## Suggested Answers Problem Set 2 ECON 60303

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1. Given  $Y_{it} = \alpha + X_{it}\beta + u_i + v_t + \varepsilon_{it}$  but only two observations per block, generate the difference

$$Y_{i2} = \alpha + X_{i2}\beta + u_i + v_2 + \varepsilon_{i2}$$
$$-Y_{i1} = \alpha + X_{i1}\beta + u_i + v_1 + \varepsilon_{i1}$$
$$\Delta Y_i = \Delta X_i\beta + (v_2 - v_1) + \Delta \varepsilon_i$$

Where  $\theta = v_2 - v_1$  in the estimating equation  $\Delta Y_i = \theta + \Delta X_i \beta + \Delta \varepsilon_i$  and this represents the growth in outcomes between years 1 and 2.

To figure out what  $\Delta Y_i = \theta + \Delta X_i \beta + \lambda_i + \Delta \varepsilon_i$  is estimating, write the original model as

$$Y_{it} = \alpha + X_{it}\beta + u_i + v_t + \lambda_i time_t + \varepsilon_{it}$$

Where  $time_t$  is a time trend that equals 1 in period 1, 2 in period 2, etc. The equation allows for a unique time trend within a particular state. The new model can be written as

$$Y_{it} = \alpha + X_{it}\beta + u_i + v_t + \lambda_i t + \varepsilon_{it}$$

And the first difference between any two adjacent years is

$$Y_{it} = \alpha + X_{it}\beta + u_i + v_t + \lambda_i t + \varepsilon_{it}$$

$$Y_{it-1} = \alpha + X_{it-1}\beta + u_i + v_{t-1} + \lambda_i (t-1) + \varepsilon_{it-1}$$

$$\Delta Y_{it} = \Delta X_{it}\beta + (v_t - v_{t-1}) + \lambda_i + \Delta \varepsilon_{it}$$

And the estimating equation is  $\Delta Y_{it} = \theta_t + \Delta X_{it}\beta + \lambda_i + \Delta \varepsilon_{it}$ . In this equation, the year effects pick up growth rates between adjacent years and  $\lambda_i$  picks up the state-specific time trend.

- 2. Given the equation  $y_{it} = \alpha + x_{it}\beta + u_i + \lambda_t + \varepsilon_{it}$ 
  - take the mean over all t<sub>i</sub> for person i:  $\overline{y}_i = \alpha + \overline{x}_i \beta + u_i + \overline{\lambda}_i + \overline{\varepsilon}_i$  where  $\overline{\lambda}_i = \frac{1}{t_i} \sum_{i=1}^{t_i} \lambda_i$ . Note that the means of the year fixed effects differ across y because each panel has different numbers of observations
  - take the mean over all n for year t:  $\overline{y}_t = \alpha + \overline{x}_t \beta + \overline{u}_t + \lambda_t + \overline{\varepsilon}_t$  where  $\overline{u}_t = \frac{1}{n_t} \sum_{i=1}^n u_i$  where  $n_t$  is the

number of panels that are observed in time period t. Note that the means of the individual effects will vary by t because each year has different numbers of observations.

• take the mean over observations:  $\overline{y} = \alpha + \overline{x}\beta + \overline{\mu} + \overline{\lambda} + \overline{\varepsilon}$ . Let M be the number of observations in the sample and hence  $\overline{\lambda} = \frac{1}{m} \sum_{i=1}^{n} \sum_{t=1}^{t_i} \lambda_t$  and  $\overline{\mu} = \frac{1}{m} \sum_{i=1}^{n} \sum_{t=1}^{t_i} \mu_i$ 

