

# Econometric Theory I

# Computer Lab Class II

Juergen Amann juergen.amann@nottingham.ac.uk Wednesday 12:00 - 13:00, C42 SCGB

## Last week

 Using earnings.xls we analysed the effect of education and work experience on earnings.

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- We estimated

$$earnings_i = \beta_1 + \beta_2 educ_i + \beta_3 workexp_i + u_i$$

#### where

- earnings; earnings of individual *i* in USD per hour,
- educ<sub>i</sub> : education of individual *i* as in years,
- workexp<sub>i</sub>: work experience of individual i in years,
- $u_i$ : idiosyncratic error of i.

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- $u_i$ : idiosyncratic error of i.
- We found educ and workexp to be highly significant and positive.

# Two exercises:

• Exercise 1: Examine the evidence of a gender pay gap.

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  - Restricted Least Squares.

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$$female_i = \begin{cases} 1 & \text{if individual } i \text{ is female} \\ 0 & \text{otherwise} \end{cases}$$
•  $male_i = \begin{cases} 1 & \text{if individual } i \text{ is male} \\ 0 & \text{otherwise} \end{cases}$ 

- We examine evidence of a gender pay gap.
- Our data set earnings2.xls contains the same variables as earnings.xls plus two dummy variables:

 We want to know if there is a a significant difference in earnings between men and women controlling for education and work experience.

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$$earnings_i = \beta_1 + \beta_2 educ_i + \beta_3 workexp_i + \beta_4 female_i + u_i$$

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Type: regress EARNINGS EDUC WORKEXP FEMALE

# Stata Code

. regress EARNINGS EDUC WORKEXP

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EARNINGS	Coef.	Std. Err.	t	P> t	[95% Conf	. Interval]
EDUC	.5624327	.2336497	11.46	0.000	2.219146	3.137105
WORKEXP		.1285136	4.38	0.000	.3099816	.8148837
_cons		4.27251	-6.20	0.000	-34.87789	-18.09213

# Stata Code

. regress EARNINGS EDUC WORKEXP

EARNINGS		Std. Err.	t			. Interval]
EDUC   WORKEXP	2.678125	.2336497 .1285136 4.27251	11.46 4.38 -6.20	0.000 0.000 0.000	2.219146 .3099816 -34.87789	3.137105 .8148837 -18.09213

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WORKEXP	.5624327	.1285136	4.38	0.000	.3099816	.8148837
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. regress EARNINGS EDUC WORKEXP FEMALE

EARNINGS	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
EDUC	2.591137	.2285497	11.34	0.000	2.142174	3.0401
WORKEXP	.4056773	.1288199	3.15	0.002	.1526236	.658731
FEMALE	-5.90905	1.113972	-5.30	0.000	-8.097337	-3.720764
_cons	-19.69195	4.36076	-4.52	0.000	-28.25822	-11.12567

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  - More specifically:

```
\widehat{earnings}_i = \begin{cases} (-19.69 - 5.91) + 2.59 * \text{educ} + 0.41 * \text{workexp} & \text{if female}_i = 1 \\ -19.69 & + 2.59 * \text{educ} + 0.41 * \text{workexp} & \text{if female}_i = 0 \end{cases}
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- Structural stability in cross-section setting:
  - A different relationship exists for different cross-sectional groups, i.e. there is a significant difference in earnings between men and women.

How important are controls in this example?
. regress EARNINGS EDUC WORKEXP FEMALE

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EDUC WORKEXP FEMALE	2.591137   .4056773   -5.90905	.2285497 .1288199	11.34 3.15 -5.30	0.000 0.002 0.000	2.142174 .1526236 -8.097337	3.0401 .658731 -3.720764
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EARNINGS	I	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
EDUC WORKEXP FEMALE _cons		2.591137 .4056773 -5.90905 -19.69195	.2285497 .1288199 1.113972 4.36076	11.34 3.15 -5.30 -4.52	0.000 0.002 0.000 0.000	2.142174 .1526236 -8.097337 -28.25822	3.0401 .658731 -3.720764 -11.12567

<sup>.</sup> regress EARNINGS FEMALE

. regress EARNI	NGS EDUC WO	RKEXP FEMALE				
EARNINGS					[95% Conf.	Interval
EDUC   WORKEXP   FEMALE	2.591137 .4056773 -5.90905 -19.69195	.2285497 .1288199 1.113972	11.34 3.15 -5.30	0.000 0.002 0.000	2.142174 .1526236 -8.097337 -28.25822	.65873 -3.72076
EARNINGS		Std. Err.			[95% Conf.	Interval
	-6.956519	1.205095	-5.77	0.000	-9.323786 21.44057	

gress EARN	INGS EDUC WO	RKEXP FEMALE				
		Std. Err.			[95% Conf.	Interval]
					2.142174	3.0401
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regress EARN	INGS FEMALE					
EARNINGS					[95% Conf.	
+					[95% Conf.	
FEMALE	-6.956519	1.205095	-5.77	0.000		-4.589251

• The gender pay gap is bigger if we do **not** control for educ and workexp.

#### How important are controls in this example?

