Interpretation

Lecture 12

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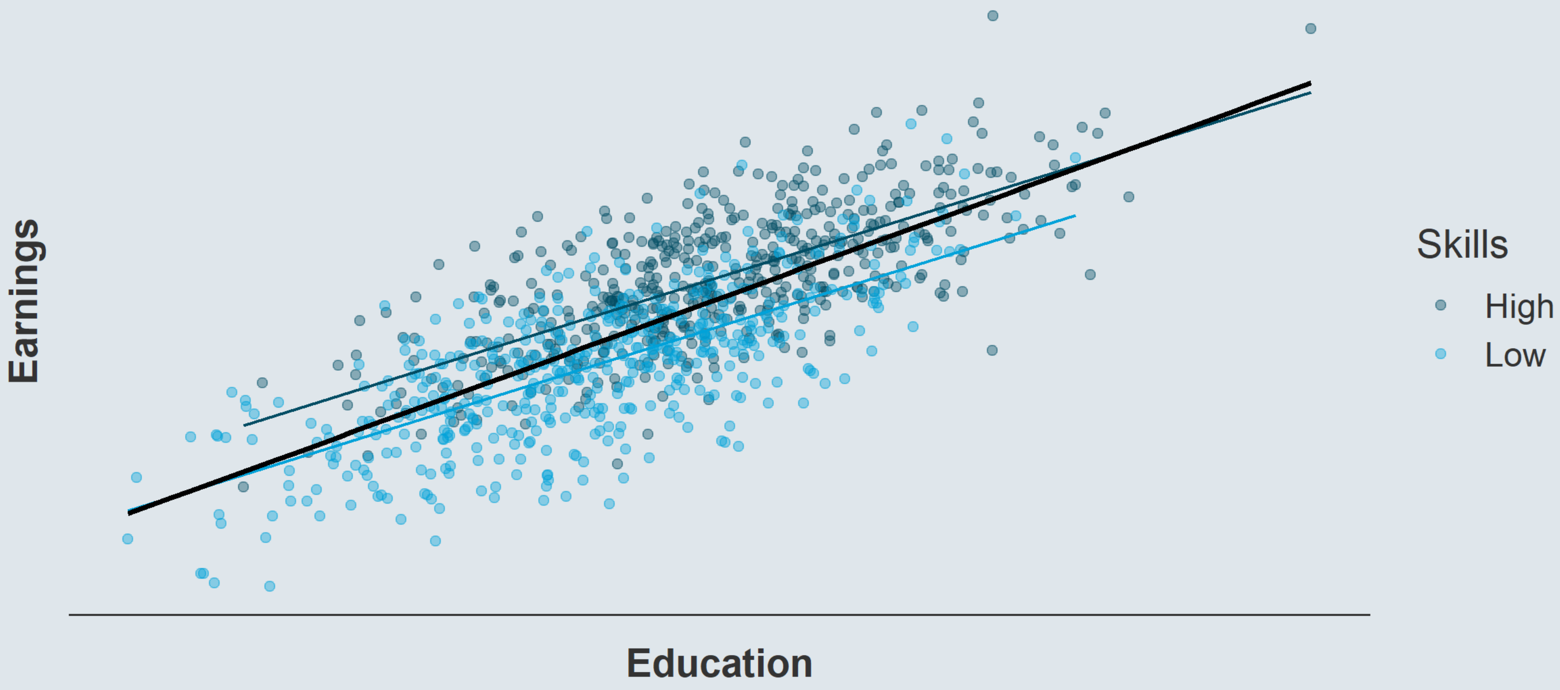
CPES 2 - Fall 2022

