

Q-Step: Week 6 Lecture

Multivariate Relationships

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Roadmap

Previously

- Research Design
- Concepts and Measurement
- Descriptive Statistics and Visualization
- Bivariate Relationships
 - ▶ Conditional means
 - ▶ Correlation
 - ▶ Bivariate regression

Today

- Multivariate OLS regression

Correlation Analysis!

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 - ▶ 0 means no correlation
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 - ▶ -1 means perfect negative correlation

Correlation Analysis!

- Correlation
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- But bad for predictions
- Only Bivariate
- The coefficient runs from -1 to +1
 - ▶ 0 means no correlation
 - ▶ 1 means perfect positive correlation
 - ▶ -1 means perfect negative correlation
- The software gives you two important measures
 - ▶ A confidence interval (i.e. a range of correlation values)
 - ▶ A p-value, i.e. a probability that the correlation is random

Correlation: Example

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- Is there a correlation between educational qualifications and Brexit?

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```
##  
## Pearson's product-moment correlation  
##  
## data: brexit$leave and brexit$noqual  
## t = 11.697, df = 377, p-value < 2.2e-16  
## alternative hypothesis: true correlation is not equal to 0  
## 95 percent confidence interval:  
## 0.4380723 0.5862924  
## sample estimates:  
## cor  
## 0.5160348
```

Bivariate OLS recap!

- Key Logic

$$Y_i = \alpha + \beta X_i$$

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Let's go back to our examples from last week!

Our theory

Our theory

% No Qualifications



% Brexit

Bivariate OLS



The OLS output in R

```
##  
## Call:  
## lm(formula = brexit$leave ~ brexit$noqual)  
##  
## Residuals:  
##      Min       1Q   Median       3Q      Max   
## -34.855  -3.593   1.971   5.958  24.182   
##  
## Coefficients:  
##              Estimate Std. Error t value Pr(>|t|)      
## (Intercept)  29.33773    2.08661   14.06  <2e-16 ***   
## brexit$noqual  1.04234    0.08911   11.70  <2e-16 ***   
## ---  
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1  
##  
## Residual standard error: 8.945 on 377 degrees of freedom  
## Multiple R-squared:  0.2663, Adjusted R-squared:  0.2643   
## F-statistic: 136.8 on 1 and 377 DF,  p-value: < 2.2e-16
```

New theory

New theory

Median Weekly Income

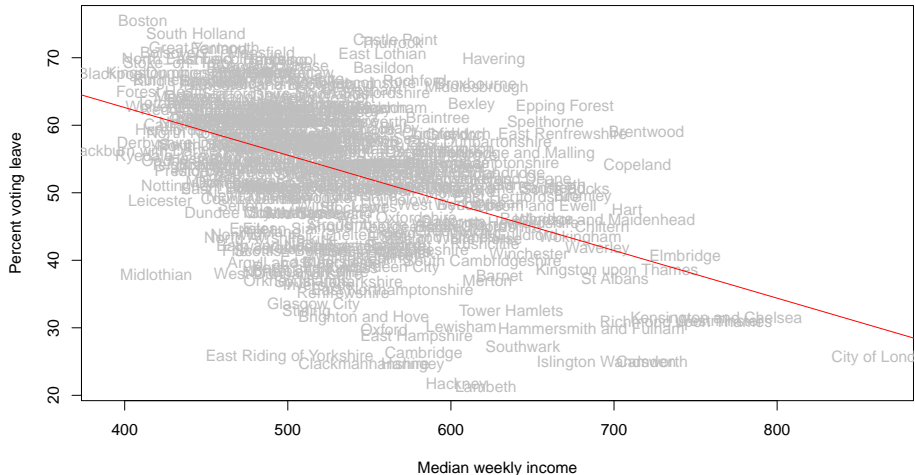


% Brexit

Bivariate OLS Regression: A Second Example