- Construct the difference  $\tilde{y}_{it} = y_{it} \overline{y}_i \overline{y}_t + \overline{y}$ . Because the observations vary by panel and the number of panels within a year vary as well, the differencing does not eliminate the means of the group and year effects and as a result,  $\tilde{y}_{it} = (x_{it} \overline{x}_i \overline{x}_t + \overline{x})\beta (\overline{\lambda}_i + \overline{\lambda}) (\overline{\mu}_t + \overline{\mu}) + (\varepsilon_{it} \overline{\varepsilon}_i \overline{\varepsilon}_t + \overline{\varepsilon})$
- 3. a. When data is sorted by year then group. Let  $Y_t = X_t \beta + V_t$  be the n observations for year t. In this case,  $E[V_t V_t']$  is (n x n) and equals  $\Omega_n = \sigma_{\varepsilon}^2 I_n + \sigma_v^2 i_t i_t'$  and then E[VV'] which is (nt x nt) is  $I_t \otimes \Omega_n$ .
  - b. When data is sorted by group then year.  $Y_i = X_i \beta + V_i$  be the t observations for group i. In this case,  $E[V_i V_i']$  is (t x t) and equals  $\Omega_t = (\sigma_{\varepsilon}^2 + \sigma_v^2)I_t$ . However, the 1<sup>st</sup> observation in panel 1 will be correlated with the 1<sup>st</sup> observation in panel 2, panel 3, etc. Therefore, E[VV'] can be generalized to read

$$E[VV'] = \begin{bmatrix} \sigma_{\varepsilon}^{2} + \sigma_{v}^{2} & 0 & \cdots & 0 \\ 0 & \sigma_{\varepsilon}^{2} + \sigma_{v}^{2} & \cdots & 0 \\ \vdots & \vdots & \cdots & \vdots \\ 0 & 0 & \cdots & \sigma_{\varepsilon}^{2} + \sigma_{v}^{2} \end{bmatrix} & \begin{pmatrix} \sigma_{v}^{2} & 0 & \cdots & 0 \\ 0 & \sigma_{v}^{2} & \cdots & 0 \\ \vdots & \vdots & \cdots & \vdots \\ 0 & 0 & \cdots & \sigma_{v}^{2} \end{pmatrix} & & \begin{pmatrix} \sigma_{\varepsilon}^{2} + \sigma_{v}^{2} & 0 & \cdots & 0 \\ 0 & \sigma_{\varepsilon}^{2} + \sigma_{v}^{2} & 0 & \cdots & 0 \\ 0 & \sigma_{\varepsilon}^{2} + \sigma_{v}^{2} & 0 & \cdots & 0 \\ \vdots & \vdots & \cdots & \vdots \\ 0 & 0 & \cdots & \sigma_{\varepsilon}^{2} + \sigma_{v}^{2} \end{pmatrix} & & & \\ \begin{bmatrix} \sigma_{v}^{2} & 0 & \cdots & 0 \\ 0 & \sigma_{v}^{2} & \cdots & 0 \\ \vdots & \vdots & \cdots & \vdots \\ 0 & 0 & \cdots & \sigma_{\varepsilon}^{2} + \sigma_{v}^{2} \end{bmatrix} & & & \\ \begin{bmatrix} \sigma_{v}^{2} & 0 & \cdots & 0 \\ 0 & \sigma_{v}^{2} & \cdots & 0 \\ \vdots & \vdots & \cdots & \vdots \\ 0 & 0 & \cdots & \sigma_{v}^{2} \end{pmatrix} & & & \\ \begin{bmatrix} \sigma_{v}^{2} & 0 & \cdots & 0 \\ 0 & \sigma_{v}^{2} & \cdots & 0 \\ 0 & \sigma_{v}^{2} & \cdots & 0 \\ \vdots & \vdots & \cdots & \vdots \\ 0 & 0 & \cdots & \sigma_{v}^{2} \end{pmatrix} & & & \\ \begin{bmatrix} \sigma_{v}^{2} & 0 & \cdots & 0 \\ 0 & \sigma_{v}^{2} & \cdots & 0 \\ 0 & \sigma_{v}^{2} & \cdots & 0 \\ 0 & \sigma_{\varepsilon}^{2} + \sigma_{v}^{2} & 0 & \cdots & 0 \\ 0 & \sigma_{\varepsilon}^{2} + \sigma_{v}^{2} & \cdots & 0 \\ \vdots & \vdots & \cdots & \vdots \\ 0 & 0 & \cdots & \sigma_{v}^{2} \end{pmatrix} \end{bmatrix}$$

Which can be re-written as

$$E[\tilde{V}\tilde{V}'] = \sigma_{\varepsilon}^2 I_{nt} + (i_n i_n \otimes \sigma_v^2 I_t).$$

