GV300 - Quantitative Political Analysis

University of Essex - Department of Government

Lorenzo Crippa

Week 23 – 2 March, 2020

NSS survey


NSS
National Student Survey
WHAT
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THINK?
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Today's activity

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- Consider only the first 100 workers, get rid of the rest of the data

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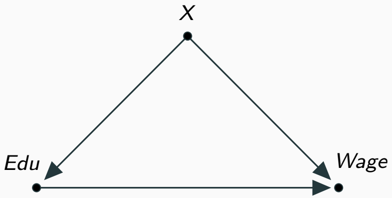
   (c) Compare the results and discuss which model best fits data based on point 2(b).

1. Causal identification

1(a) and (b) – Causal model



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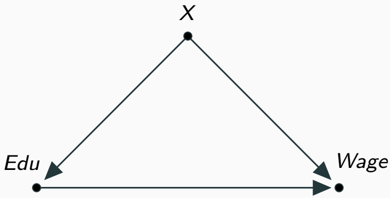

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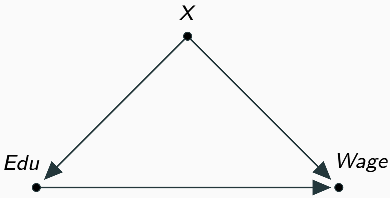

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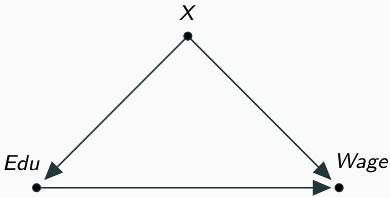

- Suppose X is a set of confounders that make each specific unit *idiosyncratic* both in treatment and outcome variables
- Then panel data help us identify the causal effect of *Edu* on *Wage* because they allow us to include a fixed (random) effect and control for it.
- **BUT** fixed/random effects are no solution for all other types of confounders (non-idiosyncratic)!

2. Data description

2(a) – Summary statistics

Variable	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
`id`	700	50.500	28.887	1	25.8	75.2	100
`t`	700	4.000	2.001	1	2	6	7
`occ`	700	0.486	0.500	0	0	1	1
`lwage`	700	6.704	0.492	5.165	6.397	7.003	8.049
`ed`	700	13.040	2.995	4	12	16	17
`exp`	700	21.280	10.788	1	12	30	51
`exp2`	700	569.060	508.066	1	144	900	2,601
`south`	700	0.327	0.470	0	0	1	1
`smsa`	700	0.627	0.484	0	0	1	1
`fem`	700	0.130	0.337	0	0	0	1
`union`	700	0.321	0.467	0	0	1	1

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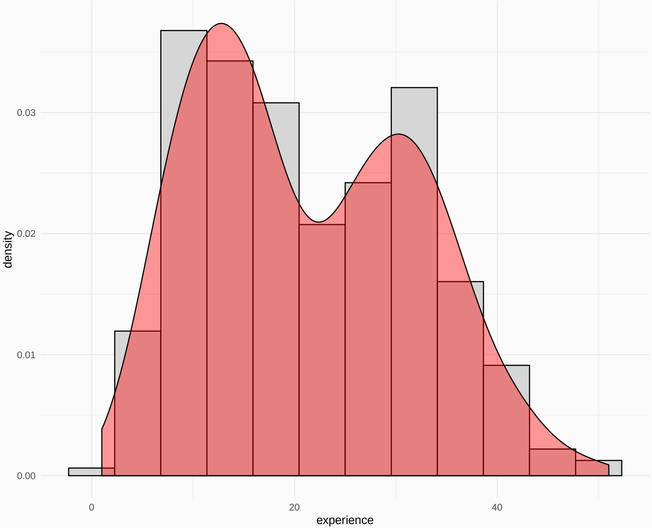