```
. regress EARNINGS EDUC WORKEXP FEMALE
             Coef. Std. Err. t P>|t| [95% Conf. Interval]
   EARNINGS |
      EDUC | 2.591137 .2285497 11.34 0.000 2.142174
                                                         3.0401
   WORKEXP |
            .4056773 .1288199
                                3.15
                                       0.002
                                            .1526236
                                                         .658731
    FEMALE I
            -5.90905 1.113972
                                -5.30 0.000 -8.097337 -3.720764
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. regress EARNINGS FEMALE
            Coef. Std. Err. t P>|t| [95% Conf. Interval]
   EARNINGS |
            -6.956519 1.205095 -5.77 0.000 -9.323786
    FEMALE |
                                                        -4 589251
            23.11448 .8521306 27.13 0.000 21.44057
     cons
                                                         24.78839
```

- The gender pay gap is bigger if we do **not** control for educ and workexp.
- This is what is meant when you hear 'The gender pay gap shrinks when we take into account ...'. In our case this is education and work experience.
- Also, there's more to the question than it seems! Let's take a look!

- Let's examine the determinants of educational attainment.
- Download education.xls and import it into Stata.

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- Download education.xls and import it into Stata.
- We estimate

$$\texttt{educ_i} = \beta_1 + \beta_2 \texttt{aptitude_i} + \beta_3 \texttt{mothereduc_i} + \beta_4 \texttt{fathereduc_i} + u_i$$

#### where

- educ<sub>i</sub>: education of individual i in years,
- aptitude<sub>i</sub>: test score of individual i attained on aptitude test.
- mothereduc<sub>i</sub>: years i's mother spent in full-time education,
- fathereduc<sub>i</sub>: years i's father spent in full-time education,
- *u<sub>i</sub>*: idiosyncratic error of *i*.

Check for significance and interpret results!

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      EDUC |
                Coef.
                       Std. Err.
                                   t P>|t|
                                                 [95% Conf. Interval]
   APTITUDE |
              .1257087
                       .0098533 12.76 0.000
                                                 .1063528
                                                           .1450646
 MOTHEREDUC |
              .0492425
                       .0390901 1.26 0.208 -.027546
                                                           .1260309
                       .0309522 3.48 0.001
                                                 .04688
 FATHEREDUC | .1076825
                                                           .1684851
     _cons | 5.370631
                       .4882155 11.00 0.000
                                                  4.41158
                                                           6.329681
```

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EDUC		Coef.	Std. Err.			[95% Conf.		
APTITUDE	İ	.1257087	.0098533	12.76	0.000	.1063528	.1450646	
MOTHEREDUC FATHEREDUC		.0492425 .1076825	.0390901 .0309522	1.26 3.48	0.001	027546 .04688	.1684851	
_cons	 	5.370631 	.4882155	11.00	0.000	4.41158	6.329681	

- All coefficients are positive.
- Coefficient for mothereduc is insignificant.

