Econometrics in R

Lecture 4

Louis SIRUGUE

M1 APE - Fall 2022

What we've seen so far

Manipulate data with `dplyr`

```
read.csv("ligue1.csv")
#
#
#
#
#
#
```

```
##      Wk Day       Date  Time           Home  xG Score xG.1          Away Attendance  ...
## 1     1 Fri 2021-08-06 21:00         Monaco 2.0   1-1  0.3        Nantes       7500  ...
## 2     1 Sat 2021-08-07 17:00           Lyon 1.4   1-1  0.8         Brest      29018  ...
## 3     1 Sat 2021-08-07 21:00         Troyes 0.8   1-2  1.2     Paris S-G      15248  ...
## 4     1 Sun 2021-08-08 13:00         Rennes 0.6   1-1  2.0          Lens      22567  ...
## 5     1 Sun 2021-08-08 15:00       Bordeaux 0.7   0-2  3.3 Clermont Foot      18748  ...
## 6     1 Sun 2021-08-08 15:00     Strasbourg 0.4   0-2  0.9        Angers      23250  ...
## 7     1 Sun 2021-08-08 15:00           Nice 0.8   0-0  0.2         Reims      18030  ...
## 8     1 Sun 2021-08-08 15:00 Saint-Étienne 2.1   1-1  1.3       Lorient      20461  ...
## 9     1 Sun 2021-08-08 17:00           Metz 0.7   3-3  1.4         Lille      15551  ...
  ...   ... ...        ...   ...            ... ...   ...  ...           ...        ...  ...
```

What we've seen so far

Manipulate data with `dplyr`

```
read.csv("ligue1.csv") %>%
  select(Home, xG, Score, xG.1, Away)                # Keep/drop certain columns
                                                     #
                                                     #
                                                     #
                                                     #
                                                     #
```

```
##               Home  xG Score xG.1          Away
## 1           Monaco 2.0   1-1  0.3        Nantes
## 2             Lyon 1.4   1-1  0.8         Brest
## 3           Troyes 0.8   1-2  1.2     Paris S-G
## 4           Rennes 0.6   1-1  2.0          Lens
## 5         Bordeaux 0.7   0-2  3.3 Clermont Foot
## 6       Strasbourg 0.4   0-2  0.9        Angers
## 7             Nice 0.8   0-0  0.2         Reims
## 8    Saint-Étienne 2.1   1-1  1.3       Lorient
## 9             Metz 0.7   3-3  1.4         Lille
 ...               ... ...   ...  ...           ...
```

What we've seen so far

Manipulate data with `dplyr`

```
read.csv("ligue1.csv") %>%
  select(Home, xG, Score, xG.1, Away) %>%          # Keep/drop certain columns
  mutate(home_winner = xG > xG.1)                  # Create a new variable
                                                   #
                                                   #
                                                   #
                                                   #
```

```
##              Home  xG Score xG.1          Away home_winner
## 1          Monaco 2.0   1-1  0.3        Nantes        TRUE
## 2            Lyon 1.4   1-1  0.8         Brest        TRUE
## 3          Troyes 0.8   1-2  1.2     Paris S-G       FALSE
## 4          Rennes 0.6   1-1  2.0          Lens       FALSE
## 5        Bordeaux 0.7   0-2  3.3 Clermont Foot       FALSE
## 6      Strasbourg 0.4   0-2  0.9        Angers       FALSE
## 7            Nice 0.8   0-0  0.2         Reims        TRUE
## 8   Saint-Étienne 2.1   1-1  1.3       Lorient        TRUE
## 9            Metz 0.7   3-3  1.4         Lille       FALSE
 ...            ... ...   ...  ...           ...         ...
```

What we've seen so far

Manipulate data with `dplyr`

```
read.csv("ligue1.csv") %>%
  select(Home, xG, Score, xG.1, Away) %>%          # Keep/drop certain columns
  mutate(home_winner = xG > xG.1) %>%              # Create a new variable
  filter(Home == "Rennes")                         # Keep/drop certain rows
                                                   #
                                                   #
                                                   #
```

```
##       Home  xG Score xG.1          Away home_winner
## 1   Rennes 0.6   1-1  2.0          Lens       FALSE
## 2   Rennes 0.9   1-0  0.5        Nantes        TRUE
## 3   Rennes 1.0   0-2  0.5         Reims        TRUE
## 4   Rennes 2.4   6-0  0.3 Clermont Foot        TRUE
## 5   Rennes 0.8   2-0  1.4     Paris S-G       FALSE
## 6   Rennes 1.5   1-0  0.6    Strasbourg        TRUE
## 7   Rennes 3.8   4-1  1.1          Lyon        TRUE
## 8   Rennes 3.1   2-0  0.7   Montpellier        TRUE
## 9   Rennes 0.8   1-2  0.6         Lille        TRUE
           ...  ...   ...  ...           ...         ...
```

What we've seen so far

Manipulate data with `dplyr`

```
read.csv("ligue1.csv") %>%
  select(Home, xG, Score, xG.1, Away) %>%          # Keep/drop certain columns
  mutate(home_winner = xG > xG.1) %>%               # Create a new variable
  filter(Home == "Rennes") %>%                      # Keep/drop certain rows
  arrange(-xG)                                      # Sort rows
                                                    #
                                                    #
```

```
##       Home  xG Score xG.1          Away home_winner
## 1   Rennes 3.8   4-1  1.1          Lyon        TRUE
## 2   Rennes 3.3   6-0  0.4      Bordeaux        TRUE
## 3   Rennes 3.3   6-1  0.9          Metz        TRUE
## 4   Rennes 3.1   2-0  0.7   Montpellier        TRUE
## 5   Rennes 2.7   2-0  0.3         Brest        TRUE
## 6   Rennes 2.6   4-1  0.4        Troyes        TRUE
## 7   Rennes 2.4   6-0  0.3 Clermont Foot        TRUE
## 8   Rennes 1.9   2-3  2.9        Monaco       FALSE
## 9   Rennes 1.7   2-0  0.3        Angers        TRUE
           ... ...   ...  ...           ...         ...
```

What we've seen so far

Manipulate data with `dplyr`

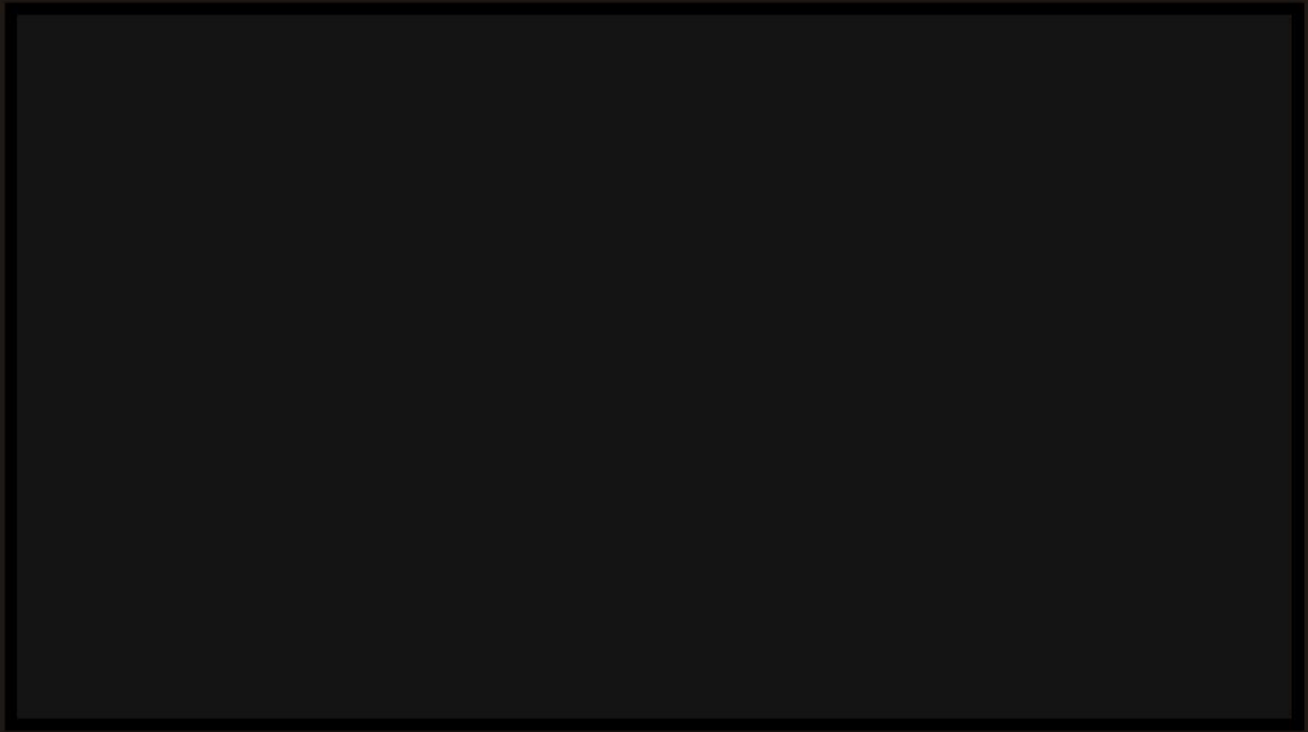
```
read.csv("ligue1.csv") %>%
  select(Home, xG, Score, xG.1, Away) %>%          # Keep/drop certain columns
  mutate(home_winner = xG > xG.1) %>%              # Create a new variable
  filter(Home == "Rennes") %>%                     # Keep/drop certain rows
  arrange(-xG) %>%                                 # Sort rows
  summarise(expected_wins = mean(home_winner),     # Aggregate into statistics
            expected_goals = sum(xG))              #
```

```
##   expected_wins expected_goals
## 1     0.8421053           36.6
```

What we've seen so far

Plot data with `ggplot()`

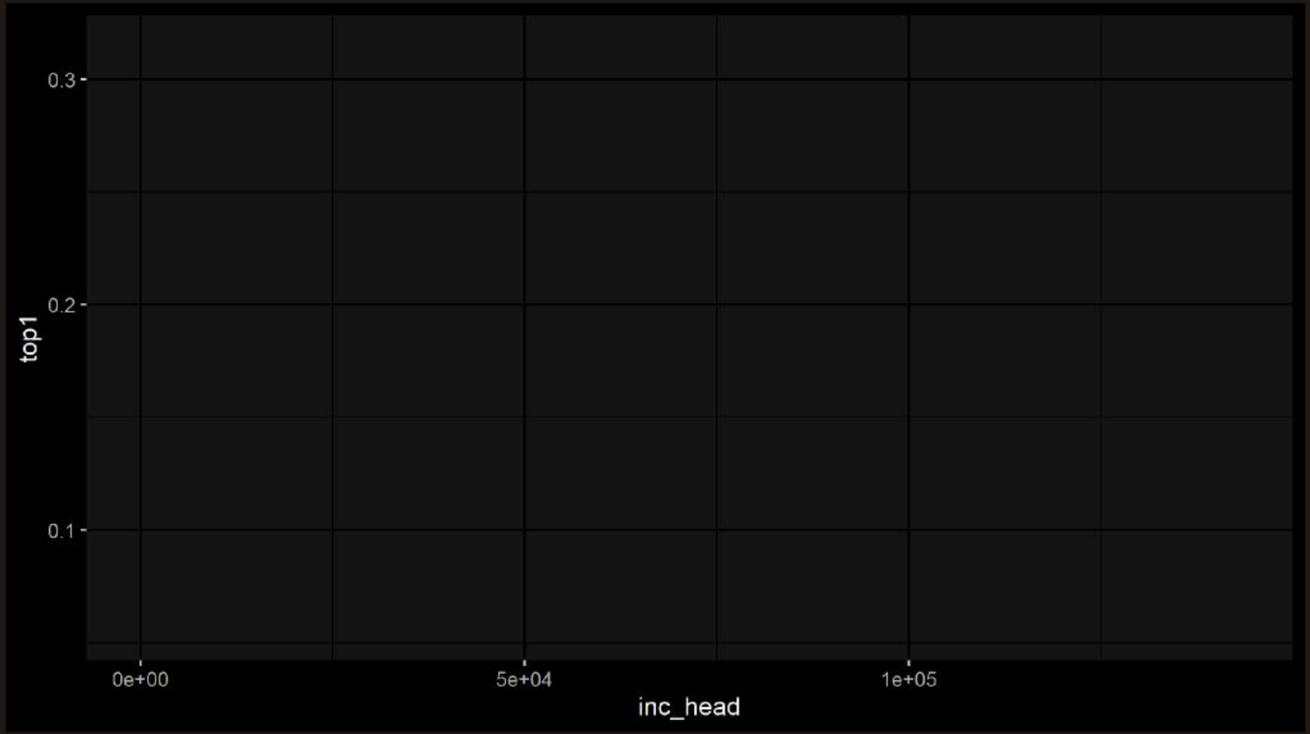
```
ggplot(read.csv("wid.csv"))                               # Data
                                                          #
```



What we've seen so far

Plot data with `ggplot()`

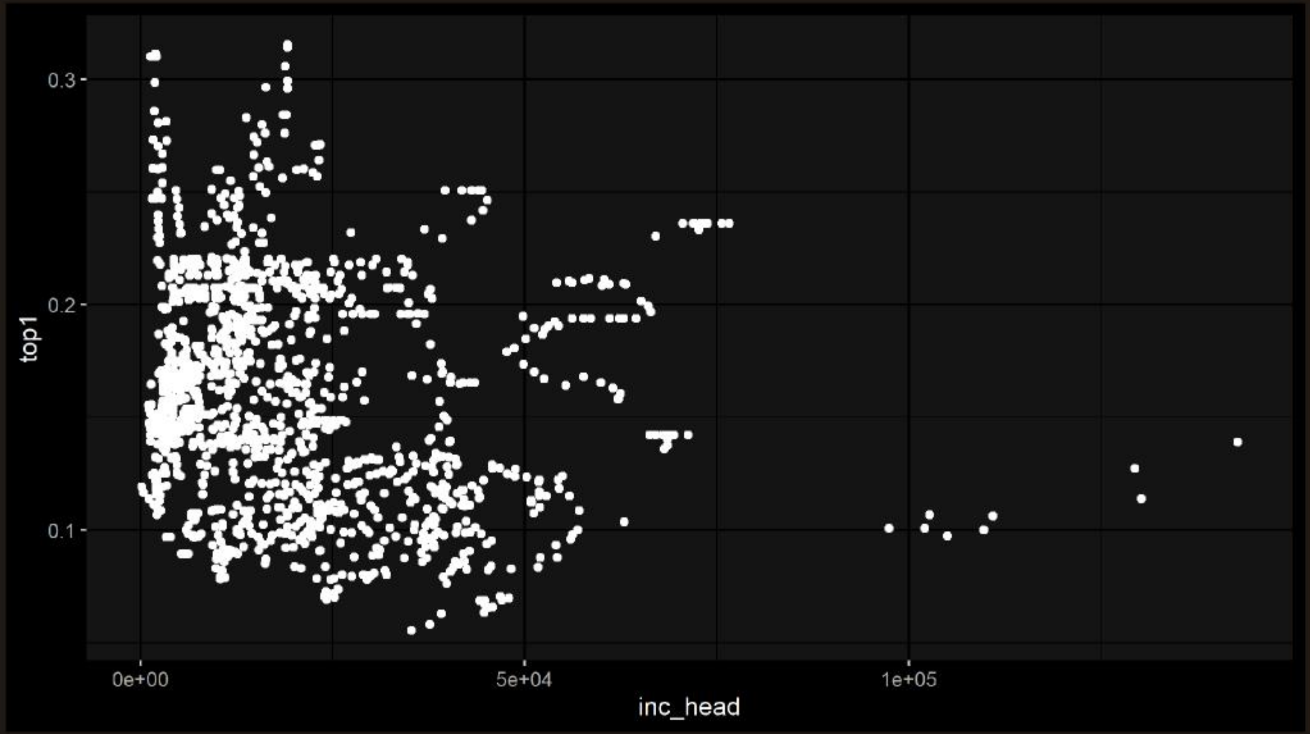
```
ggplot(read.csv("wid.csv"), aes(x = inc_head, y = top1))          # Data & aesthetics
                                                                  #
```



What we've seen so far

Plot data with `ggplot()`

```
ggplot(read.csv("wid.csv"), aes(x = inc_head, y = top1)) +          # Data & aesthetics
  geom_point()                                                       # Geometry
```



What we've seen so far

Write reports with `R markdown`

```
---
title: "Starbucks"
author: "Louis Sirugue"
output: html_document
---
```

Starbucks

Louis Sirugue

What we've seen so far

Write reports with `R markdown`

````
---
title: "Starbucks"
author: "Louis Sirugue"
output: html_document
---

```{r, echo = F, message = F, warning = F}
library(ggplot2) # Load package
starbucks <- read.csv("starbucks.csv", sep = ";") # Load data
```

Nutritional values of `r nrow(starbucks)` *starbucks* beverages
````

Starbucks

Louis Sirugue

Nutritional values of 242 *starbucks* beverages

What we've seen so far

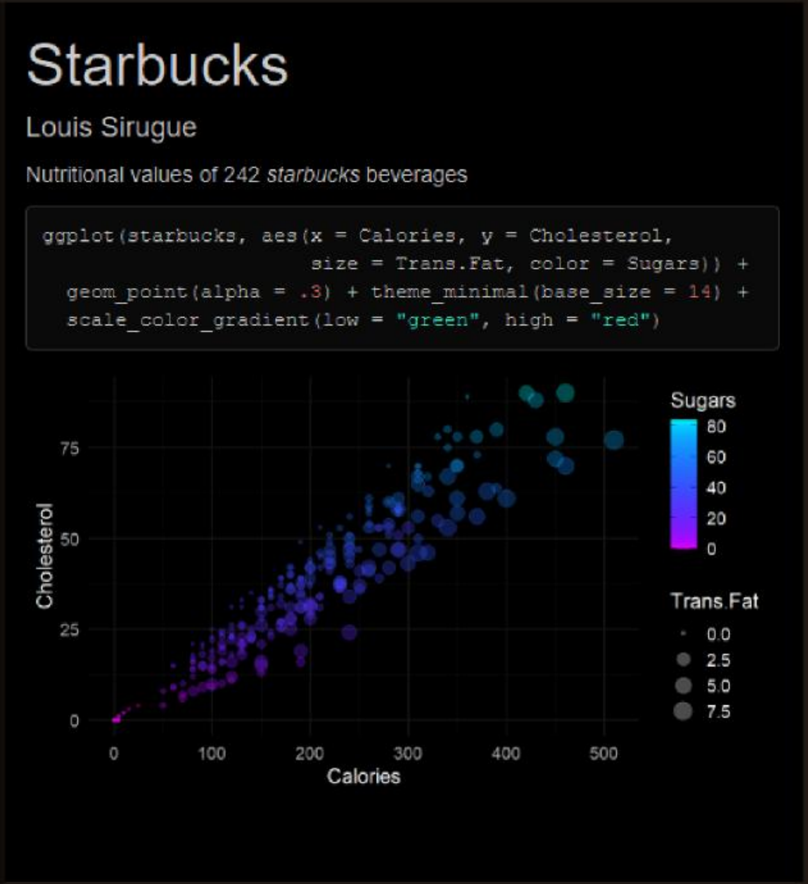
Write reports with `R markdown`

```
---
title: "Starbucks"
author: "Louis Sirugue"
output: html_document
---

```{r, echo = F, message = F, warning = F}
library(ggplot2) # Load package
starbucks <- read.csv("starbucks.csv", sep = ";") # Load data
```

Nutritional values of `r nrow(starbucks)` *starbucks* beverages

```{r, fig.height = 4}
ggplot(starbucks, aes(x = Calories, y = Cholesterol,
                      size = Trans.Fat, color = Sugars)) +
  geom_point(alpha = .3) + theme_minimal(base_size = 14) +
  scale_color_gradient(low = "green", high = "red")
```
```



Today: Econometrics in R!