```
##  
## Call:  
## lm(formula = brexit$leave ~ brexit$income)  
##  
## Residuals:  
##      Min       1Q   Median       3Q      Max   
## -29.804  -5.471   1.452   5.837  23.010   
##  
## Coefficients:  
##              Estimate Std. Error t value Pr(>|t|)      
## (Intercept)  90.853597   3.644753   24.93  <2e-16 ***   
## brexit$income -0.070581   0.006767  -10.43  <2e-16 ***   
## ---  
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1  
##  
## Residual standard error: 9.289 on 360 degrees of freedom  
## (17 observations deleted due to missingness)  
## Multiple R-squared:  0.232, Adjusted R-squared:  0.2299   
## F-statistic: 108.8 on 1 and 360 DF, p-value: < 2.2e-16
```


Bivariate OLS Regression: A Second Example



Basic Interpretation of OLS

- How do we interpret the OLS coefficient?
 - ▶ A unit increase in X predicts a coefficient increase in Y
 - ▶ In our case, if we increase median weekly income by a pound we get a 0.07 decrease in the percentage voting leave

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 - ▶ Remember that often times there is no 0 observation in our data sets!

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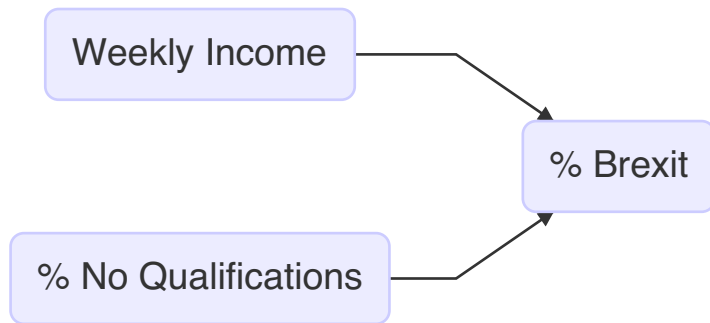
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 - ▶ In our regression all our effects are statistically significant!
- Future Steps
 - ▶ What if there is a second variable that might influence our outcome, but might also influence how our main X (e.g. weekly income) relates to Y ?

A more complex theory

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$F(\% \text{ Brexit}) \rightarrow F \rightarrow M \rightarrow A \rightarrow$

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- This time we estimate the partial correlation holding the other confounders constant
- The interpretation for e.g. β_1 is the same. Holding all other X s constant, an increase in X_1 predicts a β_1 change in Y !

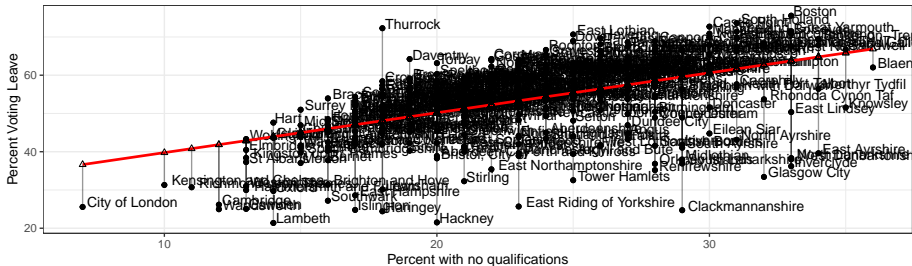
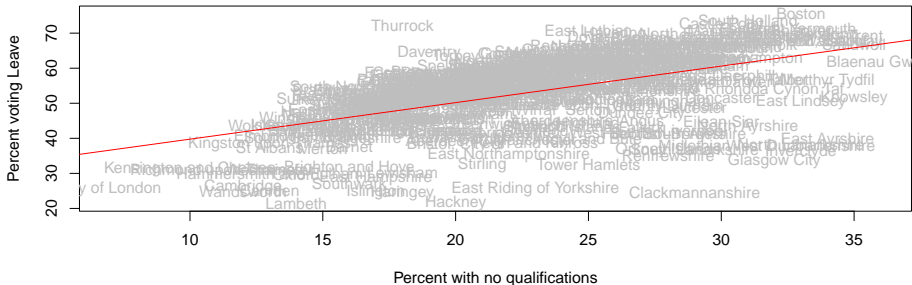
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- We still want to minimize the sum of the squared residuals

Bivariate Residuals



Estimating Multivariate Models

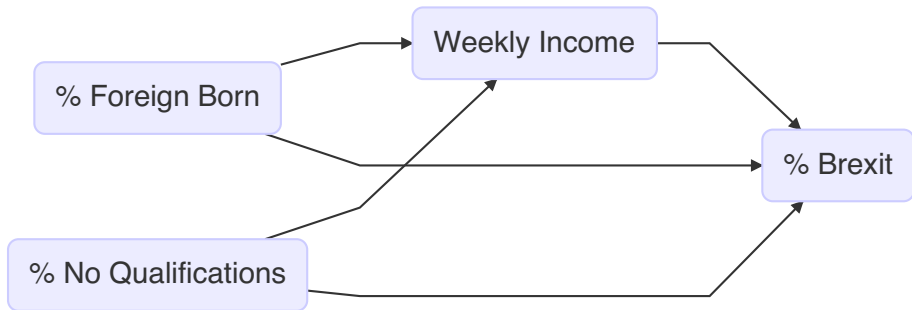
```
##
## Call:
## lm(formula = brexit$leave ~ brexit$income + brexit$noqual)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -32.518  -3.815   1.942   5.839  23.605
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  56.052694   6.866926   8.163 5.61e-15 ***
## brexit$income -0.036124   0.008729  -4.138 4.37e-05 ***
## brexit$noqual  0.721536   0.122667   5.882 9.28e-09 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 8.883 on 359 degrees of freedom
## (17 observations deleted due to missingness)
## Multiple R-squared:  0.2996, Adjusted R-squared:  0.2957
## F-statistic: 76.77 on 2 and 359 DF,  p-value: < 2.2e-16
```

Tidying up the output

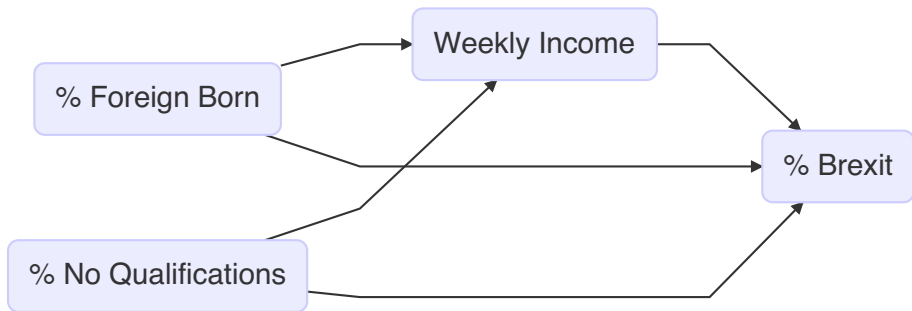
```
##
## =====
##                               Dependent variable:
##                               -----
##                               leave
## -----
## income                        -0.036***
##                               (0.009)
##
## noqual                       0.722***
##                               (0.123)
##
## Constant                     56.053***
##                               (6.867)
## -----
## Observations                  362
## R2                           0.300
## Adjusted R2                   0.296
## Residual Std. Error          8.883 (df = 359)
```

Social processes are complex!

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Social processes are complex!



- Don't read too much into the diagram, it is just to show you that social links can be complex!
- Still, multivariate models could tell us a lot about such a relationship!

How good is our model?

- We are some times interested in how well our model is performing
- The R^2 is a common fit statistic used by many
- It gives the proportion variance explained by the chosen model specification
- When one uses competing model specification, the R^2 and the adjusted- R^2 can be used
- In the past, people would place too much emphasis on model fit. I would encourage you to consider it, but don't go crazy about model fit.

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- a key problem with the above equation and R^2 more generally is that adding more variables inflates the model fit.

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$$R_{adj}^2 = 1 - (1 - R^2) \frac{n - 1}{n - p - 1}$$

where n is the number of observations and p is the number of parameters included in the model specification

Putting all models in one table

