lm(y~f+c)
>
> e<- resid(lm.OLS)
> IN<-matrix(0,10,10)
> JT<-matrix(1,20,20)
>
> diag(IN) <-1
> M<-kronecker(IN,JT)
> LM1<-200/38*(1-t(e)%*M**e/t(e)%*%e)^2
> LM1
[1,] 798.1615
[ ,1]
```

```

> JN<-matrix(1,10,10)
> IT<-matrix(0,20,20)
> diag(IT)<-1
> M2<-kronecker(JN,IT)
> LM2<-200/18*(1-t(e)**M2**e/t(e)**e)^2
> LM2

      [,1]
[1,] 6.453882

> H1<-(200/38)^.5*(t(e)**M**e/t(e)**e-1)
> H1

      [,1]
[1,] 28.25175

Critical value around 1.645 (one-sided)
∴ reject null (there are unit effects)

> H2<-(200/18)^.5*(t(e)**M2**e/t(e)**e-1)
> H2

      [,1]
[1,] -2.540449

Critical value around 1.645 (one-sided)
∴ do not reject null (there are no time effects), & BP test misled us

See Baltagi, Chang, and Li for further refinements

```

Fixed or Random Effects?

previously, we estimated (one-way) random effects $I_{it} = \alpha + \beta_1 F_{it} + \beta_2 C_{it} + u_{it}$

$$w/ u_{it} = \mu_i + v_{it}$$

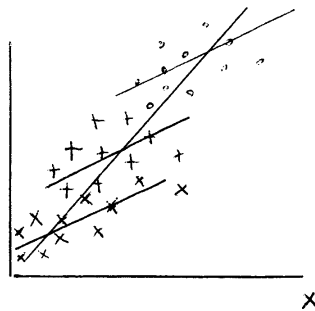
by FGLS, weighting with $\theta = 1 - \sqrt{\frac{\sigma_v^2}{T\sigma_\mu^2 + \sigma_v^2}}$

- if $\sigma_\mu^2=0$, $\theta=0$, there are no unit effects, and WLS is just OLS (as on the Baltagi table)
- if $\sigma_v^2=0$, $\theta=1$, and all the variation is within units (the within row shows $\theta=1$ on the Baltagi table)
- as T increases, θ goes to 0, and the FGLS model converges on the OLS model, and FE and RE differ less and less (Hsiao makes this point in section 3.4)

Whereas in ANOVA, we chose fixed or random effects on substantive grounds, now that we have covariates in addition to the space and time factors, the relationship between these covariates x_{it} and the effects (e.g the μ_i s) is critical. The random effects model treats them as uncorrelated; fixed effects does not. Otherwise, the models are “the same” and differ only insofar as θ differs from 0.

Hausman Test Intuition

- RE estimation does not wipe out time-invariant regressors or consume d.f. variation as FE estimation does, but it is biased when X is correlated with μ_i



common slopes
variable intercepts

$$X \uparrow \propto \mu_i$$

\therefore errors \uparrow X

given error structure

\rightarrow bias

idea behind Hausman statistic: is RE estimate significantly different from unbiased FE estimate?

Digression / Reminder

Limits

$$\lim_{x \rightarrow a} f(x) = A \quad \text{or} \quad f(x) \rightarrow A$$

means $\forall \epsilon > 0 \exists \delta > 0 \Rightarrow$

$$|f(x) - A| < \epsilon \quad \text{if } x \in D_f \text{ and}$$

$$0 < |x - a| < \delta$$

(D_f is domain of f)

Probability Limits

A necessary condition for consistency of estimator $\hat{\theta}_n$ (which is an estimator of population parameter θ) is that the ultimate distribution of $\hat{\theta}_n$ be degenerate at some point on the real line (i.e. converges to a single point).

The probability limit of $\hat{\theta}_n$ is the point on the real line to which its sampling distribution converges as the sample size increases without limit.

• $\hat{\theta} \xrightarrow{P} \theta_0$ (read as "converges in probability to")

• $\text{plim } \hat{\theta} = \theta_0$

• $\text{plim}_{n \rightarrow \infty} \hat{\theta}_n = \theta_0$