Today: Econometrics in R!

1. Regressions

1.1. On continuous variables

- For this part we're going to work with the ***'Great Gatsby Curve'***
  - It refers to the positive relationship between **inequality** and **intergenerational income persistence**
  - The term was coined by Alan Krueger based on the research of Miles Corak

```
ggcurve <- read.csv("ggcurve.csv")
str(ggcurve)
```

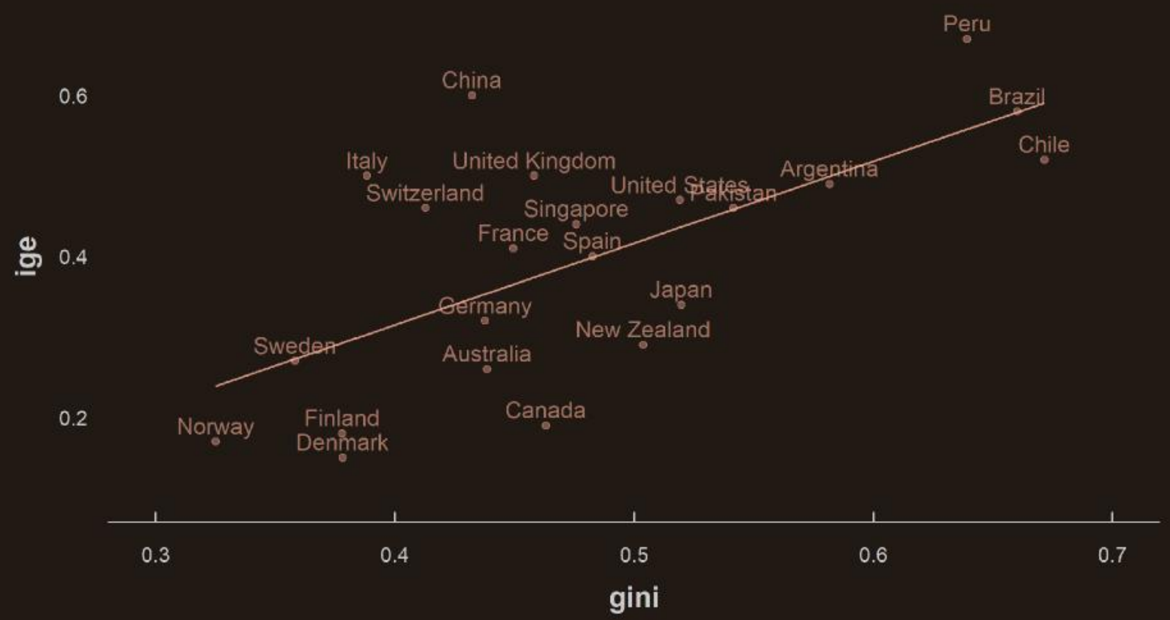
```
## 'data.frame':    22 obs. of  3 variables:
##  $ country: chr  "Denmark" "Norway" "Finland" "Canada" ...
##  $ ige    : num  0.15 0.17 0.18 0.19 0.26 0.27 0.29 0.32 0.34 0.4 ...
##  $ gini   : num  0.378 0.325 0.378 0.463 0.439 ...
```

- For **22 countries** we have the following variables
  - **ige:** The intergenerational income elasticity, the higher the closer child income to parent income
  - **gini:** The Gini coefficient of income inequality, the higher the more concentrated the income

1. Regressions

1.1. On continuous variables

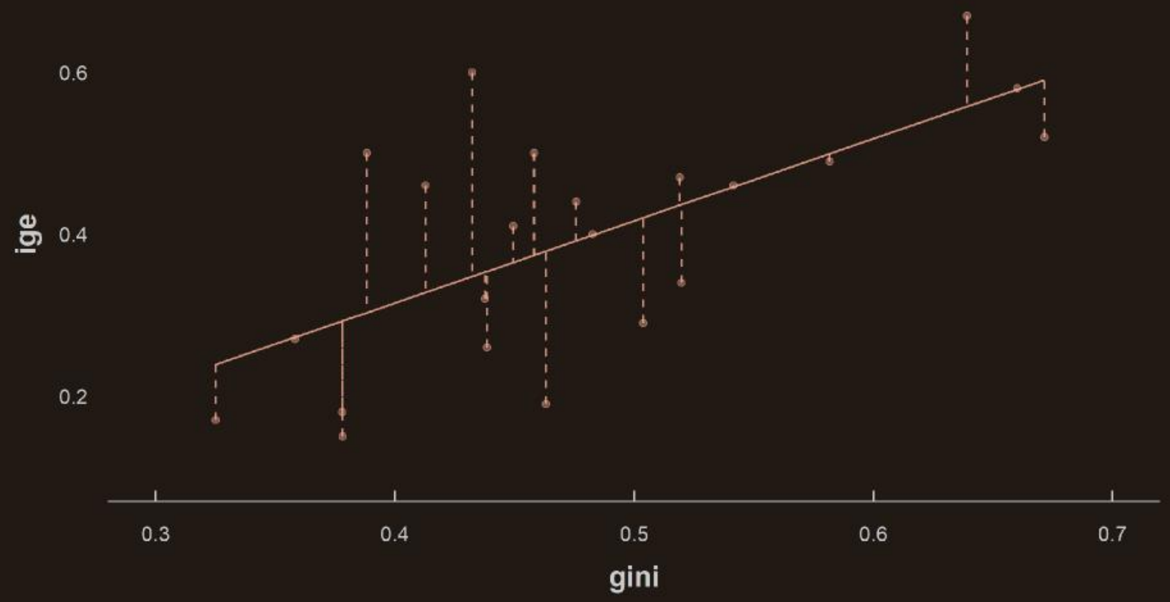
- You must already be quite familiar with univariate **regressions** $y = \alpha + \beta x + \varepsilon$



1. Regressions

1.1. On continuous variables

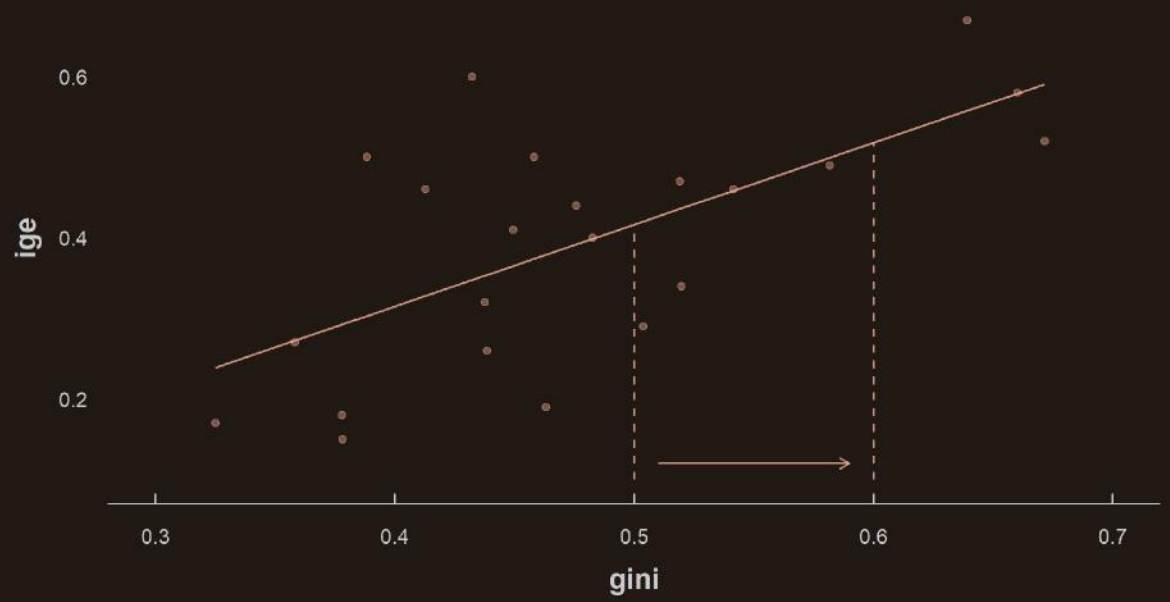
- You must already be quite familiar with univariate **regressions** $y = \alpha + \beta x + \varepsilon$
  - We're looking for the line $\hat{y}_i = \hat{\alpha} + \hat{\beta} x_i$ that **mimimizes distance** to the data points $\sum \varepsilon_i^2$



1. Regressions

1.1. On continuous variables

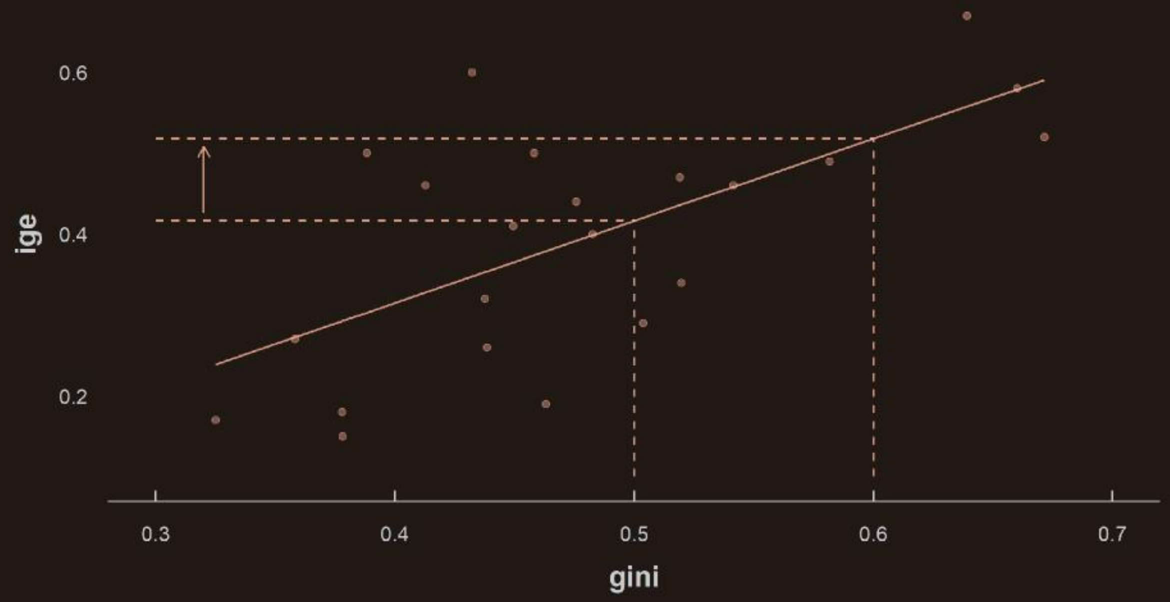
- You must already be quite familiar with univariate **regressions** $y = \alpha + \beta x + \varepsilon$
  - We're looking for the line $\hat{y}_i = \hat{\alpha} + \hat{\beta} x_i$ that **mimimizes distance** to the data points $\sum \varepsilon_i^2$
  - Such that for a **one unit increase** in x



1. Regressions

1.1. On continuous variables

- You must already be quite familiar with univariate **regressions** $y = \alpha + \beta x + \varepsilon$
  - We're looking for the line $\hat{y}_i = \hat{\alpha} + \hat{\beta} x_i$ that **mimimizes distance** to the data points $\sum \varepsilon_i^2$
  - Such that for a **one unit increase** in x
  - Its slope $\hat{\beta}$ indicates the associated **expected change** in y



1. Regressions

1.1. On continuous variables

- In R we can **estimate a regression** model using the **lm()** command *(for **L**inear **M**odel)*
    1.
    2.

```
lm( , )
```

1. Regressions

1.1. On continuous variables

- In R we can **estimate a regression** model using the **lm()** command *(for **L**inear **M**odel)*
    1. The first argument is the **formula**, written as **y ~ x**
    2.

```
lm(ige ~ gini, )
```

1. Regressions

1.1. On continuous variables

- In R we can **estimate a regression** model using the **lm()** command *(for **L**inear **M**odel)*
  1. The first argument is the **formula**, written as **y ~ x**
  2. The second argument is the **data** containing the variables

```
lm(ige ~ gini, ggcurve)
```

```
##
## Call:
## lm(formula = ige ~ gini, data = ggcurve)
##
## Coefficients:
## (Intercept)         gini
##    -0.09129      1.01546
```

- This is great but the **output** is a bit minimalistic
  - To get a more **exhaustive description** of our regression we can apply the **summary()** function to lm()

```
ggmodel <- lm(ige ~ gini, ggcurve) %>% summary()
```

1. Regressions

1.1. On continuous variables

```
ggmodel
```

```
##
## Call:
## lm(formula = ige ~ gini, data = ggcurve)
##
## Residuals:
##       Min        1Q    Median        3Q       Max
## -0.188991 -0.088238 -0.000855  0.047284  0.252310
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) -0.09129    0.12870  -0.709  0.48631
## gini         1.01546    0.26425   3.843  0.00102 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.1159 on 20 degrees of freedom
## Multiple R-squared:  0.4247,    Adjusted R-squared:  0.396
## F-statistic: 14.77 on 1 and 20 DF,  p-value: 0.001016
```

1. Regressions

1.1. On continuous variables

- It gives back the **command**

```
##
## Call:
## lm(formula = ige ~ gini, data = ggcurve)
##
##
##
##
##
##
##
##
##
##
##
##
##
##
##
```

← Command

1. Regressions

1.1. On continuous variables

- A description of the **distribution** of **residuals**

```
##
## Call:
## lm(formula = ige ~ gini, data = ggcurve)
##
## Residuals:
##       Min        1Q    Median        3Q       Max
## -0.188991 -0.088238 -0.000855  0.047284  0.252310
##
##
##
##
##
##
##
##
##
##
##
```

← Command

← Residuals distribution

1. Regressions

1.1. On continuous variables

- **Coefficients** along with their **standard error**, **t-value**, and **p-value**

```
##
## Call:
## lm(formula = ige ~ gini, data = ggcurve)
##
## Residuals:
##       Min        1Q    Median        3Q       Max
## -0.188991 -0.088238 -0.000855  0.047284  0.252310
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) -0.09129    0.12870  -0.709  0.48631
## gini         1.01546    0.26425   3.843  0.00102
##
##
##
##
##
##
```

← Command

← Residuals distribution

← Coefs, s.e., t-/p-values

1. Regressions

1.1. On continuous variables

- **Significance** thresholds with symbols

```
##
## Call:
## lm(formula = ige ~ gini, data = ggcurve)
##
## Residuals:
##       Min        1Q    Median        3Q       Max
## -0.188991 -0.088238 -0.000855  0.047284  0.252310
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) -0.09129    0.12870  -0.709  0.48631
## gini         1.01546    0.26425   3.843  0.00102 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
##
##
```

← Command

← Residuals distribution

← Coefs, s.e., t-/p-values

← Significance

1. Regressions

1.1. On continuous variables

- The **residual standard error** $\sqrt{\sum (y_i - \hat{y}_i)^2/\text{df}}$ and **degrees of freedom**

```
##
## Call:
## lm(formula = ige ~ gini, data = ggcurve)
##
## Residuals:
##       Min        1Q    Median        3Q       Max
## -0.188991 -0.088238 -0.000855  0.047284  0.252310
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) -0.09129    0.12870  -0.709  0.48631
## gini         1.01546    0.26425   3.843  0.00102 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.1159 on 20 degrees of freedom
##
##
```

← Command

← Residuals distribution

← Coefs, s.e., t-/p-values

← Significance

← Residual s.e. & df.

1. Regressions

1.1. On continuous variables

- The R^2 and **adjusted** R^2

```
##
## Call:
## lm(formula = ige ~ gini, data = ggcurve)
##
## Residuals:
##       Min        1Q    Median        3Q       Max
## -0.188991 -0.088238 -0.000855  0.047284  0.252310
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) -0.09129    0.12870  -0.709  0.48631
## gini         1.01546    0.26425   3.843  0.00102 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.1159 on 20 degrees of freedom
## Multiple R-squared:  0.4247,    Adjusted R-squared:  0.396
##
```

← Command

← Residuals distribution

← Coefs, s.e., t-/p-values

← Significance

← Residual s.e. & df.

← R^2 & adjusted R^2

1. Regressions

1.1. On continuous variables

- The result of an **F-test** ($H_0 : \beta_k = 0 \ \forall k$)

```
##
## Call:
## lm(formula = ige ~ gini, data = ggcurve)
##
## Residuals:
##       Min        1Q    Median        3Q       Max
## -0.188991 -0.088238 -0.000855  0.047284  0.252310
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) -0.09129    0.12870  -0.709  0.48631
## gini         1.01546    0.26425   3.843  0.00102 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.1159 on 20 degrees of freedom
## Multiple R-squared:  0.4247,    Adjusted R-squared:  0.396
## F-statistic: 14.77 on 1 and 20 DF,  p-value: 0.001016
```

← Command

← Residuals distribution

← Coefs, s.e., t-/p-values

← Significance

← Residual s.e. & df.

