University of Nottingham
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Autumn 2018

Econometric Theory I

Computer Lab Class III

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Wednesday 12:00 - 13:00, C42 SCGB

Last week

Two exercises:

- **Exercise 1:** Examine the evidence of a gender pay gap.
  - Dummy variables.
  - What does it mean when we *'control for (a) variable(s)'*?
- **Exercise 2:** Examine the determinants of educational attainment.
  - Joint parameter hypothesis testing of coefficients; e.g. $H_0 : \beta_2 = \beta_3$.
  - Restricted Least Squares.

This week

Modelling the birth weights of infants

- Identify factors that may determine a child's birth weight.

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- Homoskedasticity vs. heteroskedasticity.

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- Our data set `bwght.xls` contains $N = 1,388$ observations on the following variables:
  - $\texttt{bwght}_\texttt{i}$: birth weight in ounces,
  - $\texttt{faminc}_\texttt{i}$: family income in USD 1,000,
  - $\texttt{order}_\texttt{i}$: birth order of child,
  - $\texttt{cigs}_\texttt{i}$: cigarettes smoked per day by mother during pregnancy,
  - $\texttt{mothereduc}_\texttt{i}$: number of years mother spent in full-time education.

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- What is the expected sign for the variables? Which variables do you expect to be significant?

Regression 1

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      Source |       SS           df       MS      Number of obs   =     1,388
-------------+----------------------------------   F(2, 1385)      =     11.15
       Model |  9103.2286         2  4551.6143   Prob > F        =    0.0000
    Residual |  565508.491     1,385  408.30938   R-squared       =    0.0158
-------------+----------------------------------   Adj R-squared   =    0.0144
       Total |  574611.72     1,387  414.283864   Root MSE        =    20.207

------------------------------------------------------------------------------
       bwght |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      faminc |   .1235904   .0290392     4.26   0.000     .0666249    .1805559
       order |   1.439648   .6086762     2.37   0.018     .2456214    2.633675
       _cons |   112.7618    1.45622    77.43   0.000     109.9052    115.6185
------------------------------------------------------------------------------
```

- Test if variables are significant, interpret signs and magnitudes.

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Results

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- All coefficients are found to be highly significant.

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- Remember [Slides 4, p.10]: *'One useful special case of the F-test is in testing whether all the explanatory variables taken together are significant in the regression model.'*

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Model	9103.2286	2	4551.6143	Number of obs	=	1,388
Residual	565508.491	1,385	408.30938	F(2, 1385)	=	11.15
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- Remember [Slides 4, p.10]: *'One useful special case of the F-test is in testing whether all the explanatory variables taken together are significant in the regression model.'*
- For our multivariate regression

$$\texttt{bwght}_i = \beta_1 + \beta_2 \texttt{faminc}_i + \beta_3 \texttt{order}_i + u_i$$

this means $H_0 : \beta_2 = \beta_3 = 0$.

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- This test statistic follows an $F_{(q,n-k)}$ distribution under H_0 where $q = 2$ and $(n - k) = 1,385$.

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  this means $H_0 : \beta_2 = \beta_3 = 0$.
- This test statistic follows an $F_{(q,n-k)}$ distribution under H_0 where $q = 2$ and $(n-k) = 1,385$.
- Compare test statistic against critical value (and/or use p-value): We reject H_0 here; variables are 'jointly significant'. Let's do the same 'by hand'!

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- See Slides 4, p.19-21 for more details.

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- Main message: Our model fits the data only very poorly (very low R^2)!

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- Main message: Our model fits the data only very poorly (very low R^2)!
- Only about 1.58% of the variation of the dependent variable about its mean is explained by regression 1.
- As before, we can calculate the R^2 using other parts of the regression output. See how it's done!

Regression 2

- Estimate a regression of birth weight on a constant, family income, birth order **and cigs**.

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      Source |       SS           df       MS      Number of obs   =     1,388
-------------+----------------------------------   F(3, 1384)      =     16.63
       Model |  19996.5211         3  6665.50703   Prob > F        =    0.0000
    Residual |  554615.199     1,384  400.733525   R-squared       =    0.0348
-------------+----------------------------------   Adj R-squared   =    0.0327
       Total |   574611.72     1,387  414.283864   Root MSE        =    20.018

------------------------------------------------------------------------------
       bwght |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      faminc |   .0979201   .0291868     3.35   0.001      .040665    .1551752
       order |   1.616372    .603955     2.68   0.008     .4316058    2.801138
        cigs |  -.4771537    .091518    -5.21   0.000    -.6566827   -.2976247
       _cons |   114.2143     1.4693    77.73   0.000     111.3321    117.0966
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- Observe how the regression output has changed!

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```

- Observe how the regression output has changed!
- Conduct a 1-sided test on the cigs coefficient using statistical tables!

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One- vs two-sided tests?

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  - Testing for the possibility of the relationship in both directions.

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  - Given a fixed significance level of, say, $\alpha = 0.05$, a two-sided test allots half of our α to testing the statistical significance in **one** direction and the other half of α to test in the **other** direction.
  - This means `cigs` is considered significantly different from 0 if the test statistic is in the top 2.5% or bottom 2.5% of its probability distribution, resulting in a p-value of less than 0.05.

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  - Tests either if the estimated parameter is significantly greater **or** significantly smaller than zero, but not both.

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  - A one-sided test allots **all** of our α to testing the statistical significance in **one** direction only.
  - This means that, depending on the chosen tail, `cigs` is considered significantly lower (higher) than 0 if the test statistic is in the bottom (top) 5% of its probability distribution, resulting in a p-value of less than 0.05.

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- One-sided:
  - Tests either if the estimated parameter is significantly greater **or** significantly smaller than zero, but not both.
  - IOW: It tests for the possibility of the relationship in **one** direction and completely disregarding the other direction.
  - A one-sided test allots **all** of our α to testing the statistical significance in **one** direction only.
  - This means that, depending on the chosen tail, `cigs` is considered significantly lower (higher) than 0 if the test statistic is in the bottom (top) 5% of its probability distribution, resulting in a p-value of less than 0.05.
  - The one-tailed test provides more power to detect an effect in one direction by not testing the effect in the other direction.

Regression 2

- One-sided test in our example

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```

- Above $H_0 : \beta_{cigs} = 0, \;\; H_a : \beta_{cigs} \neq 0$ (two-sided).
- We want to test for the one-sided alternative that $\beta_{cigs} < 0$. Note that the effect has the correct 'predicted sign'.
- To get the p-value, simply divide $p - Val_{cigs}/2$ because the effect is going in the 'predicted' direction. This is P($|-5.21|$).
- We reject H_0 in favour of the one-sided alternative indicating that smoking has a significantly negative impact on birth weight.

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      Source |       SS           df       MS      Number of obs   =     1,388
-------------+----------------------------------   F(4, 1383)      =     12.49
       Model |  20031.4556         4  5007.8639    Prob > F        =    0.0000
    Residual |  554580.264     1,383  400.998022   R-squared       =    0.0349
-------------+----------------------------------   Adj R-squared   =    0.0321
       Total |   574611.72     1,387  414.283864   Root MSE        =    20.025

------------------------------------------------------------------------------
       bwght |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      faminc |   .0937846   .0323843     2.90   0.004     .0302569    .1573122
       order |   1.631028   .6061915     2.69   0.007     .4418743    2.820183
        cigs |  -.4730827   .0925814    -5.11   0.000    -.6546978   -.2914676
  mothereduc |    .076161   .2580337     0.30   0.768    -.4300187    .5823408
       _cons |    113.317   3.376943    33.56   0.000     106.6925    119.9415
------------------------------------------------------------------------------
```