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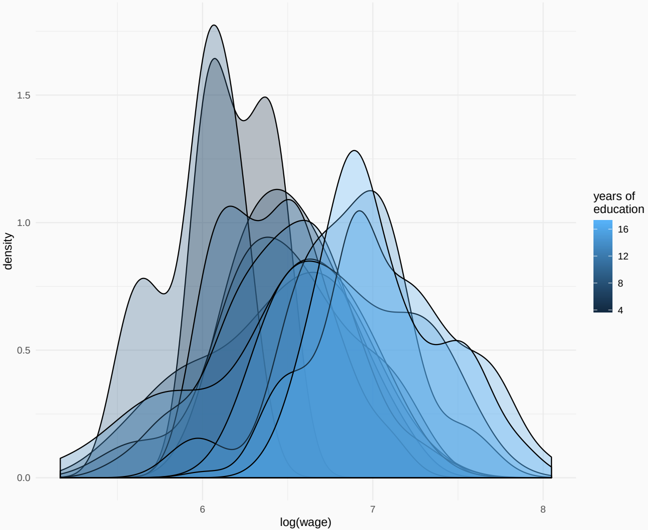

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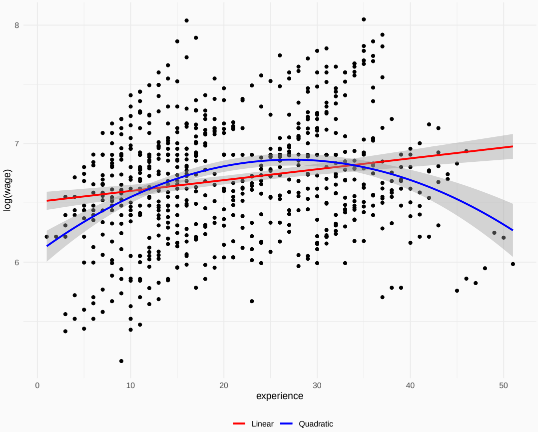
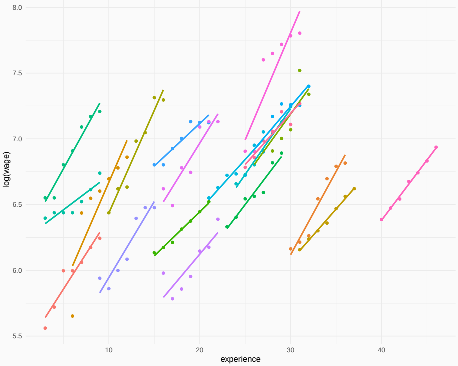


Our usual linear model doesn't really seem to fit this cloud. Why?

2(b) – Fixed effect

Take a look at this graph (only first 20 individuals). What does it suggest about the relationship we are studying?



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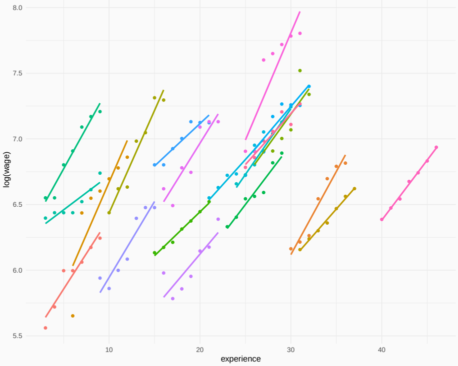
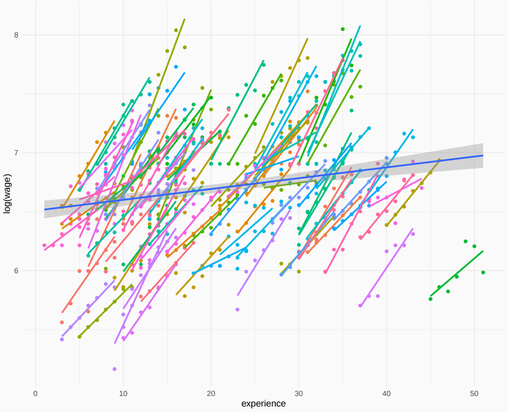


The slopes of the regression lines by individual seem similar, only between-units intercepts are different!

Now look at the following (all 100 individuals, plus pooled):



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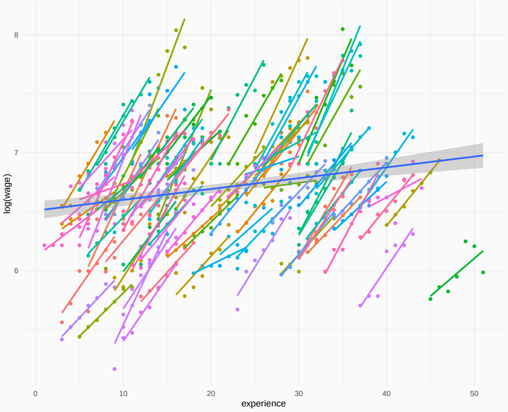

A typical example of a fixed effect: slopes and intercepts of lines by individuals are different from those of pooled line.