← R^2 & adjusted R^2

← F-test results

1. Regressions

1.1. On continuous variables

- All these elements are then easily accessible using the `$` operator

```
str(ggmodel, give.attr = F)
```

```
## List of 11
##  $ call         : language lm(formula = ige ~ gini, data = ggcurve)
##  $ terms        :Classes 'terms', 'formula'  language ige ~ gini
##  $ residuals    : Named num [1:22] -0.1427 -0.0687 -0.1125 -0.189 -0.094 ...
##  $ coefficients : num [1:2, 1:4] -0.0913 1.0155 0.1287 0.2642 -0.7093 ...
##  $ aliased      : Named logi [1:2] FALSE FALSE
##  $ sigma        : num 0.116
##  $ df           : int [1:3] 2 20 2
##  $ r.squared    : num 0.425
##  $ adj.r.squared: num 0.396
##  $ fstatistic   : Named num [1:3] 14.8 1 20
##  $ cov.unscaled : num [1:2, 1:2] 1.23 -2.48 -2.48 5.19
```

➜ Let's try it out!

1. Regressions

1.1. On continuous variables

- Take the **coefficients** for instance

```
ggmodel$coefficients
```

```
##                Estimate Std. Error    t value    Pr(>|t|)
## (Intercept) -0.09129311  0.1287045 -0.7093234 0.486311455
## gini         1.01546204  0.2642477  3.8428420 0.001015706
```

- We can **subset** this matrix like we would do with a regular `data.frame`

```
ggmodel$coefficients[2, 1]
```

```
## [1] 1.015462
```

```
ggmodel$coefficients[, "Pr(>|t|)"]
```

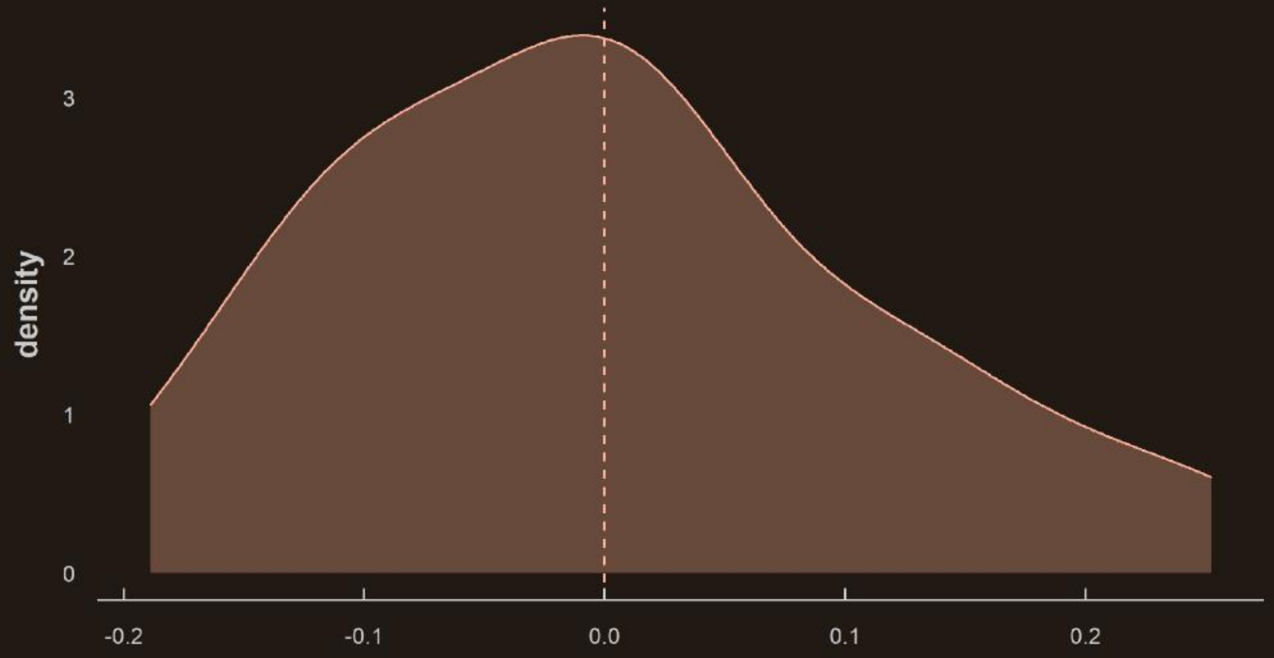
```
## (Intercept)        gini
## 0.486311455 0.001015706
```

1. Regressions

1.1. On continuous variables

- We can also easily **plot** the **distribution** of our **residuals**

```
ggplot(data.frame(x = ggmodel$residuals), aes(x = x)) +
  geom_density() + geom_vline(xintercept = 0, linetype = "dashed")
```

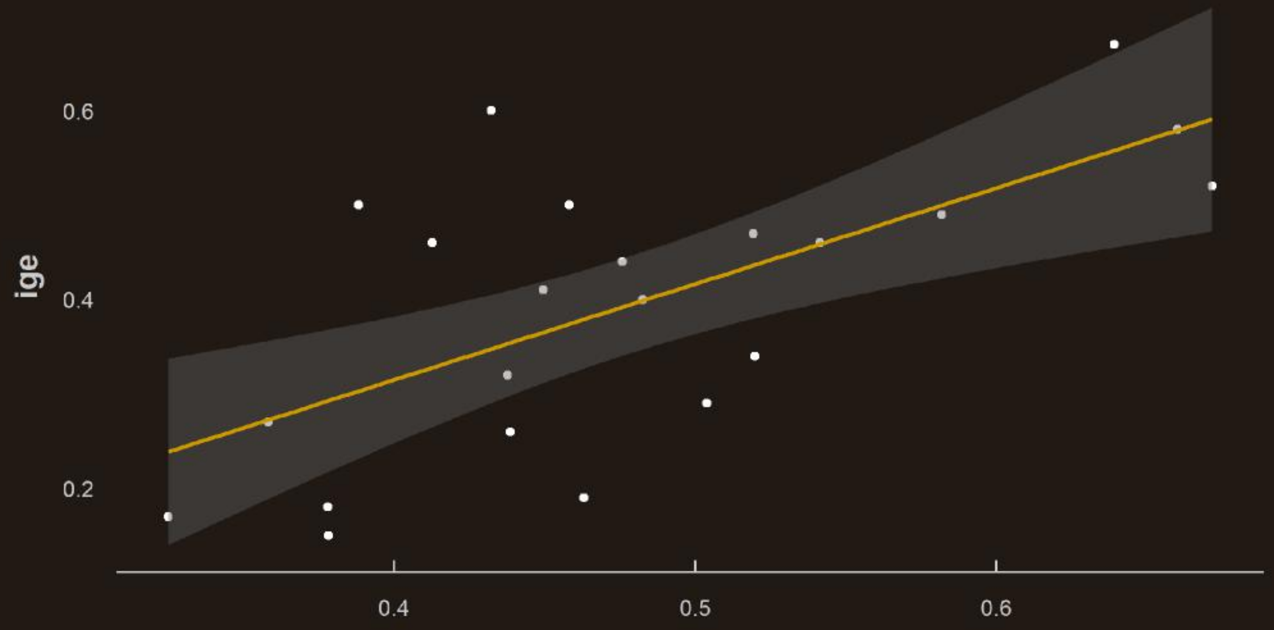


1. Regressions

1.1. On continuous variables

- Note that ggplot() has a dedicated **geometry for fitted values:** `geom_smooth()`

```
ggplot(ggcurve, aes(x = gini, y = ige)) +
  geom_point() + geom_smooth(method = "lm")
```



Practice

10:00

Check that lm() works fine by computing the R^2 manually

1) Start by creating a variable for $\hat{\beta}$, then for $\hat{\alpha}$, $\hat{y}_i$, and $\hat{\varepsilon}_i$.

$$\hat{\beta} = \frac{\text{Cov}(x,y)}{\text{Var}(x)} \quad ; \quad \hat{\alpha} = \bar{y} - \hat{\beta} \times \bar{x}$$

You're gonna need the `cov()` and `var()` functions

2) Summarise the data into only $\hat{\alpha}$, $\hat{\beta}$, and the R^2

$$R^2 = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y}_i)^2}$$

You've got 10 minutes!

Solution

```
ggcurve %>%
    mutate(beta = cov(gini, ige) / var(gini))
#
#
#
#
#
#
```

```
##             country  ige      gini     beta
## 1           Denmark 0.15 0.3781796 1.015462
## 2            Norway 0.17 0.3250102 1.015462
## 3           Finland 0.18 0.3779868 1.015462
## 4            Canada 0.19 0.4631237 1.015462
## 5         Australia 0.26 0.4385511 1.015462
## 6            Sweden 0.27 0.3582480 1.015462
## 7       New Zealand 0.29 0.5039373 1.015462
## 8           Germany 0.32 0.4377010 1.015462
## 9             Japan 0.34 0.5198383 1.015462
## 10            Spain 0.40 0.4826243 1.015462
## 11           France 0.41 0.4495654 1.015462
## ..              ...  ...       ...      ...
```

Solution

```
ggcurve %>%
    mutate(beta = cov(gini, ige) / var(gini),
           alpha = mean(ige) - beta * mean(gini))
#
#
#
#
#
```

```
##          country  ige      gini     beta       alpha
## 1        Denmark 0.15 0.3781796 1.015462 -0.09129311
## 2         Norway 0.17 0.3250102 1.015462 -0.09129311
## 3        Finland 0.18 0.3779868 1.015462 -0.09129311
## 4         Canada 0.19 0.4631237 1.015462 -0.09129311
## 5      Australia 0.26 0.4385511 1.015462 -0.09129311
## 6         Sweden 0.27 0.3582480 1.015462 -0.09129311
## 7    New Zealand 0.29 0.5039373 1.015462 -0.09129311
## 8        Germany 0.32 0.4377010 1.015462 -0.09129311
## 9          Japan 0.34 0.5198383 1.015462 -0.09129311
## 10         Spain 0.40 0.4826243 1.015462 -0.09129311
## 11        France 0.41 0.4495654 1.015462 -0.09129311
## ..           ...  ...       ...      ...         ...
```

Solution

```
ggcurve %>%
    mutate(beta = cov(gini, ige) / var(gini),
           alpha = mean(ige) - beta * mean(gini),
           fit = alpha + beta * gini)
#
#
#
#
```

```
##            country  ige      gini     beta       alpha       fit
## 1          Denmark 0.15 0.3781796 1.015462 -0.09129311 0.2927339
## 2           Norway 0.17 0.3250102 1.015462 -0.09129311 0.2387424
## 3          Finland 0.18 0.3779868 1.015462 -0.09129311 0.2925381
## 4           Canada 0.19 0.4631237 1.015462 -0.09129311 0.3789915
## 5        Australia 0.26 0.4385511 1.015462 -0.09129311 0.3540389
## 6           Sweden 0.27 0.3582480 1.015462 -0.09129311 0.2724942
## 7      New Zealand 0.29 0.5039373 1.015462 -0.09129311 0.4204361
## 8          Germany 0.32 0.4377010 1.015462 -0.09129311 0.3531757
## 9            Japan 0.34 0.5198383 1.015462 -0.09129311 0.4365829
## 10           Spain 0.40 0.4826243 1.015462 -0.09129311 0.3987935
## 11          France 0.41 0.4495654 1.015462 -0.09129311 0.3652234
## ..             ...  ...       ...      ...         ...       ...
```

Solution

```
ggcurve %>%
    mutate(beta = cov(gini, ige) / var(gini),
           alpha = mean(ige) - beta * mean(gini),
           fit = alpha + beta * gini,
           residuals = ige - fit)
#
#
#
```

```
##          country  ige      gini     beta       alpha       fit     residuals
## 1        Denmark 0.15 0.3781796 1.015462 -0.09129311 0.2927339 -0.1427339244
## 2         Norway 0.17 0.3250102 1.015462 -0.09129311 0.2387424 -0.0687424324
## 3        Finland 0.18 0.3779868 1.015462 -0.09129311 0.2925381 -0.1125381050
## 4         Canada 0.19 0.4631237 1.015462 -0.09129311 0.3789915 -0.1889914561
## 5      Australia 0.26 0.4385511 1.015462 -0.09129311 0.3540389 -0.0940388831
## 6         Sweden 0.27 0.3582480 1.015462 -0.09129311 0.2724942 -0.0024941569
## 7    New Zealand 0.29 0.5039373 1.015462 -0.09129311 0.4204361 -0.1304360777
## 8        Germany 0.32 0.4377010 1.015462 -0.09129311 0.3531757 -0.0331756674
## 9          Japan 0.34 0.5198383 1.015462 -0.09129311 0.4365829 -0.0965829037
## 10         Spain 0.40 0.4826243 1.015462 -0.09129311 0.3987935  0.0012065012
## 11        France 0.41 0.4495654 1.015462 -0.09129311 0.3652234  0.0447765627
## ..           ...  ...       ...      ...         ...       ...           ...
```

Solution

```
ggcurve %>%
    mutate(beta = cov(gini, ige) / var(gini),
           alpha = mean(ige) - beta * mean(gini),
           fit = alpha + beta * gini,
           residuals = ige - fit) %>%
    summarise(alpha = alpha[1],
              beta = beta[1],
              r2 = 1 - sum(residuals^2)/sum((ige - mean(ige))^2))
```

```
##         alpha     beta       r2
## 1 -0.09129311 1.015462 0.424749
```

```
ggmodel$coefficients[, "Estimate"]
```

```
## (Intercept)        gini
## -0.09129311  1.01546204
```

```
ggmodel$r.squared
```

```
## [1] 0.424749
```

1. Regressions

1.2. On binary variables

- Now consider that we want to know the **relationship** between **not** being a **European country** and the **ige**

```
ggcurve$country
```

```
##  [1] "Denmark"        "Norway"         "Finland"        "Canada"
##  [5] "Australia"      "Sweden"         "New Zealand"    "Germany"
##  [9] "Japan"          "Spain"          "France"         "Singapore"
## [13] "Pakistan"       "Switzerland"    "United States"  "Argentina"
## [17] "Italy"          "United Kingdom" "Chile"          "Brazil"
## [21] "China"          "Peru"
```

```
europe <- c("Denmark", "Norway", "Finland", "Sweden", "Germany", "Spain",
            "France", "Switzerland", "Italy", "United Kingdom")
```

```
ggcurve <- ggcurve %>%
  mutate(continent = ifelse(country %in% europe, "Europe", "Other"))
```

1. Regressions

1.2. On binary variables

- Can we just **regress** ige **on** continent even though it's a **character** variable?

```
lm(ige ~ continent, ggcurve)
```

```
##
## Call:
## lm(formula = ige ~ continent, data = ggcurve)
##
## Coefficients:
##   (Intercept)  continentOther
##        0.3360          0.1065
```

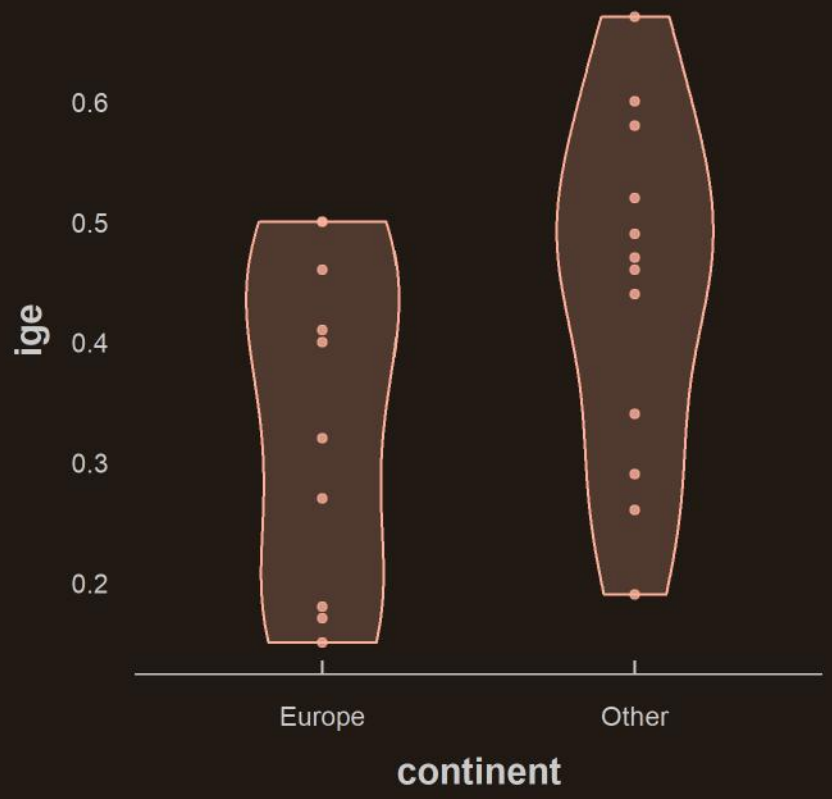
- Seems like we can!

➜ ***But what's actually going on?***

1. Regressions

1.2. On binary variables

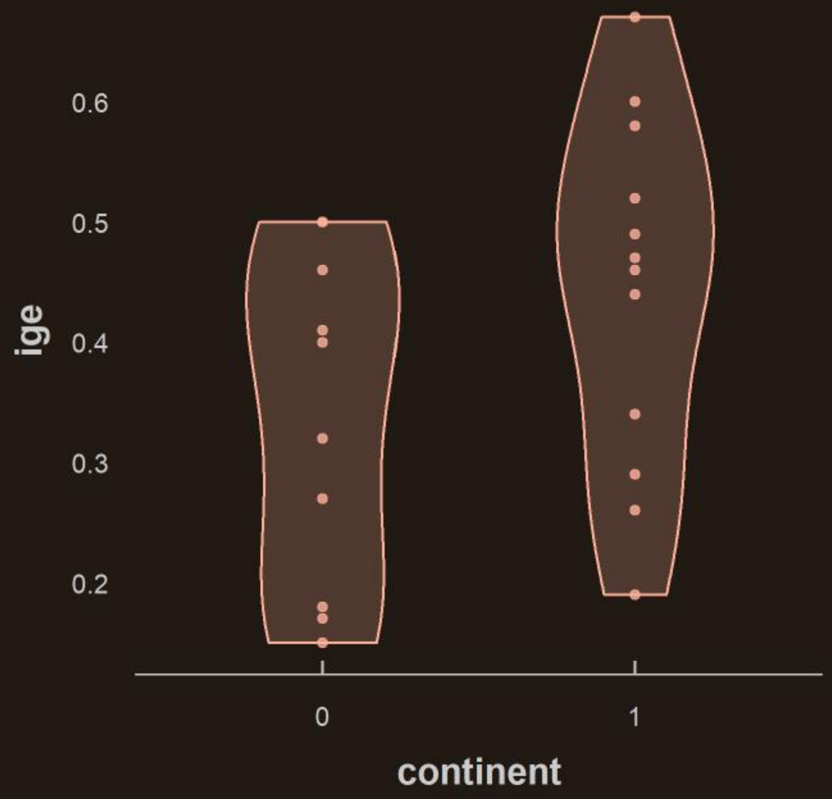
- R implicitely **converts** character variables into **binary** variables



1. Regressions

1.2. On binary variables

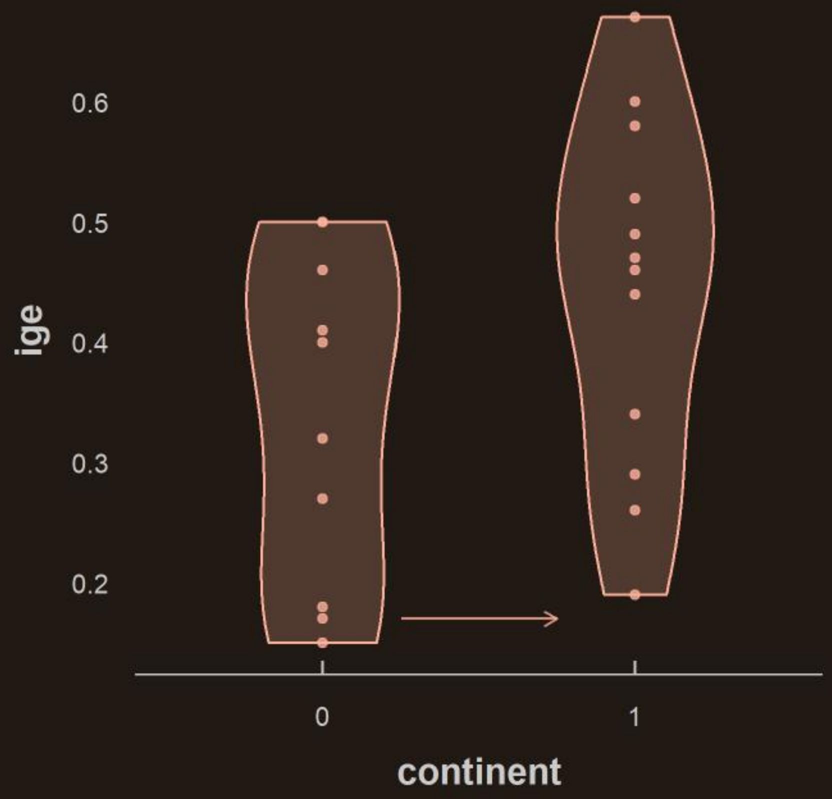
- Such that just **like** in the **continuous** case...