5. a. Putting the results from class and the previous problem together, it is clear that

Therefore 
$$E[VV'] = \sigma_{\varepsilon}^2 I_{nt} + (i_n i_n \otimes \sigma_{\lambda}^2 I_t) + (I_n \otimes \sigma_u^2 i_t i_t') = \Omega$$

b. 
$$\hat{\beta} = (X' \Omega^{-1} X)^{-1} (X' \Omega^{-1} Y)$$

6. Note that  $\overline{y}^{00} = \alpha + \overline{\varepsilon}^{00}$  and  $\overline{y}^{01} = \alpha + \theta + \overline{\varepsilon}^{01}$ . Because  $y_i = \alpha + G_i \gamma + A_i \theta + D_i \beta + \varepsilon_i$  then  $y_i^1$  or only the observations for the treatment group become  $y_i^1 = \alpha + \gamma + A_i \theta + A_i \beta + \varepsilon_i$  because  $A_i = D_i$  in this sample. Let  $y_i^{10}$  be the observations for the treatment group before the intervention and  $y_i^{11}$  be the observations after the intervention. Then

 $y_i^1 - [(1 - A_i)\overline{y}^{00} + A_i\overline{y}^{01}]$  can be written as  $(1 - A_i)(y_i^{10} - \overline{y}^{00}) + A_i(y_i^{11} - \overline{y}^{01})$ . Let's take each of these terms separately.

$$(y_i^{10} - \overline{y}^{00}) = \alpha + \gamma + \varepsilon_i - \alpha - \overline{\varepsilon}^{00} = \gamma + (\varepsilon_i - \overline{\varepsilon}^{00})$$
$$(y_i^{11} - \overline{y}^{01}) = \alpha + \gamma + \theta + \beta + \varepsilon_i - \alpha - \theta - \overline{\varepsilon}^{01} = \gamma + \beta + \varepsilon_i - \overline{\varepsilon}^{01}$$

Therefore

$$y_{i}^{1} - [(1 - A_{i})\overline{y}^{00} + A_{i}\overline{y}^{01}] = (1 - A_{i})(y_{i}^{10} - \overline{y}^{00}) + A_{i}(y_{i}^{11} - \overline{y}^{01}) = (1 - A_{i})[\gamma + (\varepsilon_{i} - \overline{\varepsilon}^{00})] + A_{i}[\gamma + \beta + \varepsilon_{i} - \overline{\varepsilon}^{01}]$$

Which can be reduced to read  $y_i^1 = \gamma + A_i \beta + \varepsilon_i - (1 - A_i)\overline{\varepsilon}^{00} - A_i \overline{\varepsilon}^{01} = \gamma + A_i \beta + u_i$ 

7. There are two things wrong with the numbers. We know that random effects are a weighted average of between and within group estimates so they random effect estimates should lie between the two values. In this case it does not. Second, random effect is efficient estimation and the variance should be smaller than the fixed-effect estimate. Again, it is not.

The Hausman test is  $\hat{q} = (\hat{\beta}_{fe} - \hat{\beta}_{re})' \left[ Var(\hat{\beta}_{fe}) - var(\hat{\beta}_{re}) \right]^{-1} (\hat{\beta}_{fe} - \hat{\beta}_{re})$  but when the parameter is a scaler, the test statistic reduces to  $\hat{q} = (\hat{\beta}_{fe} - \hat{\beta}_{re})^2 / \left[ Var(\hat{\beta}_{fe}) - var(\hat{\beta}_{re}) \right] = (0.04813 - 0.0635)^2 / [(0.02429)^2 - (0.02137)^2] = 1.77$ 

The p-value for a chi-square distribution with 1 degree of freedom evaluated at 1.77 is 0.18, so we cannot reject the null the random and fixed-effect estimates are the same.