Quick reminder

Omitted variable bias

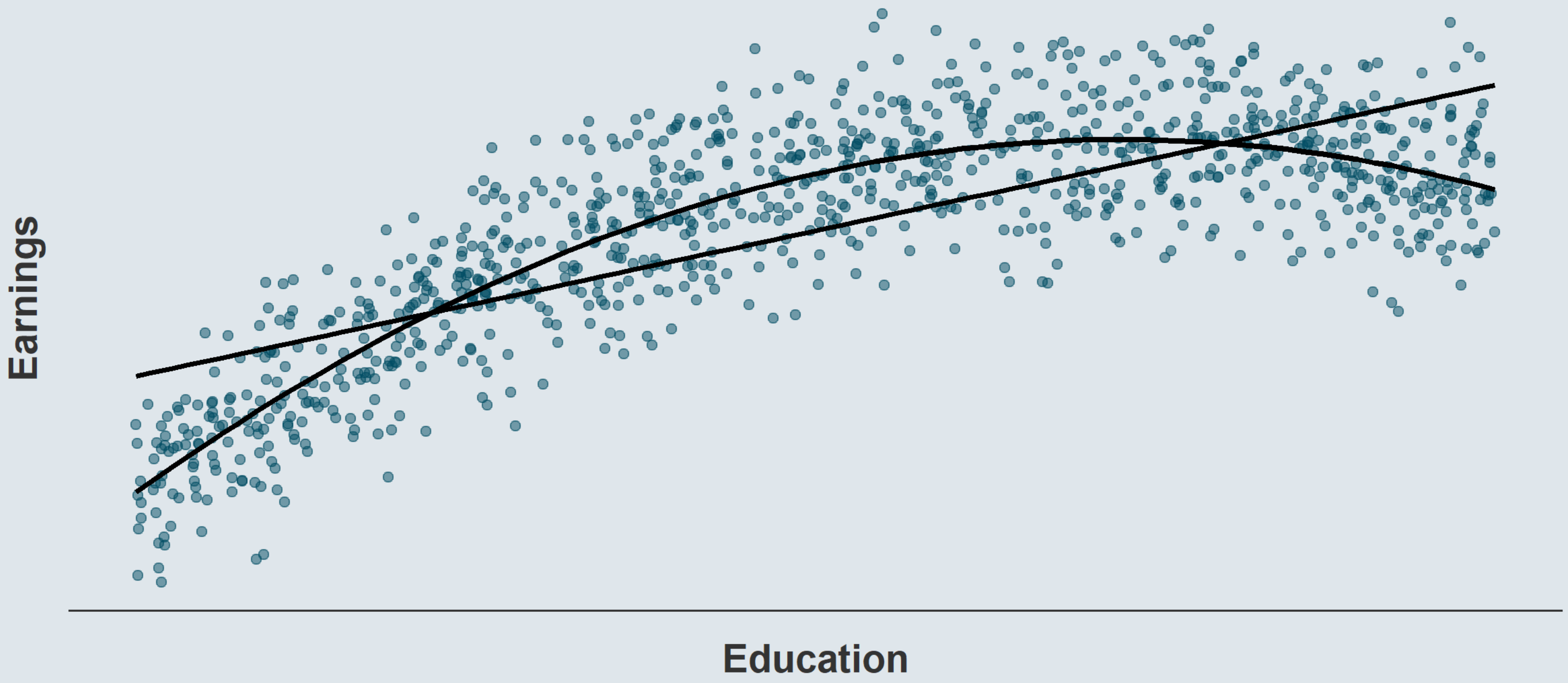
- If a third **variable** is correlated with both x and y, it would **bias the relationship**
  - We must then **control** for such variables
  - And if we can't we must acknowledge that our estimate is not causal with ***'ceteris paribus'***



Quick reminder

Functional form

- Not capture the **right functional** form correctly might also lead to biased estimations:
    - Polynomial order, interactions, logs, discretization matter
    - **Visualizing the relationship** is key



Quick reminder

Selection bias

- **Self-selection** is also a common threat to causality

- What is the impact of going to a better neighborhood on your children outcomes?
  - We cannot just regress children outcomes on a mobility dummy
  - Individuals who move may be different from those who stay: **self-selection issue**
  - Here it is not that the sample is not representative of the population, but that **the outcomes of those who stayed are different from the outcomes those who moved would have had, if they had stayed**