Fixed and random effect made intuitive

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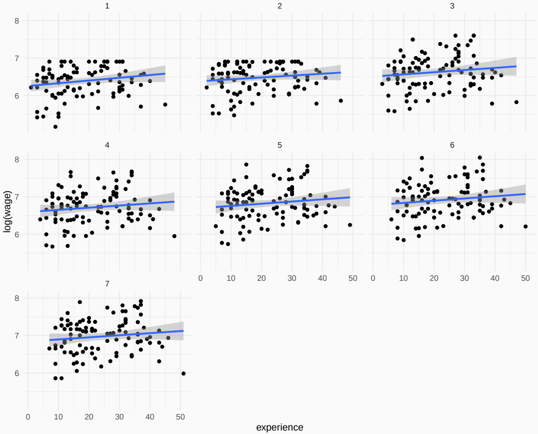
- **Both** fixed and random have different intercepts of the reg lines by units (or time)!
- Intuitively: you include a fixed effect in a pooled model $\rightarrow$ you have no clue of what's the difference between units, so you get rid of it. Random effect $\rightarrow$ you can explain part of it.

2(b) – What about time?

Are the time-points we have absolutely different from each others?



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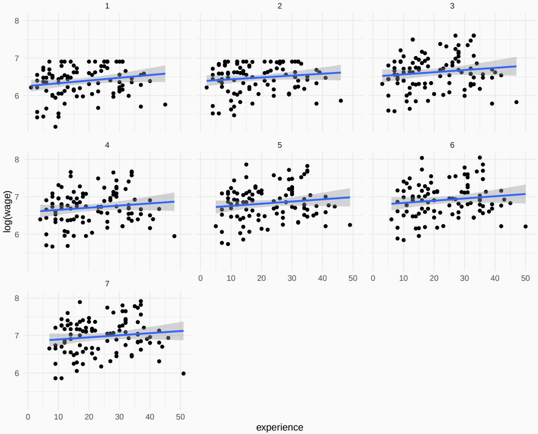
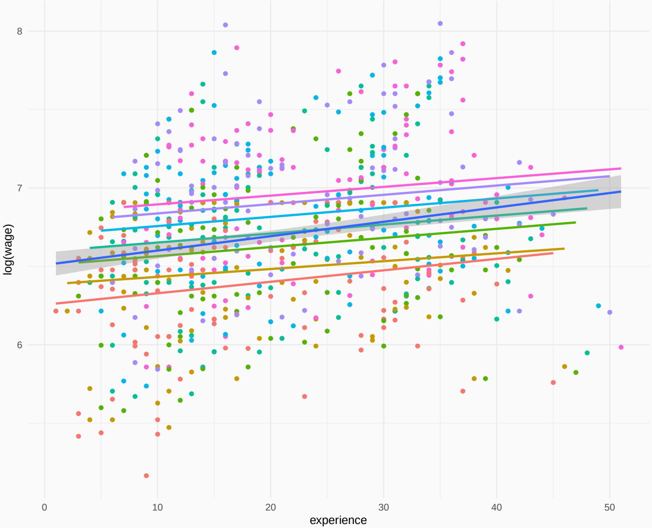


In R we can even animate our graphs using `gganimate`!

2(b) – Time fixed effect?

Look at the following lines: is a time-fixed effect appropriate here?