1. Regressions

1.2. On binary variables

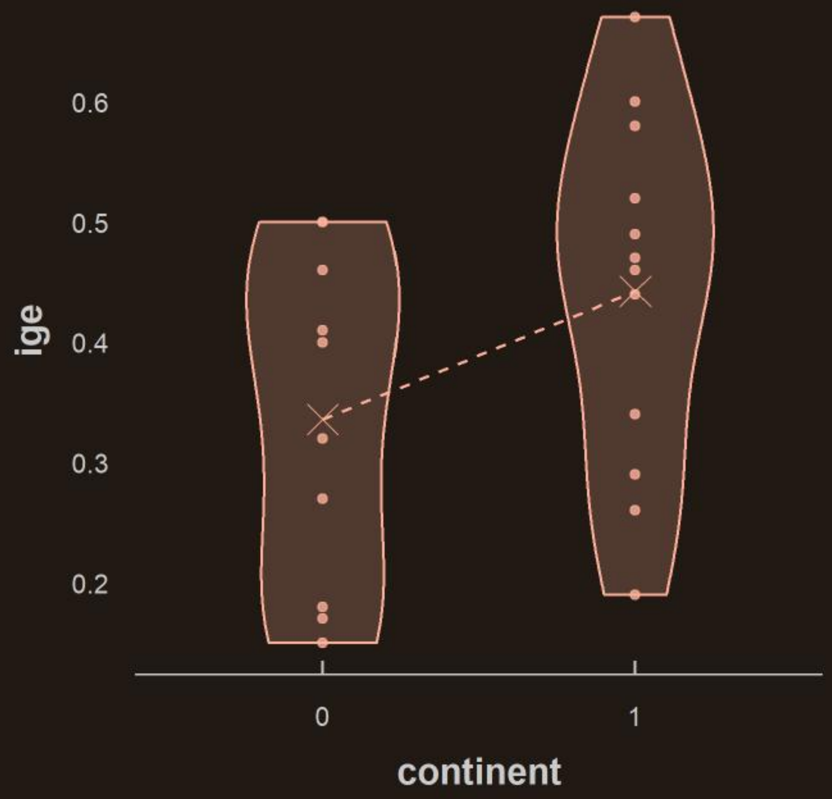
- ... we're looking at a **1-unit increase** in x *(i.e., swiching from 0 (Europe) to 1 (Other))*



1. Regressions

1.2. On binary variables

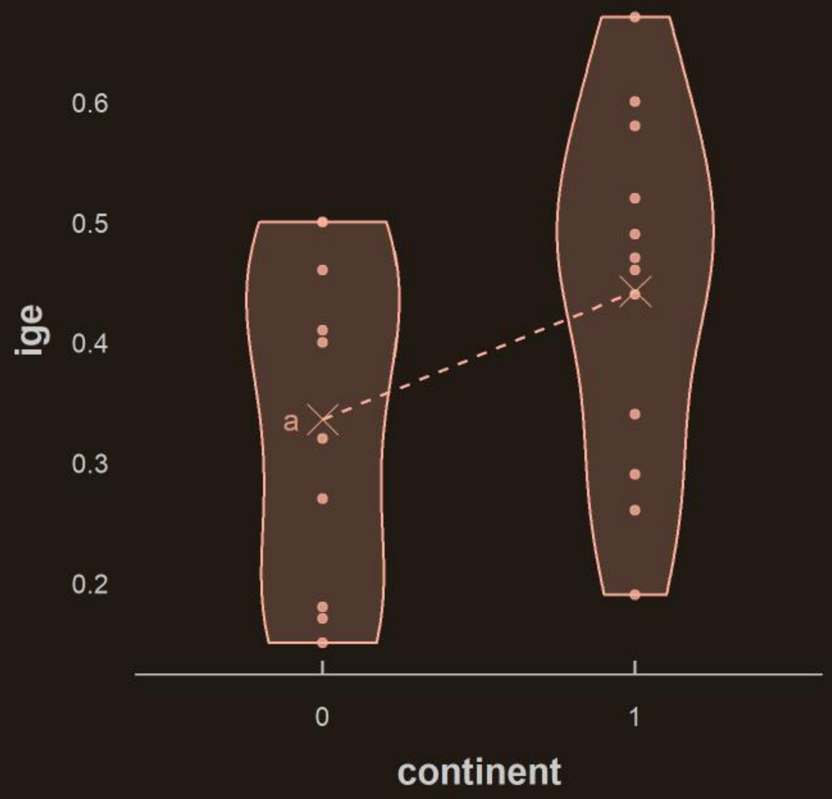
- As you know the **fit** is necessarily going through the **mean of each category**



1. Regressions

1.2. On binary variables

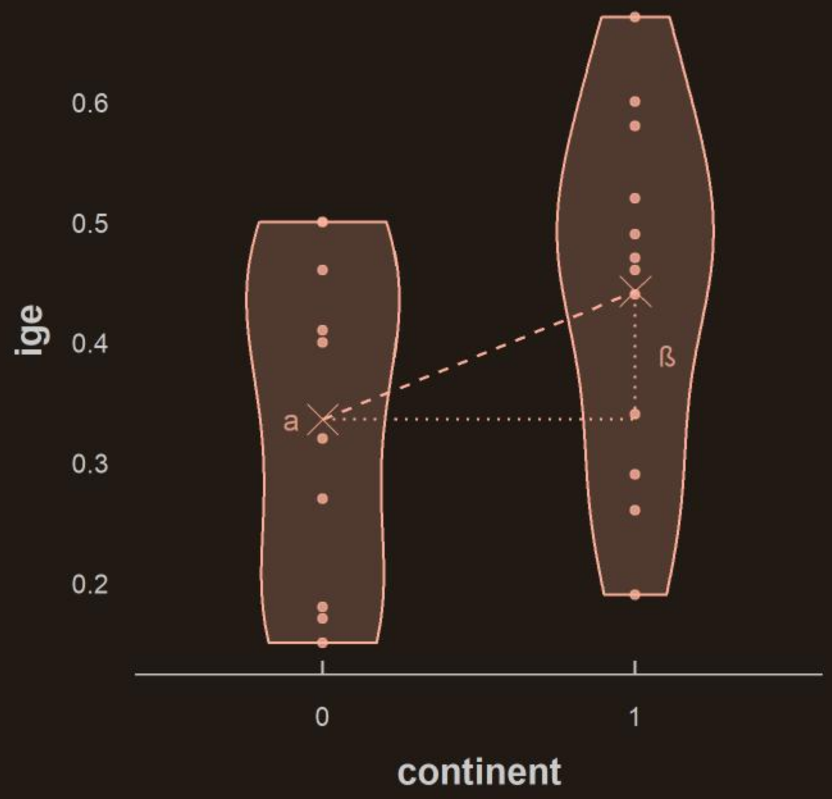
- Such that $\hat{\alpha}$ is the **mean of the reference group**



1. Regressions

1.2. On binary variables

- And $\hat{\beta}$ is the **difference in means**



1. Regressions

1.2. On binary variables

- We can verify that easily:

```
ggcurve %>%
  group_by(continent) %>%
  summarise(ybar = mean(ige)) %>%
  mutate(relative = ybar - ybar[1])
```

```
## # A tibble: 2 x 3
##   continent  ybar relative
##   <chr>     <dbl>    <dbl>
## 1 Europe    0.336    0
## 2 Other     0.442    0.106
```

```
lm(ige ~ continent, ggcurve)
```

```
##
## Call:
## lm(formula = ige ~ continent, data = ggcurve)
##
## Coefficients:
##    (Intercept)  continentOther
##         0.3360          0.1065
```

➜ And what about discrete variables with more than 2 categories?

1. Regressions

1.3. On categorical variables

- Let's work on the 2020 Annual Social and Economic (ASEC) Supplement to the US CPS
  - Here is an extract on 64,336 working individuals with positive earnings
  - For which I kept only 4 variables:

```
asec <- read.csv("asec.csv")
str(asec)
```

```
## 'data.frame':    64336 obs. of  4 variables:
##  $ Sex     : chr  "Female" "Male" "Female" "Male" ...
##  $ Earnings: int  52500 34000 40000 8424 58000 42000 55000 28000 200 25000 ...
##  $ Race    : chr  "White" "White" "White" "White" ...
##  $ Hours   : int  40 40 44 21 60 40 40 40 20 40 ...
```

- Let's say we want to regress earnings on Race

```
unique(asec$Race)
```

```
## [1] "White" "Other" "Black"
```

1. Regressions

1.3. On categorical variables

- Just like the **2-category** variable was equivalent to **1 dummy** variable
  - An **n-category** variable is equivalent to **n-1 dummy** variables

Continent	Other		Race	Other	White
Europe	0		Black	0	0
Europe	0		Black	0	0
Europe	0		Other	1	0
Other	1		Other	1	0
Other	1		White	0	1
Other	1		White	0	1

```
lm(Earnings ~ Race, asec)
```

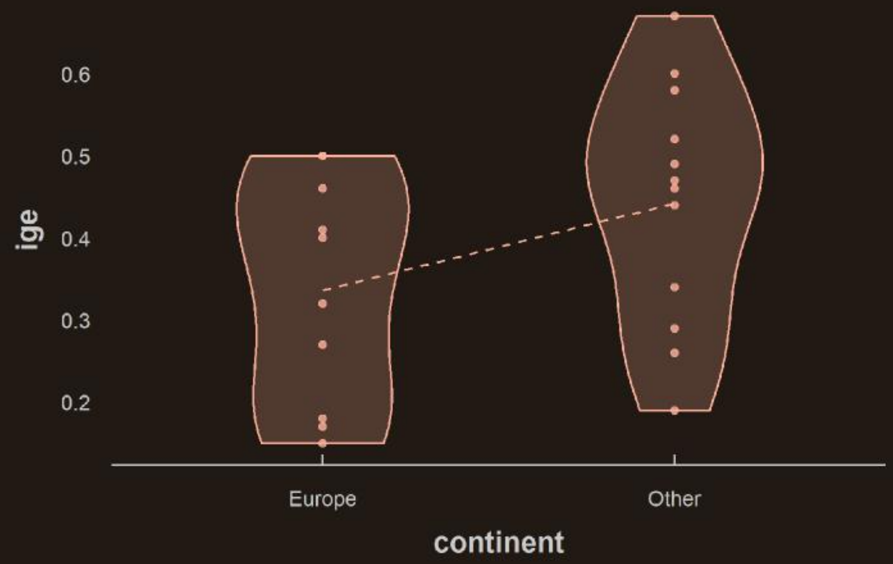
```
##
## Call:
## lm(formula = Earnings ~ Race, data = asec)
##
## Coefficients:
## (Intercept)    RaceOther    RaceWhite
##       50577        17477        12303
```

- Instead of 1 x axis we're going to have n-1 x axes

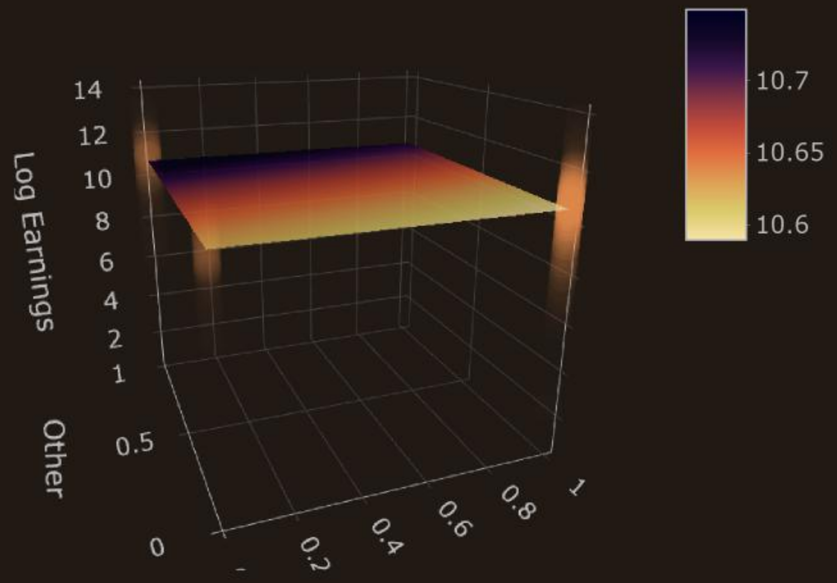
1. Regressions

1.3. On categorical variables

2-category variable



3-category variable



1. Regressions

1.3. On categorical variables

- Once again the **constant** is the **average** y for the reference category
  - And the **slopes** are the relative **differences in means**

```
lm(Earnings ~ Race, asec)
```

```
##
## Call:
## lm(formula = Earnings ~ Race, data = asec)
##
## Coefficients:
## (Intercept)    RaceOther    RaceWhite
##       50577        17477        12303
```

```
asec %>%
  group_by(Race) %>%
  summarise(ybar = mean(Earnings)) %>%
  mutate(relative = ybar - ybar[1])
```

```
## # A tibble: 3 x 3
##   Race    ybar relative
##   <chr>  <dbl>    <dbl>
## 1 Black 50577.        0
## 2 Other 68055.   17477.
## 3 White 62880.   12303.
```

- Note that R always sorts **character** variables by **alphabetical order**
  - But it would be more natural to interpret relative to the **majority group**
  - Then how to change the **reference category** in the regression?

1. Regressions

1.3. On categorical variables

- The function to set the reference category is **relevel()**
  - The first argument is the **vector** to indicate the reference of
  - The second argument is the value of the **reference group**

```
lm(Earnings ~ relevel(Race, "White"), asec)
```

```
## Error in relevel.default(Race, "White"): 'relevel' only for (unordered) factors
```

- Oops! I need to introduce you a **new class** of R objects first: `factors`

```
as.factor(asec$Race) %>%
  levels()
```

```
## [1] "Black" "Other" "White"
```

```
as.factor(asec$Race) %>%
  relevel("White") %>%
  levels()
```

```
## [1] "White" "Black" "Other"
```

1. Regressions

1.3. On categorical variables

- The **factor class** is made for variables whose values **indicate** different **groups**
  - Values are just **arbitrary group classifiers**

```
individuals <- as.factor(c(1, 2, 3, 4, 5))
individuals[1]
```

```
## [1] 1
## Levels: 1 2 3 4 5
```

- With **factors**, R understands that the different values **do not mean anything**
  - And applying **standard operations** to factors **does not make sense**

```
individuals * 2
```

```
## Warning in Ops.factor(individuals, 2): '*' not meaningful for factors
```

```
## [1] NA NA NA NA NA
```

Practice

05:00

1) Open the data from the World Inequality Database we used in lecture 2

2) Regress the income share of the top 1% on the year variable

3) Redo the same regression after having converted the year variable as a `factor`

You've got 5 minutes!