if: $P(|\hat{\theta}_n - \theta_0| \leq \varepsilon) = 1$ as $n \rightarrow \infty \quad \forall \varepsilon > 0$

or
 $\lim_{n \rightarrow \infty} P(-\varepsilon \leq \hat{\theta}_n - \theta_0 \leq \varepsilon) = 1$

HAUSMAN TEST

IF FE & RE MODELS ARE THE SAME EXCEPT FOR ASSUMPTIONS ABOUT $\text{cov}(\mu_i, x_{it})$, AND THEY DIFFER ONLY AS

$$\frac{\sigma_u^2}{T\sigma_{\mu}^2 + \sigma_u^2} \text{ DIFFERS FROM } 0 \text{ THEN}$$

• UNDER H_0 : $\text{cov}(\mu_i, x_{it}) = 0$, BOTH FE & RE ARE CONSISTENT, BUT RE MORE EFFICIENT

• UNDER H_A : $\text{cov}(\mu_i, x_{it}) \neq 0$, FE ESTIMATOR CONSISTENT, RE NOT

USE

$$\hat{q}_1 = \hat{\beta}_{GLS} - \tilde{\beta}_W$$

UNDER H_0 : $\text{plim } \hat{q}_1 = 0$

$$\text{cov}(\hat{q}_1, \hat{\beta}_{GLS}) = 0$$

$$\hat{\beta}_{GLS} - \beta = (X' \Omega^{-1} X)^{-1} X' \Omega^{-1} u$$

$$\tilde{\beta}_W - \beta = (X' Q X)^{-1} X' Q u, \quad Q = I_N \otimes C_T$$

∴ Hausman test stat

$$m_1 = \hat{q}'_1 [\text{var}(\hat{q}_1)]^{-1} \hat{q}_1 \stackrel{H_0}{\sim} \chi^2_k$$

We don't know Ω , so we use $\hat{\Omega}$ & $\hat{\beta}_{GLS}$
is actually $\hat{\beta}_{GLS}$

Hausman & Taylor derive equivalent tests from
comparisons using $\hat{\beta}_B$

$$\hat{q}_1 = \hat{\beta}_{GLS} - \tilde{\beta}_W$$

$$\hat{q}_2 = \hat{\beta}_{GLS} - \hat{\beta}_B$$

$$\hat{q}_3 = \tilde{\beta}_W - \hat{\beta}_B$$

$$m_i = \hat{q}'_i V_i^{-1} \hat{q}_i \quad V_i = \text{var}(\hat{q}_i)$$

all $\stackrel{H_0}{\sim} \chi^2_k$

Baltagi added $\hat{q}_4 = \hat{\beta}_{GLS} - \hat{\beta}_{OLS}$

$$Q = C_N \otimes C_T = I_N \otimes I_T - I_N \otimes \bar{J}_T - \bar{J}_N \otimes I_T + \bar{J}_N \otimes \bar{J}_T$$

$NT \times NT$
 $NT \times NT$

AND $\tilde{u} = Qu$ HAS ELEMENTS

$$\tilde{u}_{it} = (u_{it} - \bar{u}_i - \bar{u}_t + \bar{u}_{..})$$

(SO THIS $Q = W^*$ IN THE NERLOVE APPENDIX)

$$\therefore E(\hat{q}_1) = 0$$

$$\begin{aligned} \text{cov}(\hat{\beta}_{GLS}, \hat{q}_1) &= \text{var}(\hat{\beta}_{GLS}) - \text{cov}(\hat{\beta}_{GLS}, \tilde{\beta}_w) \\ &= (X' \Omega^{-1} X)^{-1} - (X' \Omega^{-1} X)^{-1} X \Omega^{-1} E(uu') \Omega X (X' \Omega^{-1} X)^{-1} \\ &= (X' \Omega^{-1} X)^{-1} - (X' \Omega^{-1} X)^{-1} = 0 \end{aligned}$$

$$\tilde{\beta}_w = \hat{\beta}_{GLS} - \hat{q}_1 \quad \text{so}$$

$$\text{var}(\tilde{\beta}_w) = \text{var}(\hat{\beta}_{GLS}) + \text{var}(\hat{q}_1)$$

$$\text{since } \text{cov}(\hat{\beta}_{GLS}, \hat{q}_1) = 0$$

$$\begin{aligned} \therefore \text{var}(\hat{q}_1) &= \text{var}(\tilde{\beta}_w) - \text{var}(\hat{\beta}_{GLS}) \\ &= \sigma_v^2 (X' \Omega X)^{-1} - (X' \Omega^{-1} X)^{-1} \end{aligned}$$

Baltagi Table 2.1 (1st.ed)

	β_1	β_2	$\theta=1-(\sigma_2/\sigma_1)$
OLS	0.11556 (0.00584)	0.23068 (0.02548)	0
Between	0.13465 (0.02875)	0.03203 (0.19094)	∞
Within	0.11012 (0.01186)	0.31007 (0.01735)	1
WALHUS	0.10973 (0.01029)	0.30765 (0.01724)	0.845779
AMEMIYA	0.10979 (0.01052)	0.30817 (0.01717)	0.863097
SWAR	0.10978 (0.01049)	0.30811 (0.01718)	0.861224
NERLOVE	0.10978 (0.01049)	0.30810 (0.01718)	0.860717
IMLE	0.10976 (0.01042)	0.30794 (0.01720)	0.855359

Grunfeld Data: one-way model Hausman test