```
##
## =====
##                               Dependent variable:
##                               -----
##                               leave
##                               (1)      (2)      (3)
## -----
## income                -0.071***      -0.036***
##                       (0.007)          (0.009)
##
## noqual                1.042***      0.722***
##                       (0.089)          (0.123)
##
## Constant              90.854***      29.338***      56.053***
##                       (3.645)          (2.087)          (6.867)
## -----
## Observations           362            379            362
## R2                     0.232            0.266            0.300
## Adjusted R2            0.230            0.264            0.296
## Residual Std. Error    9.289 (df = 360)    8.945 (df = 377)    8.883 (df = 359)
## F Statistic            108.780*** (df = 1; 360) 136.828*** (df = 1; 377) 76.765*** (df = 2; 359)
## =====
## Note:                                     *p<0.1; ***p<0.05; ***p<0.01
```

Summary

Today

- We learned about Multivariate OLS
- It is the foundation of the vast majority of analyses in the social sciences
- It allows to test multiple hypotheses
- And make conditional predictions about continuous dependent variables
- We also talked about model fit
- What is left to wrap up OLS modeling?
- Uncertainty and Significance

Next Week

- A good overview of statistical inference
- Next week's lecture will help you grow your confidence in estimating regressions
- Some aspects of inference require a *leap of faith*, but most of it is straight forward!

Thank You

Click on the link below to download the data:

<https://tinyurl.com/yc776n68>