Solution

1) Open the data from the World Inequality Database we used in lecture 2

```
wid <- read.csv("wid.csv")
```

2) Regress the income share of the top 1% on the year variable

```
lm(top1 ~ year, wid)
```

```
##
## Call:
## lm(formula = top1 ~ year, data = wid)
##
## Coefficients:
## (Intercept)         year
##   2.242e-01   -3.131e-05
```

Solution

3) Redo the same regression after having converted the year variable as a `factor`

```
lm(top1 ~ year, wid %>% mutate(year = as.factor(year)))
```

```
##
## Call:
## lm(formula = top1 ~ year, data = wid %>% mutate(year = as.factor(year)))
##
## Coefficients:
## (Intercept)     year2011     year2012     year2013     year2014     year2015
##   0.1621494   -0.0011366   -0.0026891   -0.0013401   -0.0004469   -0.0008683
##    year2016     year2017     year2018     year2019
##  -0.0001450   -0.0004857   -0.0015236   -0.0018488
```

1. Regressions

1.3. On categorical variables

- Another option to include categorical variables is to ***one hot encode*** the data
  - It simply means **converting** the discrete variables into dummies such that **everything** is **numeric**

```
asec <- asec %>% mutate(White = as.numeric(Race == "White"),
                        Black = as.numeric(Race == "Black"),
                        Other = as.numeric(Race == "Other"))
```

- Then we can use the `+` symbol to include n-1 categories in the regression

```
lm(Earnings ~ Black + Other, asec)
```

```
##
## Call:
## lm(formula = Earnings ~ Black + Other, data = asec)
##
## Coefficients:
## (Intercept)        Black        Other
##       62880       -12303         5174
```

1. Regressions

1.3. On categorical variables

- But do we really need to **omit** one **category?**
  - As we are in the multivariate case let's move from $\hat{\beta} = \frac{\text{Cov}(x,y)}{\text{Var}(x)}$
  - To $\hat{\beta} = (X'X)^{-1}X'y$

```
y <- as.matrix(asec$Earnings)

X <- asec %>%
  mutate(constant = 1) %>%
  select(constant, White, Black, Other) %>%
  as.matrix()
```

```
dim(X)
```

```
## [1] 64336     4
```

```
dim(t(X))
```

```
## [1]     4 64336
```

```
dim(t(X) %*% X)
```

```
## [1] 4 4
```

1.3. On categorical variables

- Because of perfect **multicollinearity** it will not be possible to invert $X'X$

```
solve(t(X) %*% X)
```

```
## Error in solve.default(t(X) %*% X): system is computationally singular
```

- We have to **remove one category**

```
X <- asec %>% mutate(constant = 1) %>%
  select(constant, Black, Other) %>%
  as.matrix()

solve(t(X) %*% X) %*% (t(X) %*% y)
```

```
##                 [,1]
## constant   62880.488
## Black     -12302.993
## Other       5174.141
```

- Or to **remove the constant**

```
X <- asec %>% #mutate(constant = 1) %>%
  select(White, Black, Other) %>%
  as.matrix()

solve(t(X) %*% X) %*% (t(X) %*% y)
```

```
##            [,1]
## White 62880.49
## Black 50577.49
## Other 68054.63
```

1. Regressions

1.3. On categorical variables

- Note that you can remove the constant in lm() by adding `- 1` in the formula

```
lm(Earnings ~ White + Black + Other - 1, asec)
```

```
## Coefficients:
## White  Black  Other
## 62880  50577  68055
```

- And that it would drop a category anyway

```
lm(Earnings ~ White + Black + Other, asec)
```

```
## Coefficients:
## (Intercept)        White        Black        Other
##       68055        -5174       -17477           NA
```

But it's not because multicollinearity does not break lm() that you should not pay attention to it!

Overview

Overview

1. Regressions ✓

1.1. On continuous variables
1.2. On binary variables
1.3. On categorical variables

2. Case study

2.1. Variable transformation
2.2. Functional form
2.3. Control variables
2.4. Interactions

2. Case study

2.1. Variable transformation

- Imagine you want to estimate the **relationship** between **weekly hours** of work and **annual earnings**

$$\text{Earnings}_i = \alpha + \beta\text{Hours}_i + \varepsilon_i$$

- We can **estimate it in R** using the Annual Social and Economic Supplement to the US CPS

```
lm(Earnings ~ Hours, asec)
```

```
## Coefficients:
## (Intercept)        Hours
##      -20039         2078
```

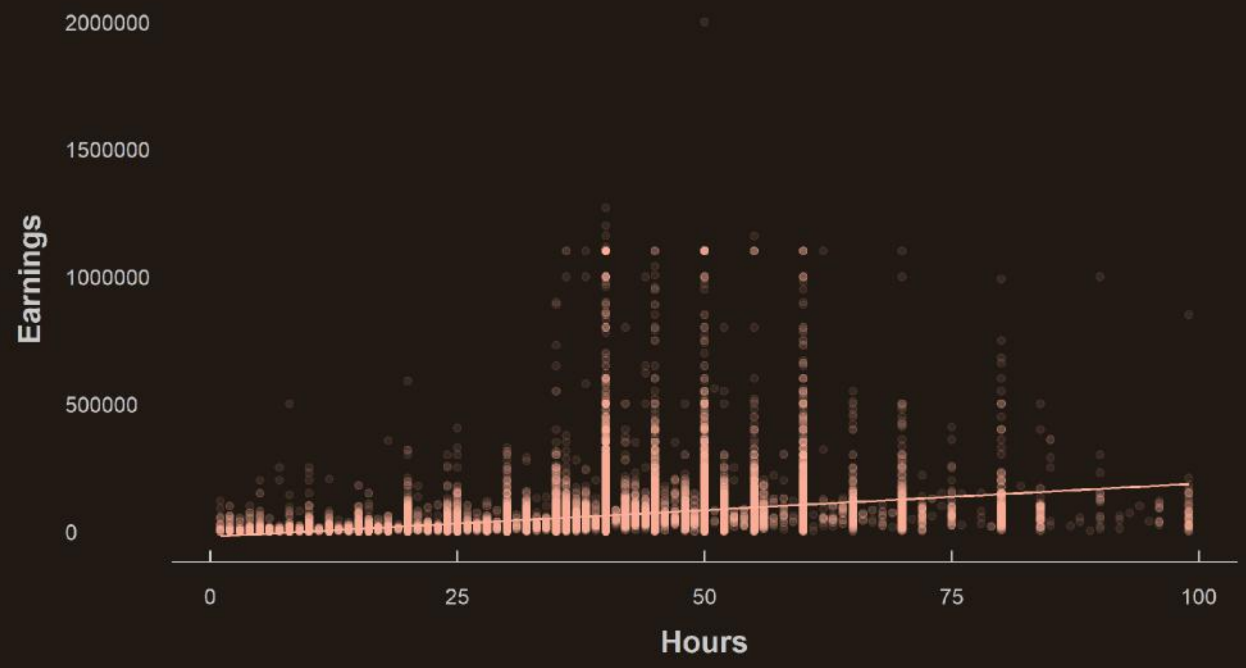
- Are we done?

➜ Let's take a look at what we just did!

2. Case study

2.1. Variable transformation

```
ggplot(asec, aes(x = Hours, y = Earnings)) +
  geom_point() + geom_smooth(method = "lm")
```



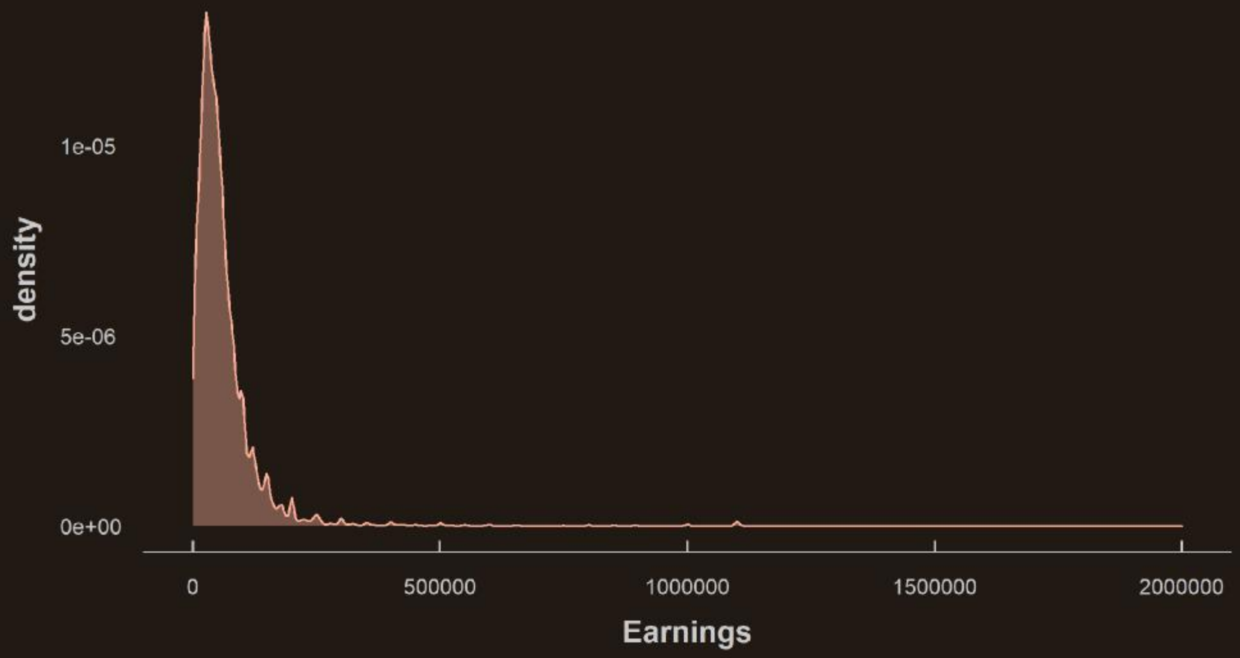
→ Not very satisfactory

- The joint distribution does **not seem adequate** on the the **y dimension**
- Let's take a **look** at the earnings **distribution**

2. Case study

2.1. Variable transformation

```
ggplot(asec, aes(x = Earnings)) +
  geom_density()
```



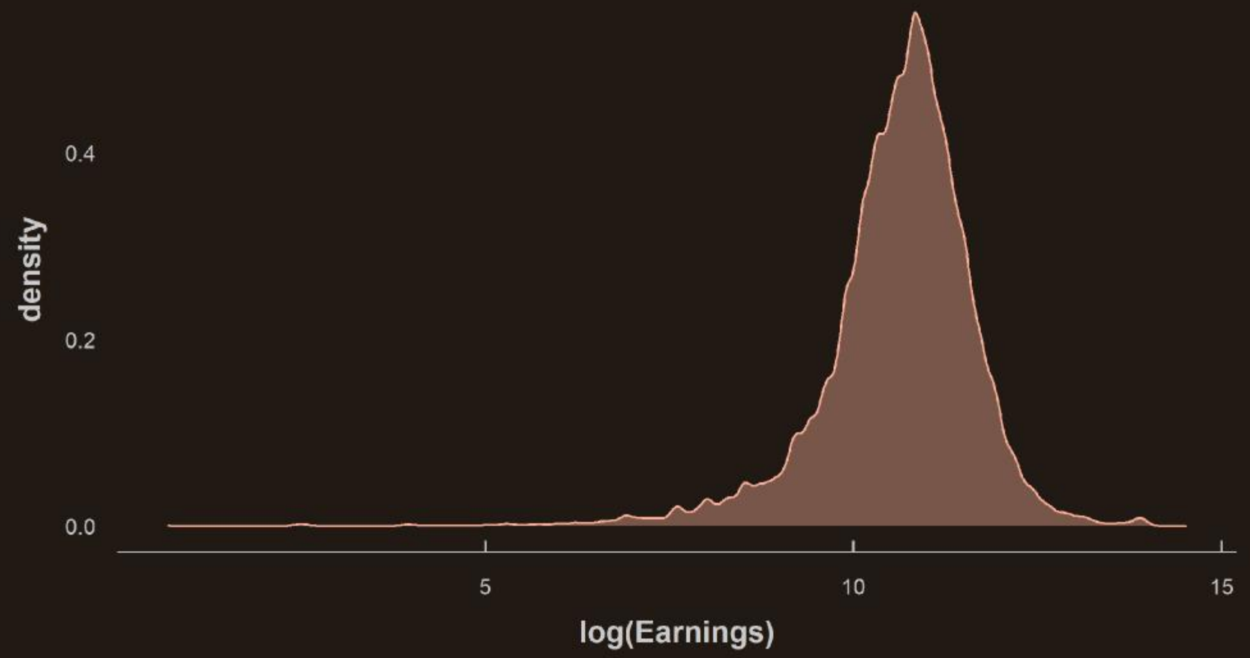
It's clearly **log-normal**

→ Let's **plot the log** of it

2. Case study

2.1. Variable transformation

```
ggplot(asec, aes(x = log(Earnings))) +
  geom_density()
```



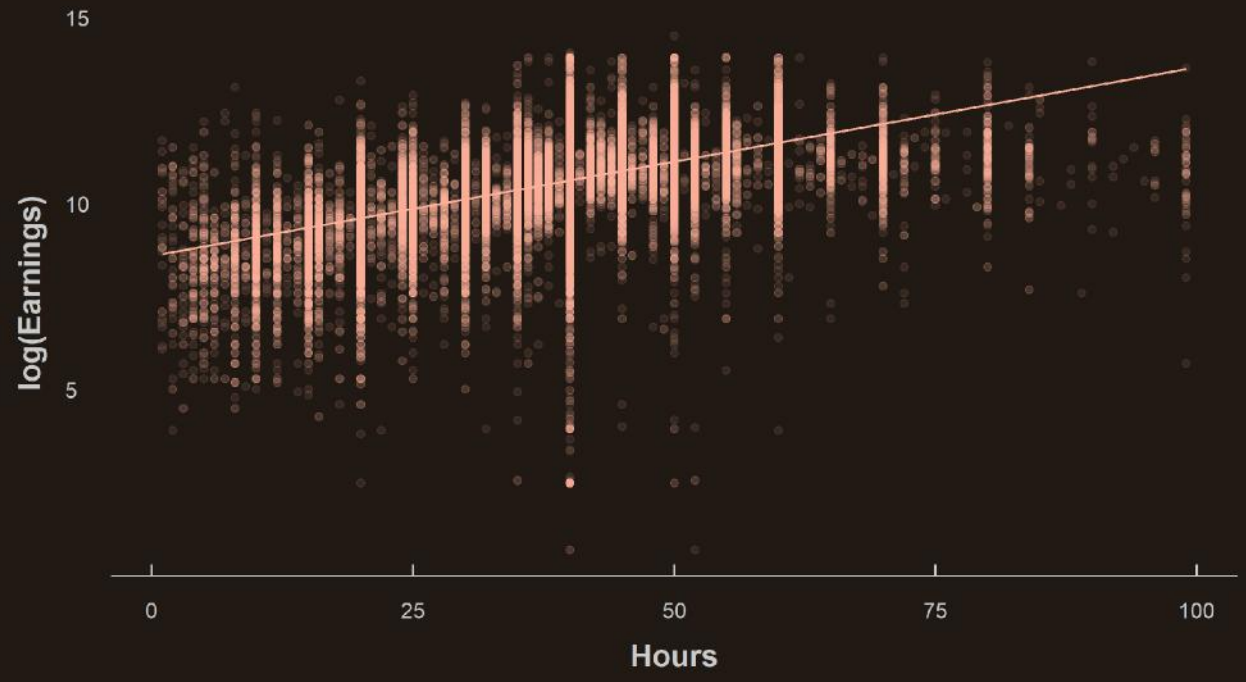
Better!

→ Let's **update** the **scatterplot**

2. Case study

2.2. Functional form

```
ggplot(asec, aes(x = Hours, y = log(Earnings))) +
  geom_point(alpha = .1) + geom_smooth(method = "lm")
```



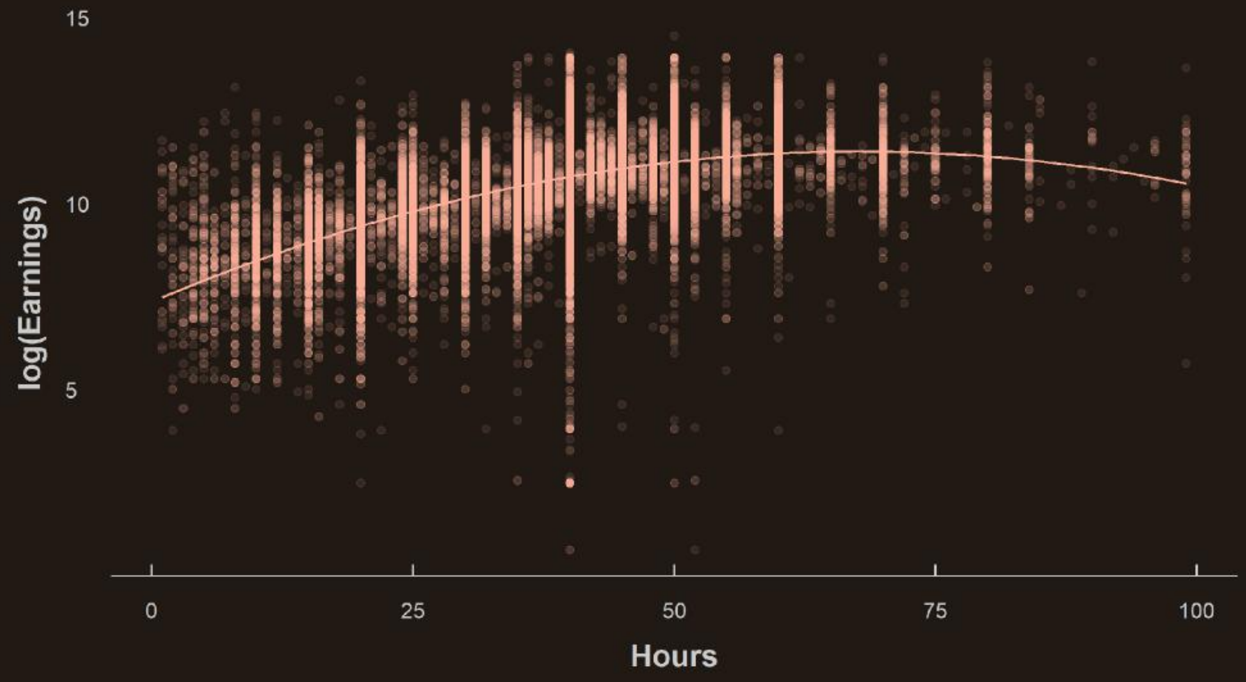
Definitely better!

→ But something **still** feels **off**

2. Case study

2.2. Functional form

```
ggplot(asec, aes(x = Hours, y = log(Earnings))) +
  geom_point(alpha = .1) + geom_smooth(method = "lm", formula = y ~ poly(x, 2))
```



→ ***There we go***

2. Case study

2.2. Functional form

- We'd better rewrite our model as:

$$\log(\text{Earnings}_i) = \alpha + \beta_1 \text{Hours}_i + \beta_2 \text{Hours}_i^2 + \varepsilon_i$$

- Create the new variables

```
asec <- asec %>%
  mutate(lEarnings = log(Earnings),
         sqHours = Hours^2)
```

- And run the regression

```
lm(lEarnings ~ Hours + sqHours, asec)
```

```
## Coefficients:
## (Intercept)        Hours      sqHours
##   7.3637848    0.1192609   -0.0008804
```

Is that it?

Isn't there something we could/should add in our regression?