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  - $H_0: \beta_f \beta_m = 0, H_a: \beta_f \beta_m \neq 0$

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$$\bullet \ \ F_{1,T-k-1} = \left(\frac{(\hat{\beta}_f - \hat{\beta}_m) - (\beta_f - \beta_m)}{\sqrt{se_{\beta_f}^2 + se_{\beta_m}^2 + 2 \times se_{\beta_f} se_{b_m}}}\right)^2, H_0 : \left(\frac{(\hat{\beta}_f - \hat{\beta}_m)}{\sqrt{se_{\beta_f}^2 + se_{\beta_m}^2 + 2 \times se_{\beta_f} se_{\beta_m}}}\right)^2$$

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- $se^2 = \hat{\sigma}^2$ , the sample variance
- $\hat{\beta}_i$ , the estimated coefficient
- As before: Observed Value Value Predicted under H<sub>0</sub> (here equal to 0) divided by the estimated standard error of the estimator.

. regress EDUC APTITUDE MOTHEREDUC FATHEREDUC

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EDUC	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
+						
APTITUDE	.1257087	.0098533	12.76	0.000	.1063528	.1450646
MOTHEREDUC	.0492425	.0390901	1.26	0.208	027546	.1260309
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EDUC	I	Coef.	Std. Err	. t	P> t	[95% Conf	. Interval]
APTITUDE MOTHEREDUC FATHEREDUC	1 1 1	.1257087 .0492425 .1076825 5.370631	.0098533 .0390901 .0309522	12.76 1.26 3.48	0.000 0.208 0.001 0.000	.1063528 027546 .04688 4.41158	.1450646 .1260309 .1684851
	·						

. test MOTHEREDUC = FATHEREDUC

```
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      EDUC |
              Coef. Std. Err. t P>|t|
                                                [95% Conf. Interval]
            .1257087
                      .0098533 12.76 0.000
                                                .1063528
   APTITUDE |
                                                          .1450646
 MOTHEREDUC | .0492425 .0390901 1.26 0.208 -.027546 .1260309
 FATHEREDUC | .1076825 .0309522 3.48 0.001 .04688 .1684851
     cons | 5.370631 .4882155 11.00 0.000
                                                4.41158
                                                          6.329681
. test MOTHEREDUC = FATHEREDUC
( 1) MOTHEREDUC - FATHEREDUC = 0
     F(1, 536) = 0.90
         Prob > F = 0.3440
```

- We fail to reject  $H_0$  as the F-statistic is smaller than the critical value.
- Important: This is not a test of joint significance of both coefficients (we'll do this next tutorial)!
- You can also get the above F-statistic 'by hand'. → See how it's done!

• Re-estimate the regression imposing the constraint that

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  - $educ_i = \beta_1 + \beta_2 aptitude_i + \beta_3 mothereduc_i + \beta_4 fathereduc_i + u_i$

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  - $\bullet \ \mathtt{educ_i} = \beta_1 + \beta_2 \mathtt{aptitude_i} + \beta_3 \left( \mathtt{mothereduc_i} + \mathtt{fathereduc_i} \right) + u_i$

parentseduc<sub>i</sub>

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  - If  $\beta_3 = \beta_4$  then our model becomes:
  - $educ_i = \beta_1 + \beta_2 aptitude_i + \beta_3 (mothereduc_i + fathereduc_i) + u_i$

 $parentseduc_i$ 

. generate PARENTSEDUC = MOTHEREDUC + FATHEREDUC

- Re-estimate the regression imposing the constraint that  $\beta_f = \beta_m \Leftrightarrow \beta_3 = \beta_4$ .
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  - $educ_i = \beta_1 + \beta_2 aptitude_i + \beta_3 \underbrace{(mothereduc_i + fathereduc_i)} + u_i$

 $parentseduc_i$ 

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- . regress EDUC APTITUDE PARENTSEDUC