Simultaneity

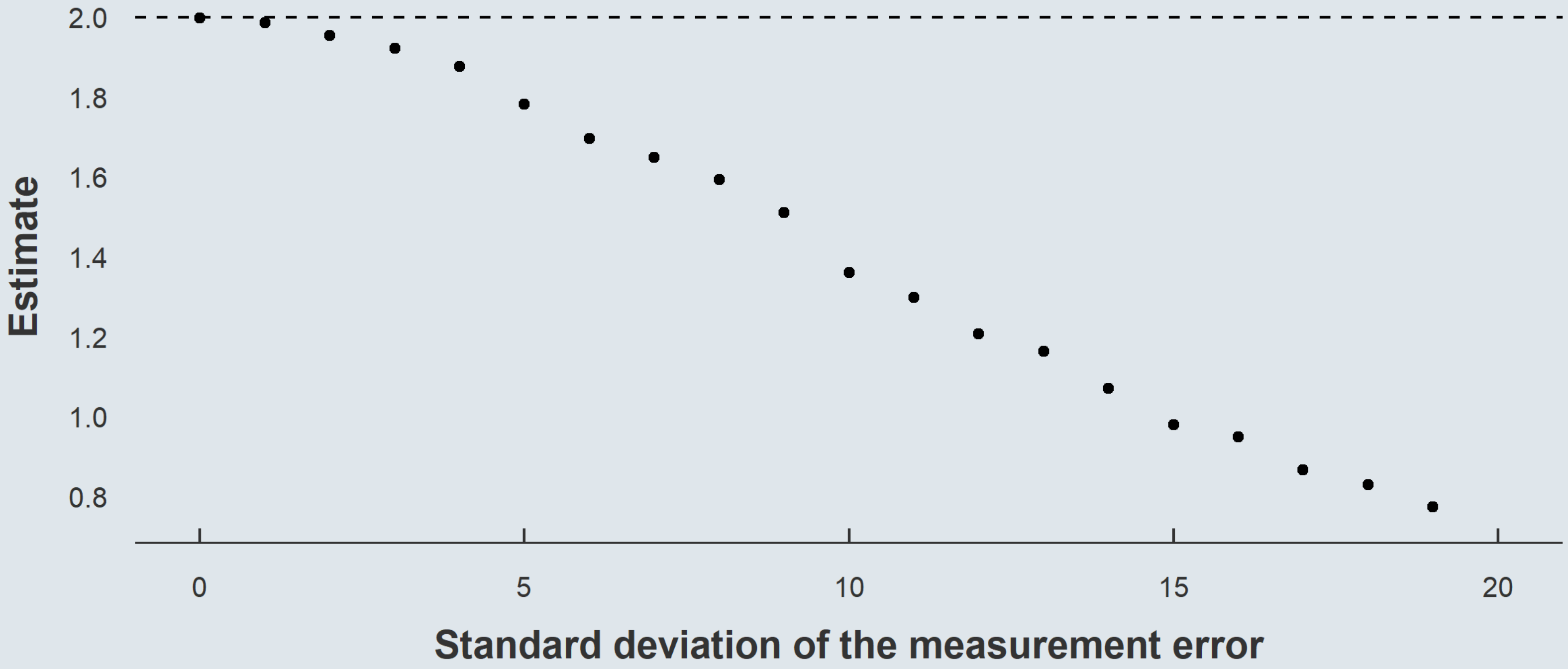
- Consider the relationship between **crime** rate and **police coverage** intensity

- What is the **direction of the relationship?**
  - We cannot just regress crime rate on police intensity
  - It's likely that more crime would cause a positive response in police activity
  - And also that police activity would deter crime

Quick reminder

Measurement error

- **Measurement error** in the independent variable also induces a bias
  - The resulting estimation would mechanically be **downward biased**
  - The **noisier** the measure, the **larger the bias**



Quick reminder

Randomized Controlled Trials

- A Randomized Controlled Trial (RCT) is a type of experiment in which the thing we want to know the impact of (called the treatment) is **randomly allocated** in the population
  - The two **groups** would then have the same characteristics on expectation, and would be **comparable**
  - It is a way to obtain **causality** from randomness

- RCTs are very **powerful tools** to sort out issues of:
  - Omitted variables
  - Selection bias
  - Simultaneity

- But RCTs are **not immune** to every problem:
  - The sample must be representative and large enough
  - Participants should comply with their treatment status
  - Independent variables must not be noisy measures of the variable of interest
  - ...

Today: Interpretation

Today: Interpretation

1. Point estimates

1.1. Continuous variables

- In this first part, we're going to consider the **relationship** between:
  - The **income level** of young parents
  - The **health** of their **newborn**

- Consider first the following specification of the two variables:
  - A continuous measure of **annual household income in euros**
  - A continuous measure of **birth weight in grams**

$$\text{Birth weight}_i = \alpha + \beta \times \text{Household income}_i + \varepsilon_i$$

```
lm(birth_weight ~ household_income, data)$coefficients
```

```
##      (Intercept) household_income
##     3.134528e+03     2.213871e-03
```

➜ **How would you interpret $\hat{\beta}$ here?** *(Note that* e+03 *and* e-03 *mean* $\times 10^3$ *and* $\times 10^{-3}$*)*

1. Point estimates

1.1. Continuous variables

- When both x and y are continuous, the **general** template for the **interpretation** of $\hat{\beta}$ is:

"Everything else equal, a 1 [unit] increase in [x] is associated with an [in/de]crease of [beta] [units] in [y] on average."