- Interpret results!

Model specification

From the lecture [Slides 4, pp. 14]:

- If an important explanatory variable is **missing** from our model, the estimated coefficients are **biased** (omitted variable bias)!

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- Regression 3: `mothereduc` probably irrelevant; **probably over-specified.**

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- Regression 1: low R^2, `cigs` missing; **probably under-specified.**
- Regression 3: `mothereduc` probably irrelevant; **probably over-specified.**
- Regression 2: note that $adj.\ R^2_{reg.3} < adj.\ R^2_{reg.2}$; **probably best fit.**

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  - Example: More variation in consumption behaviour for rich compared to poor families.

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    $\Rightarrow$ **Hypothesis testing is invalid!**

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- Visual analysis first; e.g. for `faminc`

Homo- vs. heteroskedasticity

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- We fail to reject H_0 of homoskedasticity.
- No statistical evidence of heteroskedasticity.
- This is in line with our visual analysis.

Thank you and see you next time!

Juergen Amann

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

Overall relation 'by hand'

Go back

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 ( 2)  faminc = 0

       F(  2,  1385) =   11.15
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$$F^* = \frac{R^2/(q)}{(1 - R^2)/(n-k)}.$$

```
. display 0.0158/(1 - 0.0158) * 1385/2
11.117151
```

R^2 'by hand' ◂ Go back

From the lecture slides [Slides 3, pp.20]:

- The R^2 measure of goodness-of-fit is defined by $R^2 = \frac{ESS}{TSS} = 1 - \frac{RSS}{TSS}$.

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      Source |       SS           df       MS      Number of obs   =     1,388
-------------+----------------------------------   F(2, 1385)      =     11.15
       Model |   9103.2286         2   4551.6143   Prob > F        =    0.0000
    Residual |  565508.491     1,385   408.30938   R-squared       =    0.0158
-------------+----------------------------------   Adj R-squared   =    0.0144
       Total |   574611.72     1,387  414.283864   Root MSE        =    20.207

. display 9103.2286 /  574611.72
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```
. display 1 - ((1388-1)/(1383)*(1-20031.4556/574611.72))
0.0144
```