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  - $educ_i = \beta_1 + \beta_2 aptitude_i + \beta_3 mothereduc_i + \beta_4 fathereduc_i + u_i$
  - If  $\beta_3 = \beta_4$  then our model becomes:
  - $\operatorname{educ}_{\mathtt{i}} = \beta_1 + \beta_2 \operatorname{aptitude}_{\mathtt{i}} + \beta_3 \underbrace{\left( \operatorname{mothereduc}_{\mathtt{i}} + \operatorname{fathereduc}_{\mathtt{i}} \right)}_{\operatorname{parentseduc}_{\mathtt{i}}} + u_i$

```
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```

. regress EDUC APTITUDE PARENTSEDUC

EDUC	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
APTITUDE	.1253106	.0098434	12.73	0.000	.1059743	.1446469
PARENTSEDU	.0828368	.0164247	5.04	0.000	.0505722	.1151014
_cons	5.29617	.4817972	10.99	0.000	4.349731	6.242608

# Thank you and see you next time!

Juergen Amann

juergen.amann@nottingham.ac.uk Wednesday 12:00 - 13:00, C42 SCGB

# Exercise 1: Gender differences Go back

In our data set men have (on average) higher education and more work experience:

. tabstat EARNINGS EDUC WORKEXP, stat(mean sd) long by(FEMALE)

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. tabstat EARNINGS EDUC WORKEXP, stat(mean sd) long by(FEMALE)

FEMALE stats | EARNINGS EDUC WORKEXP

0 mean | 23.11448 13.72222 17.87201 sd | 16.05073 2.575381 3.993107

1 mean | 16.15796 13.62222 15.9287 sd | 11.59666 2.297135 4.641399

Total mean | 19.63622 13.67222 16.90036 sd | 14.41566 2.438476 4.433377

• There is more variation in earnings and educ for men (standard deviation).

# Exercise 1: Gender differences Goback

In our data set men have (on average) higher education and more work experience:

. tabstat EARNINGS EDUC WORKEXP, stat(mean sd) long by(FEMALE)

FEMALE	stats	EARNINGS	EDUC	WORKEXP
0	mean   sd	23.11448 16.05073	13.72222	17.87201
1	mean	16.15796 11.59666	13.62222 2.297135	15.9287 4.641399
Total	mean   sd		13.67222 2.438476	16.90036 4.433377

- There is more variation in earnings and educ for men (standard deviation).
- Do the blue numbers look familiar? Compare with results when running:

. regress EARNINGS FEMALE

. regress EDUC APTITUDE MOTHEREDUC FATHEREDUC

. regress EDUC APTITUDE MOTHEREDUC FATHEREDUC

EDUC	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
APTITUDE	.1257087	.0098533	12.76	0.000	.1063528	.1450646
MOTHEREDUC	.0492425	.0390901	1.26	0.208	027546	.1260309
FATHEREDUC	.1076825	.0309522	3.48	0.001	.04688	.1684851
_cons	5.370631	.4882155	11.00	0.000	4.41158	6.329681

. regress EDUC APTITUDE MOTHEREDUC FATHEREDUC

EDUC	Coef.	Std. Err.	t	P> t	L95% Conf.	Interval]
APTITUDE	.1257087	.0098533	12.76	0.000	.1063528	.1450646
MOTHEREDUC	.0492425	.0390901	1.26	0.208	027546	.1260309
FATHEREDUC	.1076825	.0309522	3.48	0.001	.04688	.1684851
_cons	5.370631	.4882155	11.00	0.000	4.41158	6.329681

. vce

. regress EDUC APTITUDE MOTHEREDUC FATHEREDUC

. vce

$$\text{Remember under } \textit{H}_0: \ \left[ (\hat{\beta}_f - \hat{\beta}_m) \times \left( \sqrt{\mathsf{se}_{\beta_f}^2 + \mathsf{se}_{\beta_m}^2 + 2 \times \mathsf{se}_{\beta_f} \mathsf{se}_{\beta_m}} \right)^{-1} \right]^2$$

```
. display ((.0492425 - .1076825 ) / (sqrt(.00152803 + .00095804 + 2 * .00066072)))^2 .89697298 <- this is the F-statistic F( 1, 536) = 0.90!
```