- So in our case the **adequate interpretation** would be:

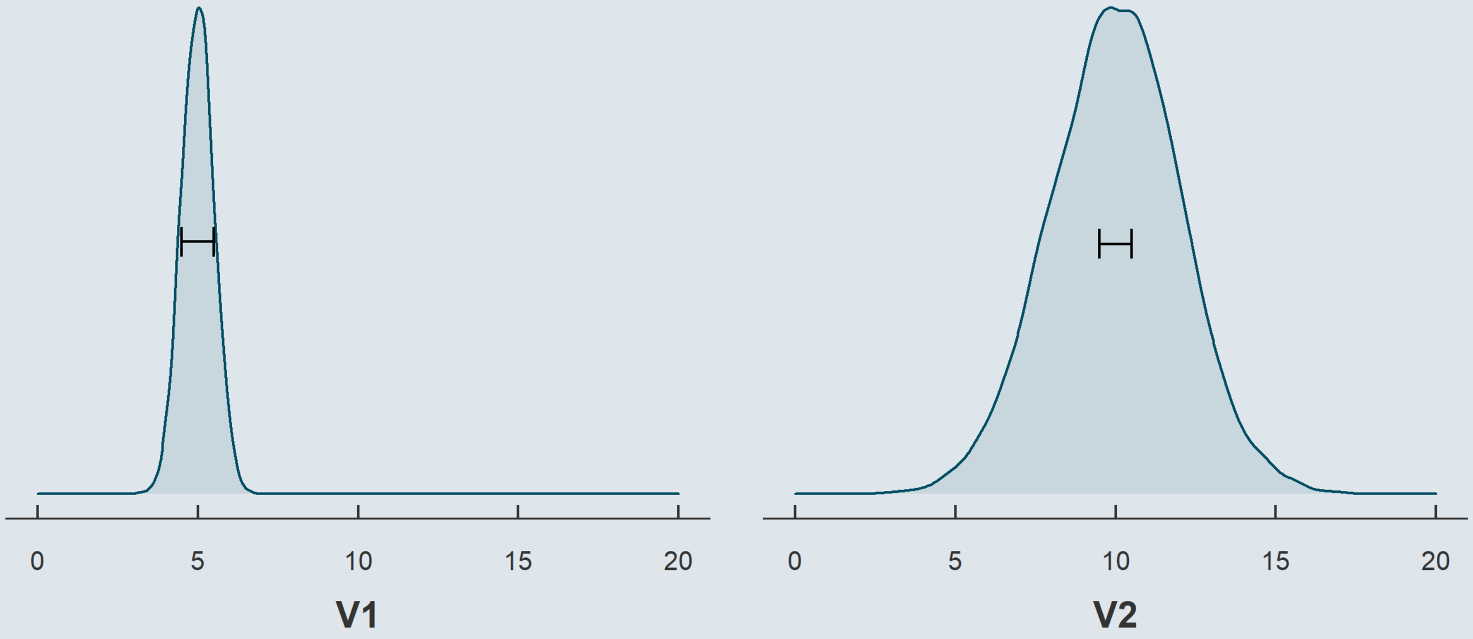
*"Everything else equal, a **1 euro increase in annual household income** is associated with an **increase of 0.003 gram in newborn birth weight** on average."*

- But it would be even better to **interpret** the results for a **meaningful variation** of x
  - For an annual household income, a **1 euro variation** is not really meaningful
  - 1 euro increase **→** 0.003 gram increase $\Leftrightarrow$ **1,000 euro increase →** 3 gram increase

1. Point estimates

1.1. Continuous variables

- A common way to obtain a coefficient for a **meaningful variation** of x is to **standardize** x
  - If we divide x by $\text{SD}(x)$, the 1 **unit increase** in $\frac{x}{\text{SD}(x)}$ is equivalent to an $\text{SD}(x)$ **increase** in x
  - An $\text{SD}(x)$ change in x is meaningful: it's low if x is very concentrated and high if x is highly spread out