```
. xtreg i f c, i(firm) re
Random-effects GLS regression           Number of obs   =   200
Group variable (i): firm                Number of groups  =   10
R-sq:  within = 0.7668                  Obs per group:   min =   20
      between = 0.8196                    avg             =  20.0
      overall  = 0.8061                    max             =   20
Random effects u_i ~ Gaussian           Wald chi2(2)     =  657.67
corr(u_i, X) = 0 (assumed)              Prob > chi2      =  0.0000
```

i	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
f	.1097811	.0104927	10.46	0.000	.0892159 .1303464
c	.308113	.0171805	17.93	0.000	.2744399 .3417861
_cons	-57.83441	28.89893	-2.00	0.045	-114.4753 -1.193537
sigma_u	84.20095				
sigma_e	52.767964				
rho	.71800838				(fraction of variance due to u_i)

```
. xthausman
(Warning: xthausman is no longer a supported command; use -hausman-. For instructions, see help hausman.)
Hausman specification test
```

----- Coefficients -----			
i	Fixed Effects	Random Effects	Difference
f	.1101238	.1097811	.0003427
c	.3100653	.308113	.0019524

Test: Ho: difference in coefficients not systematic

chi2(2) = (b-B)'[S^(-1)](b-B), S = (S_fe - S_re)

Prob>chi2 = 2.33

 = 0.3119

```

. xtreg i f c, fe i(firm)
Fixed-effects (within) regression
Group variable (i): firm
Number of obs = 200
Number of groups = 10
R-sq: within = 0.7668
      between = 0.8194
      overall = 0.8060
corr(u_i, Xb) = -0.1517
F(2,188) = 309.01
Prob > F = 0.0000

-----+-----
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
_cons | -58.74393 12.45369 -4.72 0.000 -83.31086 -34.177
-----+-----
sigma_u | 85.732501
sigma_e | 52.767964
rho | .72525012 (fraction of variance due to u_i)
F test that all u_i=0: F(9, 188) = 49.18 Prob > F = 0.0000