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We can get statistics about within, between and overall variation of a selected number of variables (see R script):

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```
within.variation
   t     lwage   ed     exp    exp2   wks
   2.00  0.235   0      2.00   95.2   3.85

between.variation
   t     lwage   ed     exp    exp2   wks
   0     0.434   3.01   10.6   501.   3.24

overall.variation
   t     lwage   ed     exp    exp2   wks
   2.00  0.492   3.00   10.8   508.   5.02
```

3. Data analysis

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$$Y_{it} = a_0 + \mathbf{X}'_{\mathbf{it}}\mathbf{b} + a_1 D_1 + a_2 D_2 + \ldots + a_{k-1} D_{k-1} + e_{it}$$

$$\mathbf{D} = D_1, D_2, \ldots, D_k = \begin{bmatrix} 1 & 0 & \ldots & 0 \\ 1 & 0 & \ldots & 0 \\ 0 & 1 & \ldots & 0 \\ 0 & 1 & \ldots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \ldots & 1 \\ 0 & 0 & \ldots & 1 \end{bmatrix}$$

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The matrix has size $N \times k$. Your software will exclude one dummy (thus $k-1$) or the intercept a_0 to avoid multicollinearity

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We can now do the group demeaning:

$$(Y_{it} - \overline{Y}_i) = (\mathbf{X_{it}'} - \overline{\mathbf{X}}_{\mathbf{i}}')\mathbf{b} + (a_i - a_i) + (e_{it} - \overline{e}_i)$$

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Thus we get rid of between-unit variation $(a_i - a_i = 0)$

Maths on random effect

Random effect:

$$(Y_{it} - \hat{\theta}_i \overline{Y}_i) = (1 - \hat{\theta}_i)a_0 + (\mathbf{X}_{it} - \hat{\theta}_i \overline{\mathbf{X}_i})'\mathbf{b} + [(1 - \hat{\theta}_i)a_i + (e_{it} - \hat{\theta}_i \overline{e}_i)]$$

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where $\hat{\theta}_i$ is an estimate of

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Notice that, for each covariate in $\mathbf{X_{it}}$, you have a (slightly) different slope for each unit i, depending on $\hat{\theta}_i$!

From random effect to fixed effect and pooled model

Now, consider:

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3. in-between these extremes: random effect

From random effect to fixed effect and pooled model

Now, consider:

$$(Y_{it} - \hat{\theta}_i \overline{Y}_i) = (1 - \hat{\theta}_i)a_0 + (\mathbf{X}_{it} - \hat{\theta}_i \overline{\mathbf{X}_i})'\mathbf{b} + [(1 - \hat{\theta}_i)a_i + (e_{it} - \hat{\theta}_i \overline{e}_i)]$$

$$\theta_i = 1 - \sqrt{\frac{\sigma_e^2}{T_i \sigma_a^2 + \sigma_e^2}}$$

1. what if $\sigma_a^2 \gg \sigma_e^2$ (huge between-unit variation)? $\theta_i \to 1$: we are back to the entity-demeaned fixed effect!
2. what if $\sigma_a^2 \ll \sigma_e^2$ (minimal between-unit variation)? $\theta_i \to 0$: we are back to the pooled model!
3. in-between these extremes: random effect

Your software will usually provide to you an estimate of θ_i (or of the variance of slopes) and related tests. Check the output!

3(c) – Model comparison

	Pooled	Pooled (clustered SE)	Fixed Effect	Random Effect
(Intercept)	4.72***	4.72***		3.20***
	(0.15)	(0.24)		(0.33)
exp	0.06***	0.06***	0.11***	0.09***
	(0.01)	(0.01)	(0.01)	(0.01)
exp2	−0.00***	−0.00***	−0.00	−0.00*
	(0.00)	(0.00)	(0.00)	(0.00)
wks	−0.00	−0.00	0.00*	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
ed	0.10***	0.10***		0.14***
	(0.01)	(0.01)		(0.02)
Adj. R^2	0.43	0.43	0.70	0.52
Num. obs.	700	700	700	700

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

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In R (Stata is very similar, see script):

```
phtest(fe, re)

##############################################
#   Hausman Test
#
# data:  lwage ~ exp + exp2 + wks + ed
# chisq = 3805.5, df = 3, p-value < 2.2e-16
# alternative hypothesis: one model is inconsistent
##############################################
```

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- We should use **clustered** SEs (on our units) when we have panel data, otherwise we are not fixing serial correlation between units
- These SEs will **also** be robust to heteroskedasticity
- Look at the education variable. Why is it omitted from the fixed effect model?
- Because for each respondent (within unit) education does not change! Thus there is no within-variation, and the within-variation is the only thing a fixed-effect looks at.

Conclusion

All clear? More questions?

Thanks and see you next week!