1. Point estimates

1.1. Continuous variables

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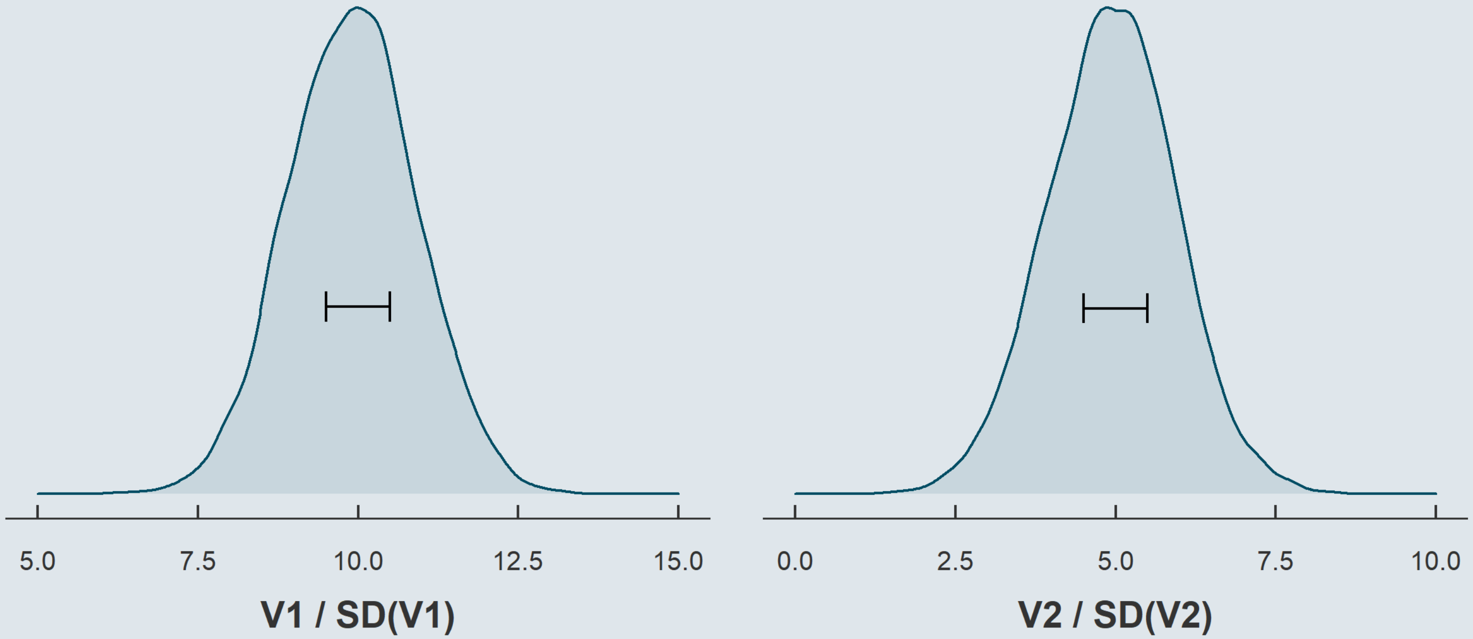


1. Point estimates

1.1. Continuous variables

- Note that if you **standardize both x and y**, the resulting $\hat{\beta}$ equals the **correlation** between x and y
  - To show that, let's first rewrite the formula of the beta coefficient:

$$\hat{\beta} = \frac{\text{Cov}(x,\, y)}{\text{Var}(x)} = \frac{\text{Cov}(x,\, y)}{\text{SD}(x) \times \text{SD}(x)}$$

$$\hat{\beta} = \frac{\text{Cov}(x,\, y)}{\text{SD}(x) \times \text{SD}(x)} \times \frac{\text{SD}(y)}{\text{SD}(y)}$$

$$\hat{\beta} = \frac{\text{Cov}(x,\, y)}{\text{SD}(x) \times \text{SD}(y)} \times \frac{\text{SD}(y)}{\text{SD}(x)}$$

$$\hat{\beta} = \text{Cor}(x,\, y) \times \frac{\text{SD}(y)}{\text{SD}(x)}$$

1. Point estimates

1.1. Continuous variables

- Starting with the previous expression, the $\hat{\beta}$ **coefficient with the standardized variables** writes:

$$\hat{\beta} = \frac{\text{Cov}\left(\frac{x}{\text{SD}(x)}, \frac{y}{\text{SD}(y)}\right)}{\text{SD}\left(\frac{x}{\text{SD}(x)}\right) \times \text{SD}\left(\frac{y}{\text{SD}(y)}\right)} \times \frac{\text{SD}\left(\frac{y}{\text{SD}(y)}\right)}{\text{SD}\left(\frac{x}{\text{SD}(x)}\right)}$$