2. Case study

2.3. Control variables

- This positive **relationship** could be **driven** by a **third variable**
  - **Males** tend both to work **part time less often** and to **earn more**
  - The **higher** the **hours**, the higher the **probability to be a male**, the higher the **expected earnings**

- Let's **control** for that in the regression

$$\log(\text{Earnings}_i) = \alpha + \beta_1 \text{Hours}_i + \beta_2 \text{Hours}_i^2 + \beta_3 \text{Male}_i + \varepsilon_i$$

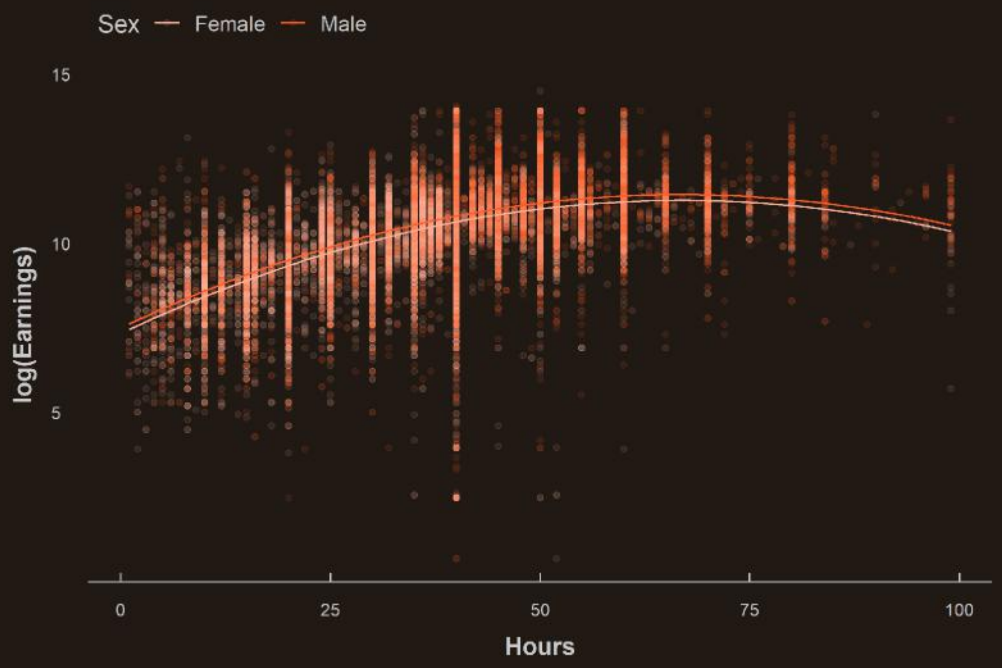
- Such that Males and Females would have
  - The **same slope**
  - **Different intercepts**

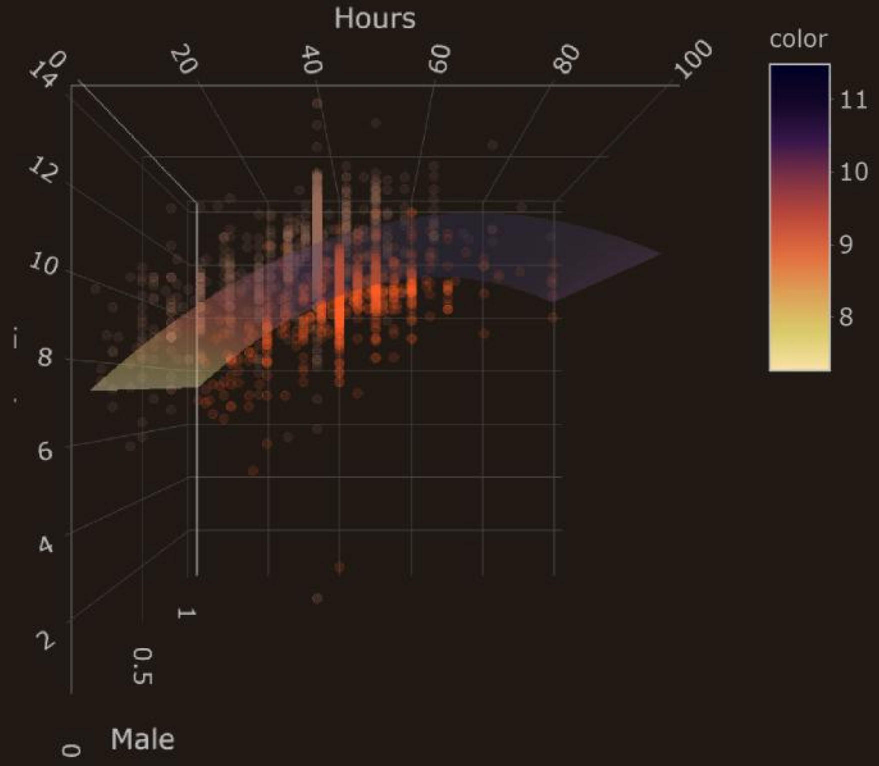
	$\text{Male} = 0$	$\text{Male} = 1$
Intercept	α	$\alpha + \beta_3$
Slope	$\beta_1 + 2\beta_2\text{Hours}$	$\beta_1 + 2\beta_2\text{Hours}$

Let's take a look

2. Case study

2.3. Control variables





2. Case study

2.3. Control variables

- Once again we can include a control variable using the `+` symbol

```
lm(lEarnings ~ Hours + sqHours + Sex, asec)
```

```
## Coefficients:
## (Intercept)        Hours      sqHours      SexMale
##   7.3356057    0.1177514   -0.0008806    0.1700972
```

```
lm(lEarnings ~ Hours + sqHours, asec)
```

```
## Coefficients:
## (Intercept)        Hours      sqHours
##   7.3637848    0.1192609   -0.0008804
```

Actually the baseline coefficient was not that inflated

2. Case study

2.4. Interactions

- But what if we were to allow for **different slopes?**
  - The **relationship** between hours and earnings might be **heterogeneous** across sex/gender
  - This is what **interactions** allow to account for

- We simply have to include the **product** of the two variables in the model

$$\log(\text{Earnings}_i) = \alpha + \beta_1 \text{Hours}_i + \beta_2 \text{Hours}_i^2 + \beta_3 \text{Male}_i + \beta_4 \text{Hours}_i \times \text{Male}_i + \varepsilon_i$$

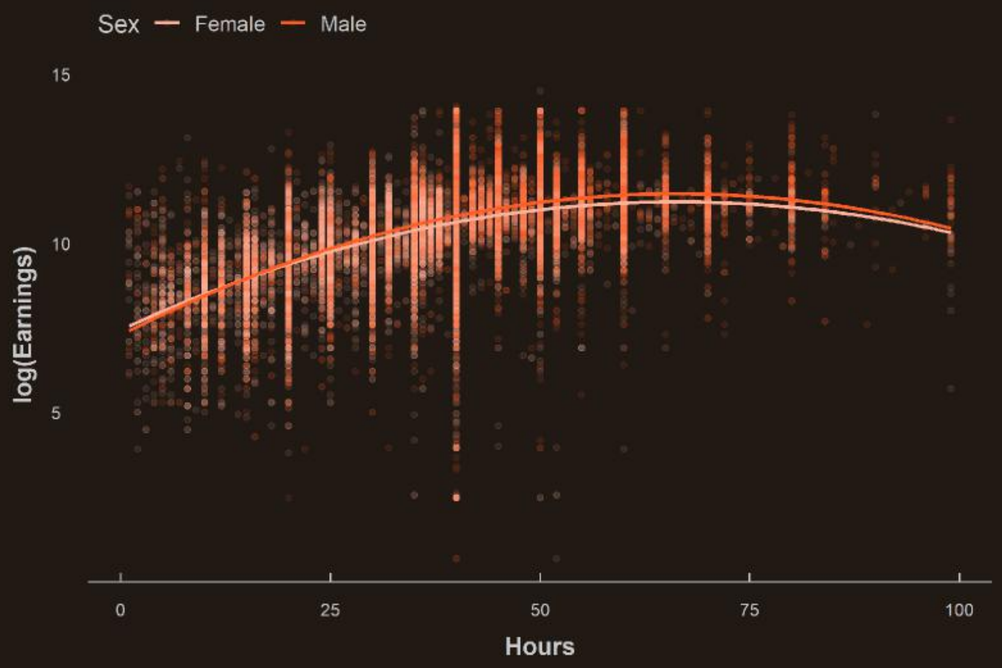
- Such that Males and Females would have
  - Not only **different intercepts**
  - But also **different slopes**

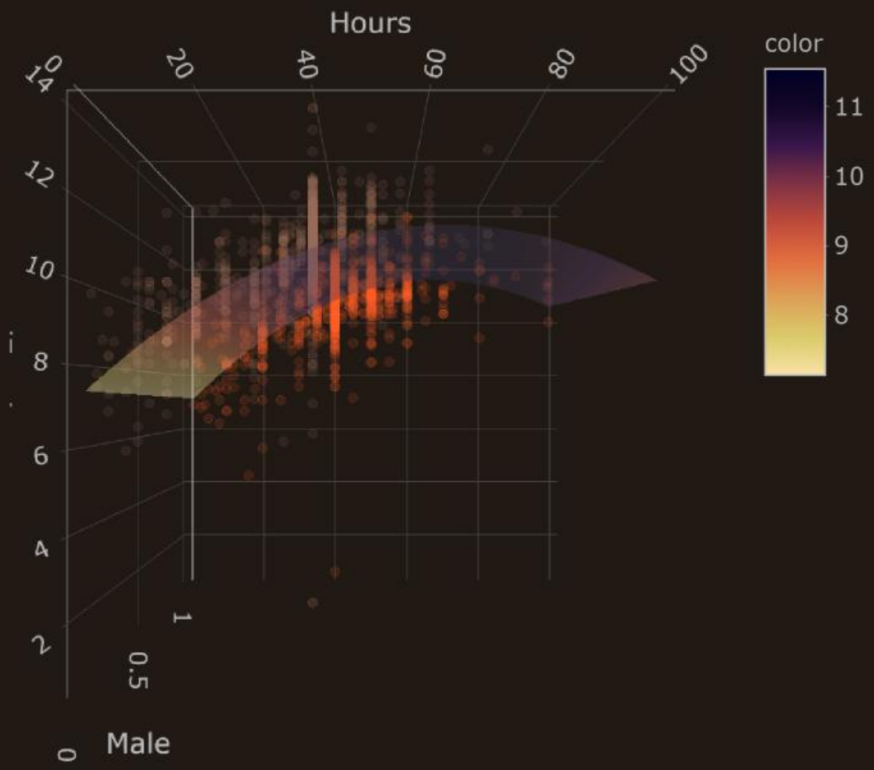
	$\text{Male} = 0$	$\text{Male} = 1$
Intercept	α	$\alpha + \beta_3$
Slope	$\beta_1 + 2\beta_2\text{Hours}$	$\beta_1 + 2\beta_2\text{Hours} + \beta_4$

Let's take a look

2. Case study

2.4. Interactions





2. Case study

2.4. Interactions

- Now we can use the `*` symbol for products

```
results <- summary(lm(lEarnings ~ Hours + sqHours + Sex + Hours * Sex, asec))$coefficients
results
```

```
##                    Estimate   Std. Error    t value     Pr(>|t|)
## (Intercept)    7.3900468002 2.319198e-02 318.646690 0.000000e+00
## Hours          0.1174998826 1.034522e-03 113.578950 0.000000e+00
## sqHours       -0.0009103523 1.321706e-05 -68.877048 0.000000e+00
## SexMale       -0.0282905673 2.753222e-02  -1.027544 3.041682e-01
## Hours:SexMale  0.0050321134 6.767013e-04   7.436240 1.048736e-13
```

What do you conclude ?

```
results[5, 1] / results[2, 1]
```

```
## [1] 0.04282654
```

→ A 4% difference

```
results[5, 4]
```

```
## [1] 1.048736e-13
```

→ Which is highly significant

Overview

Overview

3. Inference

3.1. Hypothesis testing

- According to our previous regression, $\hat{\beta}_1$ is significantly **different from 0**
  - But let's pretend that you know that this coefficient is equal to **.12 in Canada**
  - How could we test whether or not our coefficient is **different from .12?**

```
results
```

```
##                   Estimate   Std. Error    t value     Pr(>|t|)
## (Intercept)    7.3900468002 2.319198e-02 318.646690 0.000000e+00
## Hours          0.1174998826 1.034522e-03 113.578950 0.000000e+00
## sqHours       -0.0009103523 1.321706e-05 -68.877048 0.000000e+00
## SexMale       -0.0282905673 2.753222e-02  -1.027544 3.041682e-01
## Hours:SexMale  0.0050321134 6.767013e-04   7.436240 1.048736e-13
```

- We can compute the t-stat from our results

$$t = \frac{\hat{\beta} - .12}{\text{s.e.}(\hat{\beta})}$$

```
t <- (results[2, 1] - .12) / results[2, 2]
t
```

```
## [1] -2.416689
```

3. Inference

3.1. Hypothesis testing

- And then we need the value of the **area outside the interval** $[-t; t]$
  - From a **Student-t** distribution with the correct number of **degrees of freedom** (#obs - #parameters)

3. Inference

3.1. Hypothesis testing

- You can get the **area below** a certain **t-value** with the **pt()** function
    1.
    2.

```
pt( , )
```

3. Inference

3.1. Hypothesis testing

- You can get the **area below** a certain **t-value** with the **pt()** function
    1. The first argument is the **t-value**
    2.

```
pt(t, )
```

3. Inference

3.1. Hypothesis testing

- You can get the **area below** a certain **t-value** with the **pt()** function
  1. The first argument is the **t-value**
  2. The second argument is the number of **degrees of freedom**

```
pt(t, nrow(asec) - nrow(results))
```

```
## [1] 0.007832573
```

- We just have to multiply this value by 2 to obtain the p-value

```
2 * pt(t, nrow(asec) - nrow(results))
```

```
## [1] 0.01566515
```

- Had our t-stat been positive we would have needed to multiply 1 - t by 2

```
2 * (1 - pt(abs(t), nrow(asec)-nrow(results)))
```

```
## [1] 0.01566515
```

3. Inference

3.1. Hypothesis testing

- A very handy function for hypothesis testing is **linearHypothesis()** from the **car** package
  -
  -

```
linearHypothesis( , )
```

3. Inference

3.1. Hypothesis testing

- A very handy function for hypothesis testing is **linearHypothesis()** from the **car** package
  - The first argument is the **model**
  -

```
linearHypothesis(lm(lEarnings ~ Hours + sqHours + Sex + Hours * Sex, asec), )
```

3. Inference

3.1. Hypothesis testing

- A very handy function for hypothesis testing is **linearHypothesis()** from the **car** package
  - The first argument is the **model**
  - The second argument is the **hypothesis/es**

```
linearHypothesis(lm(lEarnings ~ Hours + sqHours + Sex + Hours * Sex, asec), c("Hours = .12"))
```

```
## Linear hypothesis test
##
## Hypothesis:
## Hours = 0.12
##
## Model 1: restricted model
## Model 2: lEarnings ~ Hours + sqHours + Sex + Hours * Sex
##
##   Res.Df   RSS Df Sum of Sq      F  Pr(>F)
## 1  64332 46102
## 2  64331 46098  1    4.1851 5.8404 0.01567 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

3. Inference

3.1. Hypothesis testing

- It can be used for **F tests** like the one from the summary

```
linearHypothesis(lm(lEarnings ~ Hours + sqHours + Sex + Hours * Sex, asec),
                 c("Hours = 0", "sqHours = 0", "SexMale = 0", "Hours:SexMale = 0"))
```

3. Inference

3.1. Hypothesis testing

```
linearHypothesis(lm(lEarnings ~ Hours + sqHours + Sex + Hours * Sex, asec),
                 c("Hours = 0", "sqHours = 0", "SexMale = 0", "Hours:SexMale = 0"))
```

```
## Linear hypothesis test
##
## Hypothesis:
## Hours = 0
## sqHours = 0
## SexMale = 0
## Hours:SexMale = 0
##
## Model 1: restricted model
## Model 2: lEarnings ~ Hours + sqHours + Sex + Hours * Sex
##
##   Res.Df   RSS Df Sum of Sq      F    Pr(>F)
## 1  64335 68395
## 2  64331 46098  4     22297 7779.1 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

3. Inference

```
##
## Call:
## lm(formula = lEarnings ~ Hours + sqHours + Sex + Hours * Sex,
##     data = asec)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -10.3453  -0.4299   0.0133   0.4810   4.8506
##
## Coefficients:
##                  Estimate Std. Error t value Pr(>|t|)
## (Intercept)     7.390e+00  2.319e-02 318.647  < 2e-16 ***
## Hours           1.175e-01  1.035e-03 113.579  < 2e-16 ***
## sqHours        -9.103e-04  1.322e-05 -68.877  < 2e-16 ***
## SexMale        -2.829e-02  2.753e-02  -1.028    0.304
## Hours:SexMale   5.032e-03  6.767e-04   7.436 1.05e-13 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.8465 on 64331 degrees of freedom
## Multiple R-squared:  0.326,    Adjusted R-squared:  0.326
## F-statistic:  7779 on 4 and 64331 DF,  p-value: < 2.2e-16
```

3. Inference

3.2. Confidence intervals

- Now we know how to get the area below a given value of a Student t distribution
  - But sometimes the opposite is useful as well
  - In particular to compute **confidence intervals**

- Indeed the confidence interval for a $\hat{\beta}$ coefficient is given by:

$$\hat{\beta} \pm t_{1-(\alpha/2),\text{df}} \times \text{s.e.}(\hat{\beta})$$

  - Where α denotes the desired significance level

- **qt()** gives the t-statistic below which lies the desired share of the area of a given Student t distribution
  -
  -

```
qt( , )
```

3. Inference

3.2. Confidence intervals

- Now we know how to get the area below a given value of a Student t distribution
  - But sometimes the opposite is useful as well
  - In particular to compute **confidence intervals**

- Indeed the confidence interval for a $\hat{\beta}$ coefficient is given by:

$$\hat{\beta} \pm t_{1-(\alpha/2),\text{df}} \times \text{s.e.}(\hat{\beta})$$

  - Where α denotes the desired significance level

- **qt()** gives the t-statistic below which lies the desired share of the area of a given Student t distribution
  - The first argument is $1 - (\alpha/2)$
  -

```
qt(.975, )
```

3. Inference

3.2. Confidence intervals

- Now we know how to get the area below a given value of a Student t distribution
  - But sometimes the opposite is useful as well
  - In particular to compute **confidence intervals**

- Indeed the confidence interval for a $\hat{\beta}$ coefficient is given by:

$$\hat{\beta} \pm t_{1-(\alpha/2),\text{df}} \times \text{s.e.}(\hat{\beta})$$

  - Where α denotes the desired significance level

- **qt()** gives the t-statistic below which lies the desired share of the area of a given Student t distribution
  - The first argument is $1-(\alpha/2)$
  - The second argument is the number of **degrees of freedom**

```
qt(.975, Inf)
```

```
## [1] 1.959964
```

3. Inference

3.2. Confidence intervals

- So if we want a 97% **confidence interval** for our coefficients associated with hours, we feed **qt()** with:
    -
    -

```
t003 <- qt( , )
```

3. Inference

3.2. Confidence intervals

- So if we want a 97% **confidence interval** for our coefficients associated with hours, we feed **qt()** with:
  - The **share** of the Student t **distribution** below the desired t-stat: $1-(\alpha/2)=1-(0.03/2)=0.985$
  -

```
t003 <- qt(.985, )
```

3. Inference

3.2. Confidence intervals

- So if we want a 97% **confidence interval** for our coefficients associated with hours, we feed **qt()** with:
  - The **share** of the Student t **distribution** below the desired t-stat: $1-(\alpha/2)=1-(0.03/2)=0.985$
  - The **degrees of freedom:** $\#\text{obs.}-\#\text{params}$

```
t003 <- qt(.985, nrow(asec) - nrow(results))
```

3. Inference

3.2. Confidence intervals

- So if we want a 97% **confidence interval** for our coefficients associated with hours, we feed **qt()** with:
  - The **share** of the Student t **distribution** below the desired t-stat: $1-(\alpha/2) = 1-(0.03/2) = 0.985$
  - The **degrees of freedom:** $\#\text{obs.} - \#\text{params}$

```
t003 <- qt(.985, nrow(asec) - nrow(results))
t003
```

```
## [1] 2.170139
```

- And we apply the formula:

```
results[2, 1] - (results[2, 2] * t003)
```

```
## [1] 0.1152548
```

```
results[2, 1] + (results[2, 2] * t003)
```

```
## [1] 0.1197449
```

Overview

Overview

4. Report and export results

4.1. Regression tables

- The output of the **summary()** function is very **practical** but **not** very **convenient** to report the main results
  - **Academic regression tables** rather look like that

Table 5
The effect of distance to the line on production levels.