. est store fixed

. xtreg i f c, i(firm) re
Random-effects GLS regression
Group variable (i): firm
Number of obs = 200
Number of groups = 10
R-sq: within = 0.7668
      between = 0.8196
      overall = 0.8061
Random effects u_i ~ Gaussian
corr(u_i, X) = 0 (assumed)
Wald chi2(2) = 657.67
Prob > chi2 = 0.0000

-----+-----
i | Coef. Std. Err. z P>|z| [95% Conf. Interval]
-----+-----
f | .1097811 .0104927 10.46 0.000 .0892159 .1303464
c | .308113 .0171805 17.93 0.000 .2744399 .3417861
_cons | -57.83441 28.89893 -2.00 0.045 -114.4753 -1.193537

```

```

-----
sigma_u | 84.20095
sigma_e | 52.767964
rho     | .71800838 (fraction of variance due to u.i)
-----

```

```

. hausman fixed .

```

```

----- Coefficients -----
      (b)      (B)      (b-B)      sqrt(diag(V_b-V_B))
fixed |-----+-----| Difference | S.E.
-----+-----+-----+-----
      f | .1101238 | .1097811 | .0003427 | .0055213
      c | .3100653 | .308113  | .0019524 | .0024516
-----+-----+-----+-----

```

```

      b = consistent under Ho and Ha; obtained from xtreg
      B = inconsistent under Ha, efficient under Ho; obtained from xtreg

```

```

Test: Ho: difference in coefficients not systematic

```

```

      chi2(2) = (b-B)'[(V_b-V_B)^(-1)](b-B)
              = 2.33
      Prob>chi2 = 0.3119

```

We can compute the Hausman test statistic directly from the within and between estimates

```

xtreg i f c, i(firm) fe
Fixed-effects (within) regression
Group variable (i): firm
R-sq:  within = 0.7668
      between = 0.8194
      overall = 0.8060

corr(u_i, Xb) = -0.1517

Number of obs   = 200
Number of groups = 10
Obs per group: min = 20
                avg  = 20.0
                max  = 20

F(2,188)       = 309.01
Prob > F       = 0.0000

-----+-----
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
_cons |     -58.74393   12.45369    -4.72   0.000   -83.31086   -34.177

sigma_u   = 85.732501
sigma_e   = 52.767964
rho       = .72525012 (fraction of variance due to u_i)

F test that all u_i=0:   F(9, 188) = 49.18      Prob > F = 0.0000

. matrix define bw=e(b)
. matrix define Vw=e(V)
. matrix list bw

bw[1,3]
y1      .1101238      .31006534      -58.743932
. matrix list Vw

symmetric Vw[3,3]
f      .00014058
c     -.00007747      .00030118
_cons -.13068152      .00066516      155.09442

```



```

f
y1 -.02452229 .27803387 -50.216817 C
. matrix define m=q*syminv(V)*q'
. matrix list m
symmetric m[1,1]
y1 2.1313661
. gen m=trace(m)
. summarize m
-----+-----
Variable | Obs   Mean   Std. Dev.   Min   Max
-----+-----
m        | 200  2.131366    0  2.131366  2.131366

. gen p=1-chi2(2,m)
. summarize p
-----+-----
Variable | Obs   Mean   Std. Dev.   Min   Max
-----+-----
p        | 200  .3444924    0  .3444924  .3444924

```

Hausman Test (cont'd)

- large values \rightarrow reject $H_0: \text{Cov}(\alpha_i, X_{it})=0$ and do not implement RE

- that does not mean FE necessarily correct

Chamberlain outlines follow-up test based on reduced form regression involving all leads & lags

- since it involves FE, Hausman test doesn't use time-invariant regressors

- the test should fail as $T \rightarrow \infty$

- also mis-specification can cause rejection of null so that properly specified RE would be OK

- I did Hausman test for one-way (two-way) model but the specification of different states based on B, OLS, GLS, & W is more complicated for two-way (three-way)

- Kennedy describes easy way to implement H_0 as F-test (5th ed, p 312)