- But by construction, the standard deviation of a standardized variable is 1:

$$\hat{\beta} = \frac{\text{Cov}\left(\frac{x}{\text{SD}(x)}, \frac{y}{\text{SD}(y)}\right)}{1 \times 1} \times \frac{1}{1}$$

$$\hat{\beta} = \text{Cov}\left(\frac{x}{\text{SD}(x)}, \frac{y}{\text{SD}(y)}\right)$$

$$\hat{\beta} = \frac{\text{Cov}(x,\, y)}{\text{SD}(x) \times \text{SD}(y)} = \text{Cor}(x, y)$$

- Learn the cheatsheet on moments properties:

$$\text{Var}(aX) = a^2\text{Var}(X)$$

1. Point estimates

1.2. Discrete variables

- Consider the following specification of the two variables:
  - A categorical variable for **annual household income divided in terciles**
  - Still continuous measure of **birth weight in grams**

$$\text{Birth weight}_i = \alpha + \beta_1 \text{T2}_i + \beta_2 \text{T3}_i + \varepsilon_i$$

- Recall that when including a **categorical variable** in a regression, a **reference category** must be omitted

```
lm(birth_weight ~ income_tercile, data)$coefficients
```

```
##      (Intercept) income_tercileT2 income_tercileT3
##       3112.83162         88.24778        222.65414
```

→ How would you interpret $\hat{\beta}_1$ and $\hat{\beta}_2$ here?

1. Point estimates

1.2. Discrete variables

- With a discrete x, the interpretation of the coefficient must be **relative to the reference category:**

"Everything else equal, belonging to the [x category] is associated with
a [beta] [unit] [higher/lower] average [y] relative to the [reference category]."

- So in our case, the **adequate interpretations** would be:

"Everything else equal, belonging to the ***second income tercile*** *is associated with*
a ***88 grams higher average birth weight*** *relative to the* ***first income tercile.****"*

"Everything else equal, belonging to the ***third income tercile*** *is associated with*
a ***223 grams higher average birth weight*** *relative to the* ***first income tercile.****"*

- And the **intercept** is the **average birth weight** for newborns to parents in the **first income tercile**

1. Point estimates

1.2. Discrete variables

- Consider now the following specification of the two variables:
  - A continuous measure of **annual household income in euros**
  - A **binary variable** taking the value 1 if **the newborn is underweight** and 0 otherwise

$$\text{Underweight}_i = \alpha + \beta \times \text{Household income}_i + \varepsilon_i$$

```
lm(underweight ~ household_income, data)$coefficients
```

```
##      (Intercept) household_income
##     5.214013e-02    -4.084787e-07
```

➜ How would you interpret $\hat{\beta}$ here?

➜ And would you consider its magnitude high?

1. Point estimates

1.2. Discrete variables

- With a **binary y variable**, the coefficient must be interpreted in **percentage points:**

"Everything else equal, a 1 [unit] increase in [x] is associated with a [beta] percentage point [in/de]crease in the probability that [y equals 1] on average."

- So in our case, the **adequate interpretation** would be:

*"Everything else equal, a **1 euro increase in annual household income** is associated with a **0.0000004 percentage point decrease in the probability that the newborn is underweight** on average."*

- Here the **interpretation** would be more **meaningful:**
  - For a **1,000 euro** increase **→** 0.0004 percentage point decrease
  - Compared to the **typical probability** to have an underweight newborn

1. Point estimates

1.2. Discrete variables

- The mean of a dummy variable corresponds to the share of 1s:

```
mean(data$underweight)
```

```
## [1] 0.037
```

- We can also compute the probability that $y = 1$ for the average x with our estimated coefficients:

```
5.214013e-02 + mean(data$household_income) * -4.084787e-07
```