	Dependent Variable Ln Per Capita GDP					
	(1)	(2)	(3)	(4)	(5)	(6)
Ln Distance to Historical Lines	−0.0617	−0.0434	−0.0491	−0.0581	−0.0699	−0.0681
	(0.0286)	(0.0281)	(0.0277)	(0.0265)	(0.0270)	(0.0272)
Ln Distance to Segment City		0.065	−0.061	−0.063	−0.178	−0.208
		(0.232)	(0.266)	(0.282)	(0.325)	(0.298)
Ln Distance to Segment City^2		−0.0276	−0.0089	−0.0071	0.0072	0.0101
		(0.0277)	(0.0308)	(0.0324)	(0.0372)	(0.0344)
Ln Distance to Navigable River			0.318	0.321	0.366	0.385
			(0.153)	(0.141)	(0.140)	(0.138)
Ln Distance to Navigable River^2			−0.0517	−0.0481	−0.0550	−0.0554
			(0.0200)	(0.0186)	(0.0188)	(0.0183)
Ln Area				−1.572	−1.442	−1.441
				(0.681)	(0.635)	(0.642)
Ln Area^2				0.0983	0.0911	0.0894
				(0.0486)	(0.0459)	(0.0464)
Ln Distance to Coastline					−0.243	−0.207
					(0.224)	(0.219)
Ln Distance to Coastline^2					0.0168	0.0141
					(0.0265)	(0.0259)
Ln Distance to Country Border						−16.49
						(6.097)
Ln Distance to Country Border^2						1.241
						(0.459)
Observations	2744	2744	2744	2744	2744	2744
R-squared	0.818	0.826	0.833	0.845	0.849	0.852

Notes: All regressions control for year and province fixed effects. Standard errors are clustered at the county level. These estimates use an unbalanced county-year level panel. GDP data are from Provincial Statistical Yearbooks. All geographic variables are computed by the authors.

4. Report and export results

4.1. Regression tables

- The **huxreg()** function from **huxtable** allows to create such tables.
    -
    -
    -
    -
    -
    -

```
outreg <- huxreg()
#
#
#
#
#
#
#
#
```

4. Report and export results

4.1. Regression tables

- The **huxreg()** function from **huxtable** allows to create such tables. Main arguments include:
  - As many **models** as you want, named or not
  -
  -
  -
  -
  -

```
outreg <- huxreg(Baseline = lm(lEarnings ~ Hours, asec),
                 lm(lEarnings ~ Hours + sqHours, asec),
                 lm(lEarnings ~ Hours + sqHours + Sex, asec),
                 lm(lEarnings ~ Hours + sqHours + Sex + Hours * Sex, asec))
#
#
#
#
#
```

4. Report and export results

4.1. Regression tables

- The **huxreg()** function from **huxtable** allows to create such tables. Main arguments include:
  - As many **models** as you want, named or not
  - Which **uncertainty statistic** to display (std.error, p.value, conf.low, conf.high)
  -
  -
  -
  -

```
outreg <- huxreg(Baseline = lm(lEarnings ~ Hours, asec),
                 lm(lEarnings ~ Hours + sqHours, asec),
                 lm(lEarnings ~ Hours + sqHours + Sex, asec),
                 lm(lEarnings ~ Hours + sqHours + Sex + Hours * Sex, asec),
                 error_format = "({std.error})")
#
#
#
#
```

4. Report and export results

4.1. Regression tables

- The **huxreg()** function from **huxtable** allows to create such tables. Main arguments include:
  - As many **models** as you want, named or not
  - Which **uncertainty statistic** to display (std.error, p.value, conf.low, conf.high)
  - Where to **place** the uncertainty statistic (below, same, right)
  -
  -
  -

```
outreg <- huxreg(Baseline = lm(lEarnings ~ Hours, asec),
                 lm(lEarnings ~ Hours + sqHours, asec),
                 lm(lEarnings ~ Hours + sqHours + Sex, asec),
                 lm(lEarnings ~ Hours + sqHours + Sex + Hours * Sex, asec),
                 error_format = "({std.error})",
                 error_pos = "below")
#
#
#
```

4. Report and export results

4.1. Regression tables

- The **huxreg()** function from **huxtable** allows to create such tables. Main arguments include:
  - As many **models** as you want, named or not
  - Which **uncertainty statistic** to display (std.error, p.value, conf.low, conf.high)
  - Where to **place** the uncertainty statistic (below, same, right)
  - Which **general statistics** to display (adj.r.squared, df, ...)
  -
  -

```
outreg <- huxreg(Baseline = lm(lEarnings ~ Hours, asec),
                 lm(lEarnings ~ Hours + sqHours, asec),
                 lm(lEarnings ~ Hours + sqHours + Sex, asec),
                 lm(lEarnings ~ Hours + sqHours + Sex + Hours * Sex, asec),
                 error_format = "({std.error})",
                 error_pos = "below",
                 statistics = c(N = "nobs", R2 = "r.squared"))
#
#
```

4. Report and export results

4.1. Regression tables

- The **huxreg()** function from **huxtable** allows to create such tables. Main arguments include:
  - As many **models** as you want, named or not
  - Which **uncertainty statistic** to display (std.error, p.value, conf.low, conf.high)
  - Where to **place** the uncertainty statistic (below, same, right)
  - Which **general statistics** to display (adj.r.squared, df, ...)
  - The desired **significance symbology**
  -

```
outreg <- huxreg(Baseline = lm(lEarnings ~ Hours, asec),
                 lm(lEarnings ~ Hours + sqHours, asec),
                 lm(lEarnings ~ Hours + sqHours + Sex, asec),
                 lm(lEarnings ~ Hours + sqHours + Sex + Hours * Sex, asec),
                 error_format = "({std.error})",
                 error_pos = "below",
                 statistics = c(N = "nobs", R2 = "r.squared"),
                 stars = c(`***` = 0.01, `**` = 0.05, `*` = 0.1))
#
```

4. Report and export results

4.1. Regression tables

- The **huxreg()** function from **huxtable** allows to create such tables. Main arguments include:
  - As many **models** as you want, named or not
  - Which **uncertainty statistic** to display (std.error, p.value, conf.low, conf.high)
  - Where to **place** the uncertainty statistic (below, same, right)
  - Which **general statistics** to display (adj.r.squared, df, ...)
  - The desired **significance symbology**
  - What to write in the **table footnote**

```
outreg <- huxreg(Baseline = lm(lEarnings ~ Hours, asec),
                 lm(lEarnings ~ Hours + sqHours, asec),
                 lm(lEarnings ~ Hours + sqHours + Sex, asec),
                 lm(lEarnings ~ Hours + sqHours + Sex + Hours * Sex, asec),
                 error_format = "({std.error})",
                 error_pos = "below",
                 statistics = c(N = "nobs", R2 = "r.squared"),
                 stars = c(`***` = 0.01, `**` = 0.05, `*` = 0.1),
                 note = "Dependent variable: log annual earnings. {stars}")
```

4. Report and export results

4.1. Regression tables

```
## ─────────────────────────────────────────────────────────────────────────────────────────────
##                            Baseline             (2)                 (3)                 (4)
##                       ─────────────────────────────────────────────────────────────────────────
##    (Intercept)              8.604 ***           7.364 ***           7.336 ***           7.390 ***
##                           (0.014)             (0.022)             (0.022)             (0.023)
##    Hours                    0.051 ***           0.119 ***           0.118 ***           0.117 ***
##                           (0.000)             (0.001)             (0.001)             (0.001)
##    sqHours                                     -0.001 ***          -0.001 ***          -0.001 ***
##                                               (0.000)             (0.000)             (0.000)
##    SexMale                                                          0.170 ***          -0.028
##                                                                   (0.007)             (0.028)
##    Hours:SexMale                                                                        0.005 ***
##                                                                                       (0.001)
##                       ─────────────────────────────────────────────────────────────────────────
##    N                    64336               64336               64336               64336
##    R2                       0.268               0.319               0.325               0.326
## ─────────────────────────────────────────────────────────────────────────────────────────────
##    Dependent variable: log annual earnings.  *** p < 0.01; ** p < 0.05; * p < 0.1
```

- Then export it with `quick_[latex/html/pdf/docx](outreg, file = "path/filename.format")`

4. Report and export results

4.1. Regression tables

```
\documentclass{article}
\usepackage{array}
\usepackage{caption}
\usepackage{graphicx}
\usepackage{siunitx}
\usepackage[normalem]{ulem}
\usepackage{colortbl}
\usepackage{multirow}
\usepackage{hhline}
\usepackage{calc}
\usepackage{tabularx}
\usepackage{threeparttable}
\usepackage{wrapfig}
\usepackage{adjustbox}
\usepackage{hyperref}
% These are LaTeX packages. You can install them using your LaTex management software,
% or by running `huxtable::install_latex_dependencies()` from within R.
% Other packages may be required if you use non-standard tabulars (e.g. tabulary).
\pagenumbering{gobble}

\begin{document}


  \providecommand{\huxb}[2]{\arrayrulecolor[RGB]{#1}\global\arrayrulewidth=#2pt}
  \providecommand{\huxvb}[2]{\color[RGB]{#1}\vrule width #2pt}
  \providecommand{\huxtpad}[1]{\rule{0pt}{#1}}
  \providecommand{\huxbpad}[1]{\rule[-#1]{0pt}{#1}}

\begin{table}[ht]
\begin{centerbox}
\begin{threeparttable}
 \setlength{\tabcolsep}{0pt}
\begin{tabular}{l l l l l}


\hhline{>{\huxb{0, 0, 0}{0.8}}->{\huxb{0, 0, 0}{0.8}}->{\huxb{0, 0, 0}{0.8}}->
{\huxb{0, 0, 0}{0.8}}->{\huxb{0, 0, 0}{0.8}}-}
\arrayrulecolor{black}
```

	Baseline	(2)	(3)	(4)
(Intercept)	8.604 ***	7.364 ***	7.336 ***	7.390 ***
	(0.014)	(0.022)	(0.022)	(0.023)
Hours	0.051 ***	0.119 ***	0.118 ***	0.117 ***
	(0.000)	(0.001)	(0.001)	(0.001)
sqHours		-0.001 ***	-0.001 ***	-0.001 ***
		(0.000)	(0.000)	(0.000)
SexMale			0.170 ***	-0.028
			(0.007)	(0.028)
Hours:SexMale				0.005 ***
				(0.001)
N	64336	64336	64336	64336
R2	0.268	0.319	0.325	0.326

Dependent variable: log annual earnings. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

4. Report and export results

4.1. Regression tables

```
<!DOCTYPE html>
<html lang="French-France">
<head><meta charset="utf8"><title>hux.html</title></head>
<body>

<p> </p><table class="huxtable" style="border-collapse: collapse; border: 0px; margin-bottom: 2em
<col><col><col><col><col><tr>
<th style="vertical-align: top; text-align: center; white-space: normal; border-style: solid solid sol
<tr>
<th style="vertical-align: top; text-align: left; white-space: normal; padding: 6pt 6pt 6pt 6pt; font-
<tr>
<th style="vertical-align: top; text-align: left; white-space: normal; padding: 6pt 6pt 6pt 6pt; font-
<tr>
<th style="vertical-align: top; text-align: left; white-space: normal; padding: 6pt 6pt 6pt 6pt; font-
<tr>
<th style="vertical-align: top; text-align: left; white-space: normal; padding: 6pt 6pt 6pt 6pt; font-
<tr>
<th style="vertical-align: top; text-align: left; white-space: normal; padding: 6pt 6pt 6pt 6pt; font-
<tr>
<th style="vertical-align: top; text-align: left; white-space: normal; padding: 6pt 6pt 6pt 6pt; font-
<tr>
<th style="vertical-align: top; text-align: left; white-space: normal; padding: 6pt 6pt 6pt 6pt; font-
<tr>
<th style="vertical-align: top; text-align: left; white-space: normal; padding: 6pt 6pt 6pt 6pt; font-
<tr>
<th style="vertical-align: top; text-align: left; white-space: normal; padding: 6pt 6pt 6pt 6pt; font-
<tr>
<th style="vertical-align: top; text-align: left; white-space: normal; padding: 6pt 6pt 6pt 6pt; font-
<tr>
<th style="vertical-align: top; text-align: left; white-space: normal; padding: 6pt 6pt 6pt 6pt; font-
<tr>
<th style="vertical-align: top; text-align: left; white-space: normal; border-style: solid solid solid
<tr>
<th colspan="5" style="vertical-align: top; text-align: left; white-space: normal; border-style: solid
</table>


</body></html>
```

	Baseline	(2)	(3)	(4)
(Intercept)	8.604 ***	7.364 ***	7.336 ***	7.390 ***
	(0.014)	(0.022)	(0.022)	(0.023)
Hours	0.051 ***	0.119 ***	0.118 ***	0.117 ***
	(0.000)	(0.001)	(0.001)	(0.001)
sqHours		-0.001 ***	-0.001 ***	-0.001 ***
		(0.000)	(0.000)	(0.000)
SexMale			0.170 ***	-0.028
			(0.007)	(0.028)
Hours:SexMale				0.005 ***
				(0.001)
N	64336	64336	64336	64336
R2	0.268	0.319	0.325	0.326

Dependent variable: log annual earnings. *** p < 0.01; ** p < 0.05; * p < 0.1

	Baseline	(2)	(3)	(4)
(Intercept)	8.604 ***	7.364 ***	7.336 ***	7.390 ***
	(0.014)	(0.022)	(0.022)	(0.023)
Hours	0.051 ***	0.119 ***	0.118 ***	0.117 ***
	(0.000)	(0.001)	(0.001)	(0.001)
sqHours		-0.001 ***	-0.001 ***	-0.001 ***
		(0.000)	(0.000)	(0.000)
SexMale			0.170 ***	-0.028
			(0.007)	(0.028)
Hours:SexMale				0.005 ***
				(0.001)
N	64336	64336	64336	64336
R2	0.268	0.319	0.325	0.326

Dependent variable: log annual earnings. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

4. Report and export results

4.1. Regression tables

	Baseline	(2)	(3)	(4)
(Intercept)	8.604 ***	7.364 ***	7.336 ***	7.390 ***
	(0.014)	(0.022)	(0.022)	(0.023)
Hours	0.051 ***	0.119 ***	0.118 ***	0.117 ***
	(0.000)	(0.001)	(0.001)	(0.001)
sqHours		-0.001 ***	-0.001 ***	-0.001 ***
		(0.000)	(0.000)	(0.000)
SexMale			0.170 ***	-0.028
			(0.007)	(0.028)
Hours:SexMale				0.005 ***
				(0.001)
N	64336	64336	64336	64336
R2	0.268	0.319	0.325	0.326

Dependent variable: log annual earnings. *** p < 0.01; ** p < 0.05; * p < 0.1

	Baseline	(2)	(3)	(4)
(Intercept)	8.604 ***	7.364 ***	7.336 ***	7.390 ***
	(0.014)	(0.022)	(0.022)	(0.023)
Hours	0.051 ***	0.119 ***	0.118 ***	0.117 ***
	(0.000)	(0.001)	(0.001)	(0.001)
sqHours		-0.001 ***	-0.001 ***	-0.001 ***
		(0.000)	(0.000)	(0.000)
SexMale			0.170 ***	-0.028
			(0.007)	(0.028)
Hours:SexMale				0.005 ***
				(0.001)
N	64336	64336	64336	64336
R2	0.268	0.319	0.325	0.326

Dependent variable: log annual earnings. *** p < 0.01; ** p < 0.05; * p < 0.1

Practice

10:00

Use the functions `huxreg()`, `insert_row()`, and `merge_cells()` to reproduce this table:

```
##                      Dependent variable: Log annual earnings
##                         (1)         (2)          (3)          (4)
##                   ───────────────────────────────────────────────
##   Hours worked        0.051 ***   0.119 ***    0.118 ***    0.117 ***
##                      (0.000)     (0.000)      (0.000)      (0.000)
##   (Hours worked)²                -0.001 ***   -0.001 ***   -0.001 ***
##                                  (0.000)      (0.000)      (0.000)
##   Male                                         0.170 ***    -0.028
##                                               (0.000)      (0.304)
##   Hours worked x Male                                       0.005 ***
##                                                            (0.000)
##   Constant            8.604 ***   7.364 ***    7.336 ***    7.390 ***
##                      (0.000)     (0.000)      (0.000)      (0.000)
##                   ───────────────────────────────────────────────
##   N                   64336       64336        64336        64336
##   R2                  0.268       0.319        0.325        0.326
## ──────────────────────────────────────────────────────────────────
##   Significance: *** p < 0.01; ** p < 0.05; * p < 0.1
```

Solution

Use the functions `huxreg()`, `insert_row()`, and `merge_cells()` to reproduce the table

```
huxreg(lm(lEarnings ~ Hours, asec),
       lm(lEarnings ~ Hours + sqHours, asec),
       lm(lEarnings ~ Hours + sqHours + Sex, asec),
       lm(lEarnings ~ Hours + sqHours + Sex + Hours * Sex, asec))
#
#
#
#
#
#
#
#
#
#
#
#
#
```