## **Computer problem**

A sample program (psid\_measurement\_error.do) that generates these results is on the web and the some key results from that are reported below. In the OLS model, the attenuation bias is estimated to be  $\hat{\theta} = \frac{\hat{\sigma}_t^2}{\bar{\sigma}_v^2 + \hat{\sigma}_t^2}$  which is exactly what you find. In the fixed-effects case (first difference with two observations in the panel only), with two observations, we showed in class that the attenuation bias is  $\left[1 - \frac{\sigma_v^2}{\sigma_x^2(1-\rho) + \sigma_v^2}\right]$  were  $\rho$  is the correlation in tenure over time. To estimate  $\hat{\rho}$  estimated a random effects model and calculated the fraction of variance that is due to within-panel correlation which is  $\hat{\rho} = 0.89$ 

$$\hat{\sigma}_{t}^{2} = (6.91)^{2} = 47.75$$

$$\hat{\beta}_{w/out}^{ols} = 0.0238 \text{ and } \hat{\beta}_{w/out}^{fe} = 0.0081$$

$$\overline{\hat{\sigma}}_{v}^{2} = \frac{1}{1000} \sum_{i=1}^{1000} \hat{\sigma}_{v}^{2}(i) = 1.999^{2} = 4$$

$$\overline{\hat{\beta}}_{with}^{OLS} = \frac{1}{1000} \sum_{i=1}^{1000} \hat{\beta}_{with}^{OLS}(i) = 0.0219$$

$$\overline{\hat{\beta}}_{with}^{fe} = \frac{1}{1000} \sum_{i=1}^{1000} \hat{\beta}_{with}^{fe}(i) = 0.00455$$

$$\hat{\theta} = \frac{\hat{\sigma}_{1}^{2}}{\hat{\sigma}_{1}^{2} + \hat{\sigma}_{1}^{2}} = \frac{47.75}{4 + 47.75} = 0.92$$

$$\frac{\tilde{\beta}_{max}^{OS}}{\hat{\beta}_{max}^{OS}} = \frac{0.0219}{0.0238} = 0.92$$

$$\frac{\tilde{\beta}_{max}^{OS}}{\hat{\beta}_{max}^{OS}} = \frac{0.00455}{0.00809} = 0.563$$

$$\left[1 - \frac{\sigma_{1}^{2}}{\sigma_{1}^{2}(1 - \rho) + \sigma_{1}^{2}}\right] = \left[1 - \frac{4}{47.75(1 - 0.89) + 4}\right] = 0.568$$

$$\frac{1}{1 - \sigma_{1}^{2}(1 - \rho) + \sigma_{1}^{2}}\right] = \left[1 - \frac{4}{47.75(1 - 0.89) + 4}\right] = 0.568$$

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$$\frac{1}{1 - \sigma_{1}^{2}(1 - \rho) + \sigma_{1}^{2}(1 - \sigma) + \sigma_{1}^{2}$$

. reg wagel tenure;

Source	SS	df	MS		Number of obs F( 1, 1576) Prob > F R-squared	$= 1578 \\ = 158.85 \\ = 0.0000 \\ = 0.0916 \\ = 0.0910$
Model Residual	42.6637683 423.277514	1 4 1576 .	12.6637683 268577103			
Total	465.941283	1577 .	295460547		Root MSE	= .51824
wagel	Coef.	Std. En	r. t	P> t	[95% Conf.	Interval]
tenure _cons	.0237905 2.149046	.001887	7612.6006110.74	0.000	.020088 2.110982	.0274929 2.18711
. * regression . areg wagel t Linear regress	n of ln(wagel) cenure, absorb sion, absorbin	on tenu (id); g indica	are; ators		Number of obs F( 1, 788) Prob > F R-squared Adj R-squared Root MSE	= 1578 = 4.91 = 0.0270 = 0.9077 = 0.8153 = .2336
wagel	Coef.	Std. E	r. t	P> t	[95% Conf.	Interval]
tenure _ <sup>cons</sup>	.0080944 2.268507	.00365	54 2.22 53 79.81	0.027 0.000	.0009216 2.212709	.0152671 2.324306
id   . qui save `ma	F(788, ain', replace	788) =	8.844	0.000	(789 ca	ategories)

. use psid\_measurementerror\_results;

. sum;

Variable	Obs	Mean	Std. Dev.	Min	Max
v2 m	1000	0000245	.0506558	164754	.1637709
v2 sd	1000	1.999933	.0356311	1.892301	2.10275
beta ols	1000	.0219413	.0005363	.0203601	.0238582
beta_fe	1000	.0045495	.0018241	0007662	.0108822