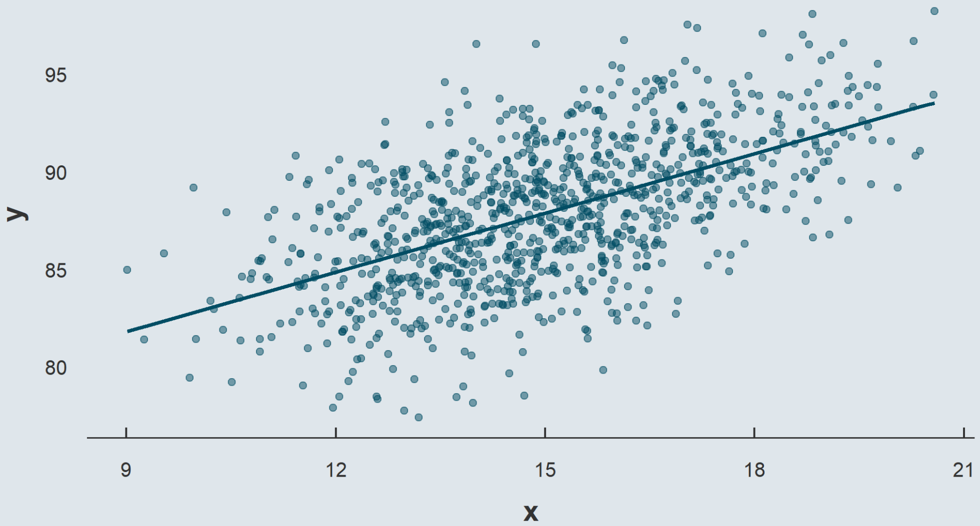
```
## [1] 0.03700001
```

For the **average household**, a **1,000 euro increase** in annual income would be associated with a **0.0004 / 0.037** $\approx$ **1% decrease in the probability** that the newborn is **underweight**

1. Point estimates

1.3. Log vs. level

- Consider now the following hypothetical relationship:



- The slope tells us by how many **units** the y variable would increase for a **1 unit** in x

- But often times in Economics we're interested in the elasticity between the two variables:
  - What is the expected **percentage change** in y for a **one percent increase** in x?

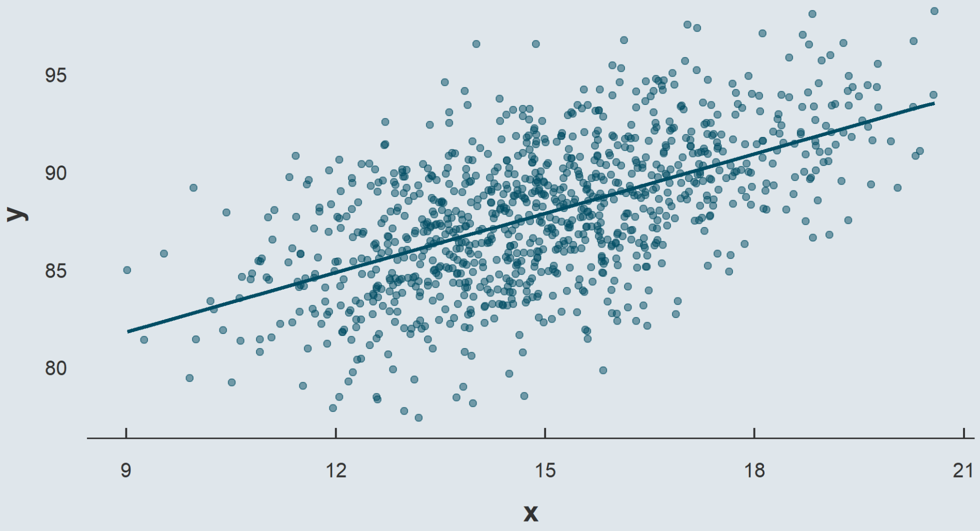
→ The log transformation can be used to easily get an approximation of that