Solution

Use the functions `huxreg()`, `insert_row()`, and `merge_cells()` to reproduce the table

```
huxreg(lm(lEarnings ~ Hours, asec),
       lm(lEarnings ~ Hours + sqHours, asec),
       lm(lEarnings ~ Hours + sqHours + Sex, asec),
       lm(lEarnings ~ Hours + sqHours + Sex + Hours * Sex, asec),
       error_format = "({p.value})",
       error_pos = "below")
#
#
#
#
#
#
#
#
#
#
#
```

Solution

Use the functions `huxreg()`, `insert_row()`, and `merge_cells()` to reproduce the table

```
huxreg(lm(lEarnings ~ Hours, asec),
       lm(lEarnings ~ Hours + sqHours, asec),
       lm(lEarnings ~ Hours + sqHours + Sex, asec),
       lm(lEarnings ~ Hours + sqHours + Sex + Hours * Sex, asec),
       error_format = "({p.value})",
       error_pos = "below",
       statistics = c(N = "nobs", R2 = "r.squared"))
#
#
#
#
#
#
#
#
#
#
```

Solution

Use the functions `huxreg()`, `insert_row()`, and `merge_cells()` to reproduce the table

```
huxreg(lm(lEarnings ~ Hours, asec),
       lm(lEarnings ~ Hours + sqHours, asec),
       lm(lEarnings ~ Hours + sqHours + Sex, asec),
       lm(lEarnings ~ Hours + sqHours + Sex + Hours * Sex, asec),
       error_format = "({p.value})",
       error_pos = "below",
       statistics = c(N = "nobs", R2 = "r.squared"),
       stars = c(`***` = 0.01, `**` = 0.05, `*` = 0.1),
       note = "Significance: {stars}")
#
#
#
#
#
#
#
#
```

Solution

Use the functions `huxreg()`, `insert_row()`, and `merge_cells()` to reproduce the table

```
huxreg(lm(lEarnings ~ Hours, asec),
       lm(lEarnings ~ Hours + sqHours, asec),
       lm(lEarnings ~ Hours + sqHours + Sex, asec),
       lm(lEarnings ~ Hours + sqHours + Sex + Hours * Sex, asec),
       error_format = "({p.value})",
       error_pos = "below",
       statistics = c(N = "nobs", R2 = "r.squared"),
       stars = c(`***` = 0.01, `**` = 0.05, `*` = 0.1),
       note = "Significance: {stars}",
       align = "c")
#
#
#
#
#
#
#
```

Solution

Use the functions `huxreg()`, `insert_row()`, and `merge_cells()` to reproduce the table

```
huxreg(lm(lEarnings ~ Hours, asec),
       lm(lEarnings ~ Hours + sqHours, asec),
       lm(lEarnings ~ Hours + sqHours + Sex, asec),
       lm(lEarnings ~ Hours + sqHours + Sex + Hours * Sex, asec),
       error_format = "({p.value})",
       error_pos = "below",
       statistics = c(N = "nobs", R2 = "r.squared"),
       stars = c(`***` = 0.01, `**` = 0.05, `*` = 0.1),
       note = "Significance: {stars}",
       align = "c",
       coefs = c("Hours worked" = "Hours",
                 "(Hours worked)²" = "sqHours",
                 "Male" = "SexMale",
                 "Hours worked x Male" = "Hours:SexMale",
                 "Constant" = "(Intercept)"))
#
#
```

Solution

Use the functions `huxreg()`, `insert_row()`, and `merge_cells()` to reproduce the table

```
huxreg(lm(lEarnings ~ Hours, asec),
       lm(lEarnings ~ Hours + sqHours, asec),
       lm(lEarnings ~ Hours + sqHours + Sex, asec),
       lm(lEarnings ~ Hours + sqHours + Sex + Hours * Sex, asec),
       error_format = "({p.value})",
       error_pos = "below",
       statistics = c(N = "nobs", R2 = "r.squared"),
       stars = c(`***` = 0.01, `**` = 0.05, `*` = 0.1),
       note = "Significance: {stars}",
       align = "c",
       coefs = c("Hours worked" = "Hours",
                 "(Hours worked)²" = "sqHours",
                 "Male" = "SexMale",
                 "Hours worked x Male" = "Hours:SexMale",
                 "Constant" = "(Intercept)")) %>%
    insert_row(c("", rep("Dependent variable: Log annual earnings", 4)), after = 0)
#
```

Solution

Use the functions `huxreg()`, `insert_row()`, and `merge_cells()` to reproduce the table

```
huxreg(lm(lEarnings ~ Hours, asec),
       lm(lEarnings ~ Hours + sqHours, asec),
       lm(lEarnings ~ Hours + sqHours + Sex, asec),
       lm(lEarnings ~ Hours + sqHours + Sex + Hours * Sex, asec),
       error_format = "({p.value})",
       error_pos = "below",
       statistics = c(N = "nobs", R2 = "r.squared"),
       stars = c(`***` = 0.01, `**` = 0.05, `*` = 0.1),
       note = "Significance: {stars}",
       align = "c",
       coefs = c("Hours worked" = "Hours",
                 "(Hours worked)²" = "sqHours",
                 "Male" = "SexMale",
                 "Hours worked x Male" = "Hours:SexMale",
                 "Constant" = "(Intercept)")) %>%
    insert_row(c("", rep("Dependent variable: Log annual earnings", 4)), after = 0) %>%
    merge_cells(1, 2:5)
```

4. Report and export results

4.2. Plot coefficients

- It can also be useful to provide a **graphical representation** of the coefficients
  - By now you should be able to work it around with **dplyr** and **ggplot**
  - But there exists a **shortcut**

- The **plot_summs()** function from the **jtools** package takes regression models as inputs and **plots the results**
  -
  -
  -
  -
  -

```
plot_summs()
#
#
#
#
#
```

4. Report and export results

4.2. Plot coefficients

- It can also be useful to provide a **graphical representation** of the coefficients
  - By now you should be able to work it around with **dplyr** and **ggplot**
  - But there exists a **shortcut**

- The **plot_summs()** function from the **jtools** package takes regression models as inputs and **plots the results**
  - First feed it with your **models**
  -
  -
  -
  -

```
plot_summs(lm(lEarnings ~ Hours + Race + Sex, asec),
           lm(lEarnings ~ Hours + Race + Sex + sqHours, asec))
#
#
#
#
```

4. Report and export results

4.2. Plot coefficients

- It can also be useful to provide a **graphical representation** of the coefficients
  - By now you should be able to work it around with **dplyr** and **ggplot**
  - But there exists a **shortcut**

- The **plot_summs()** function from the **jtools** package takes regression models as inputs and **plots the results**
  - First feed it with your **models**
  - You can choose to **omit** some **coefficients**
  -
  -
  -

```
plot_summs(lm(lEarnings ~ Hours + Race + Sex, asec),
           lm(lEarnings ~ Hours + Race + Sex + sqHours, asec),
           omit.coefs = "(Intercept)")
#
#
#
```

4. Report and export results

4.2. Plot coefficients

- It can also be useful to provide a **graphical representation** of the coefficients
  - By now you should be able to work it around with **dplyr** and **ggplot**
  - But there exists a **shortcut**

- The **plot_summs()** function from the **jtools** package takes regression models as inputs and **plots the results**
  - First feed it with your **models**
  - You can choose to **omit** some **coefficients**
  - Change the **level** of the **confidence** intervals
  -
  -

```
plot_summs(lm(lEarnings ~ Hours + Race + Sex, asec),
           lm(lEarnings ~ Hours + Race + Sex + sqHours, asec),
           omit.coefs = "(Intercept)",
           ci_level = 0.99)
#
#
```

4. Report and export results

4.2. Plot coefficients

- It can also be useful to provide a **graphical representation** of the coefficients
  - By now you should be able to work it around with **dplyr** and **ggplot**
  - But there exists a **shortcut**

- The **plot_summs()** function from the **jtools** package takes regression models as inputs and **plots the results**
  - First feed it with your **models**
  - You can choose to **omit** some **coefficients**
  - Change the **level** of the **confidence** intervals
  - Custom the **color palette**
  -

```
plot_summs(lm(lEarnings ~ Hours + Race + Sex, asec),
           lm(lEarnings ~ Hours + Race + Sex + sqHours, asec),
           omit.coefs = "(Intercept)",
           ci_level = 0.99,
           colors = c("#014D64", "#00A2D9"))
#
```

4. Report and export results

4.2. Plot coefficients

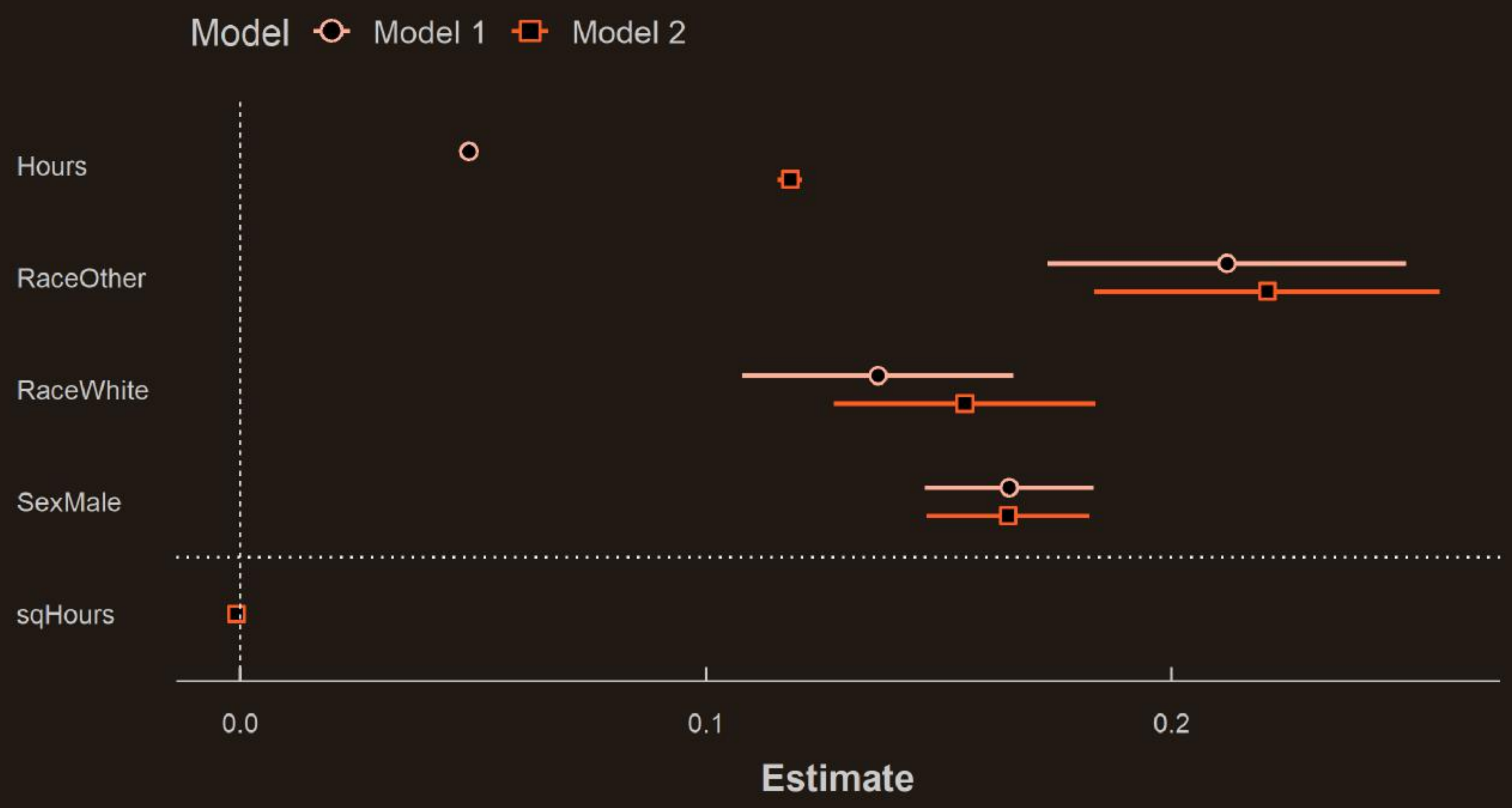
- It can also be useful to provide a **graphical representation** of the coefficients
  - By now you should be able to work it around with **dplyr** and **ggplot**
  - But there exists a **shortcut**

- The **plot_summs()** function from the **jtools** package takes regression models as inputs and **plots the results**
  - First feed it with your **models**
  - You can choose to **omit** some **coefficients**
  - Change the **level** of the **confidence** intervals
  - Custom the **color palette**
  - And add ggplot functions!

```
plot_summs(lm(lEarnings ~ Hours + Race + Sex, asec),
           lm(lEarnings ~ Hours + Race + Sex + sqHours, asec),
           omit.coefs = "(Intercept)",
           ci_level = 0.99,
           colors = c("#014D64", "#00A2D9")) +
  geom_hline(yintercept = 1.5, linetype = "dotted")
```

4. Report and export results

4.2. Plot coefficients



Overview

5. Wrap up!

Regressions in R

```r
summary(lm(formula = ige ~ gini, data = ggcurve))
```

```
##
## Call:
## lm(formula = ige ~ gini, data = ggcurve)
##
## Residuals:
##       Min        1Q    Median        3Q       Max
## -0.188991 -0.088238 -0.000855  0.047284  0.252310
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) -0.09129    0.12870  -0.709  0.48631
## gini         1.01546    0.26425   3.843  0.00102 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.1159 on 20 degrees of freedom
## Multiple R-squared:  0.4247,    Adjusted R-squared:  0.396
## F-statistic: 14.77 on 1 and 20 DF,  p-value: 0.001016
```

← Command

← Residuals distribution

← Coefs, s.e., t-/p-values

← Significance

← Residual s.e. & df.

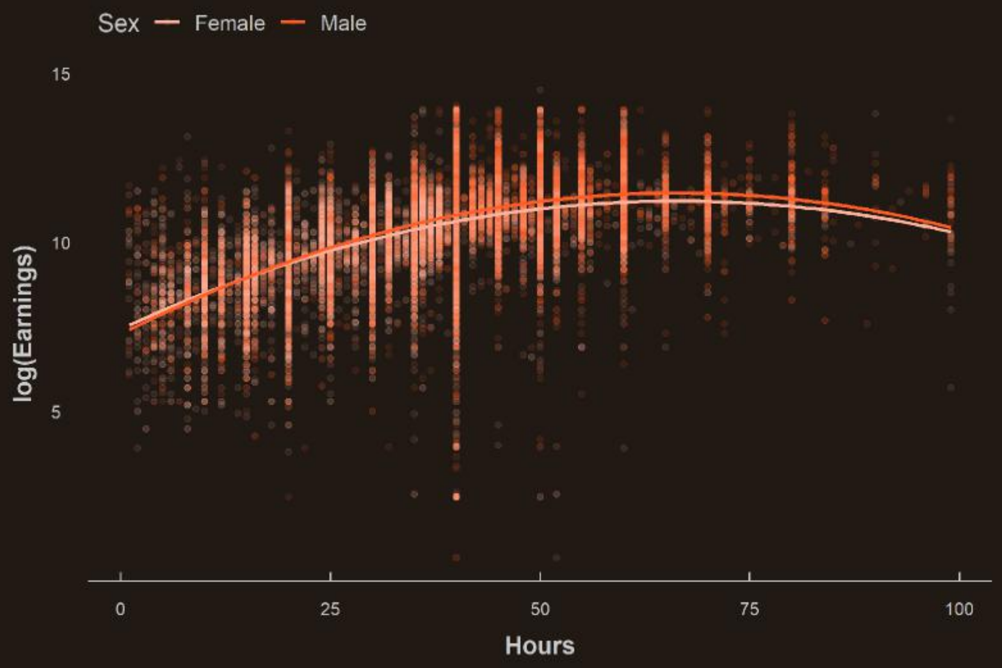
← R^2 & adjusted R^2

← F-test results

5. Wrap up!

Variable transformations, functional forms, controls, interactions

$$\log(\text{Earnings}_i) = \alpha + \beta_1 \text{Hours}_i + \beta_2 \text{Hours}_i^2 + \beta_3 \text{Male}_i + \beta_4 \text{Hours}_i \times \text{Male}_i + \varepsilon_i$$




```
summary(
  lm(lEarnings ~ Hours +
                 sqHours +
                 Sex +
                 Hours * Sex,
     asec)
)$coefficients[, 1:2]
```

```
##                   Estimate   Std. Error
## (Intercept)    7.3900468002 2.319198e-02
## Hours          0.1174998826 1.034522e-03
## sqHours       -0.0009103523 1.321706e-05
## SexMale       -0.0282905673 2.753222e-02
## Hours:SexMale  0.0050321134 6.767013e-04
```

5. Wrap up!

Hypothesis testing

```
linearHypothesis(lm(lEarnings ~ Hours + sqHours + Sex + Hours * Sex, asec),
                 c("Hours = 0", "sqHours = 0", "SexMale = 0", "Hours:SexMale = 0"))
```

```
## Linear hypothesis test
##
## Hypothesis:
## Hours = 0
## sqHours = 0
## SexMale = 0
## Hours:SexMale = 0
##
## Model 1: restricted model
## Model 2: lEarnings ~ Hours + sqHours + Sex + Hours * Sex
##
##   Res.Df   RSS Df Sum of Sq      F    Pr(>F)
## 1  64335 68395
## 2  64331 46098  4     22297 7779.1 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

5. Wrap up!

Report/export results

```r
huxreg(
  Baseline = lm(lEarnings ~ Hours, asec),
  lm(lEarnings ~ Hours + sqHours, asec),
  lm(lEarnings ~ Hours + sqHours + Sex, asec),
  lm(lEarnings ~ Hours + sqHours + Sex +
                 Hours * Sex, asec),
  error_format = "({std.error})",
  error_pos = "below",
  statistics = c(N="nobs", R2="r.squared"),
  stars = c(`***` = 0.01,
            `**` = 0.05,
            `*` = 0.1),
  note = paste("Dependent variable: log",
               "annual earnings. {stars}"
)
```

	Baseline	(2)	(3)	(4)
(Intercept)	8.604 ***	7.364 ***	7.336 ***	7.390 ***
	(0.014)	(0.022)	(0.022)	(0.023)
Hours	0.051 ***	0.119 ***	0.118 ***	0.117 ***
	(0.000)	(0.001)	(0.001)	(0.001)
sqHours		-0.001 ***	-0.001 ***	-0.001 ***
		(0.000)	(0.000)	(0.000)
SexMale			0.170 ***	-0.028
			(0.007)	(0.028)
Hours:SexMale				0.005 ***
				(0.001)
N	64336	64336	64336	64336
R2	0.268	0.319	0.325	0.326

Dependent variable: log annual earnings. *** p < 0.01; ** p < 0.05; * p < 0.1