1. Point estimates

1.3. Log vs. level

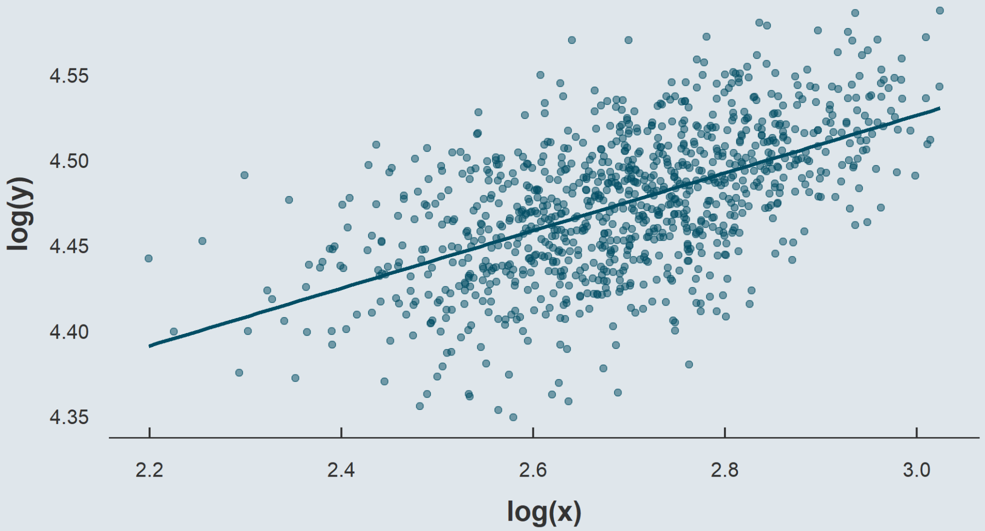
- Instead of considering

$$y_i = \alpha_{lvl} + \beta_{lvl} x_i + \varepsilon_i$$



- We consider

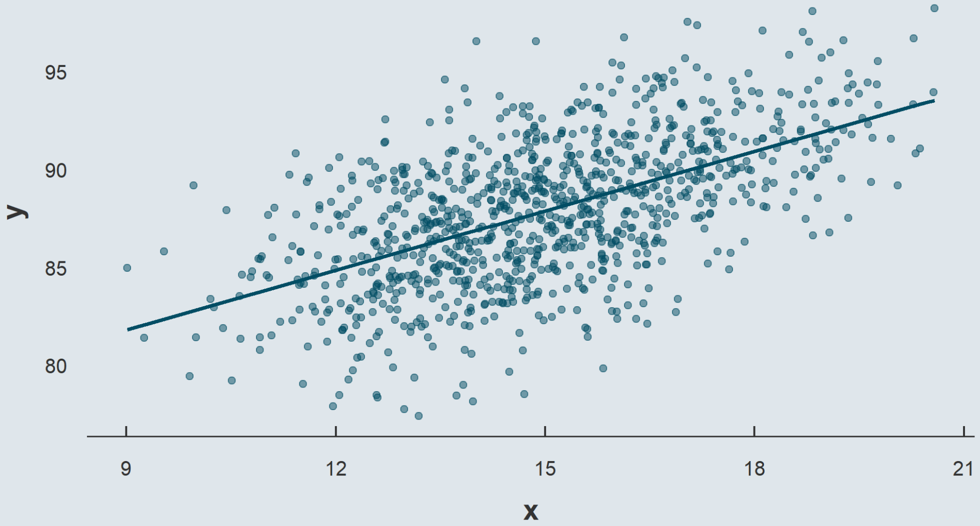
$$\log(y_i) = \alpha_{log} + \beta_{log} \log(x_i) + \varepsilon_i$$



1. Point estimates

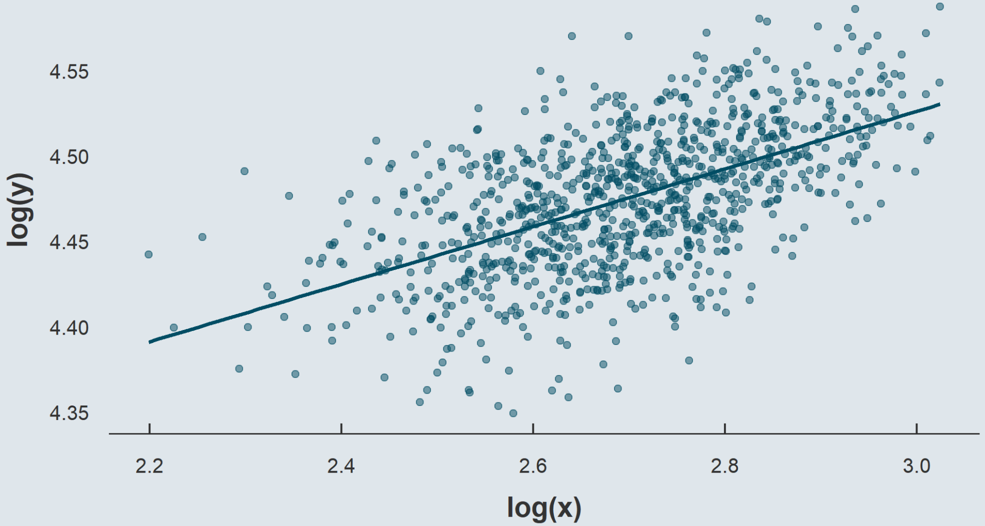
1.3. Log vs. level

$\widehat{\beta_{lvl}} = 1.0121933$



$$(15 \div 100) \times \widehat{\beta_{lvl}} \approx (15 \div 100) \times 1.0121933$$
$$\approx 0.0151829$$

$\widehat{\beta_{log}} = 0.16875$



$$0.0151829 \div 90 = 0.0001687$$
$$\approx \beta_{log}\%$$

1. Point estimates

1.3. Log vs. level

- Thus the interpretation differs depending on whether variables are in log or in level:
  - When variables are in **level** we should interpret the coefficients in terms of **unit** increase
  - When variables are in **log** we should interpret the coefficients in terms of **percentage** increase

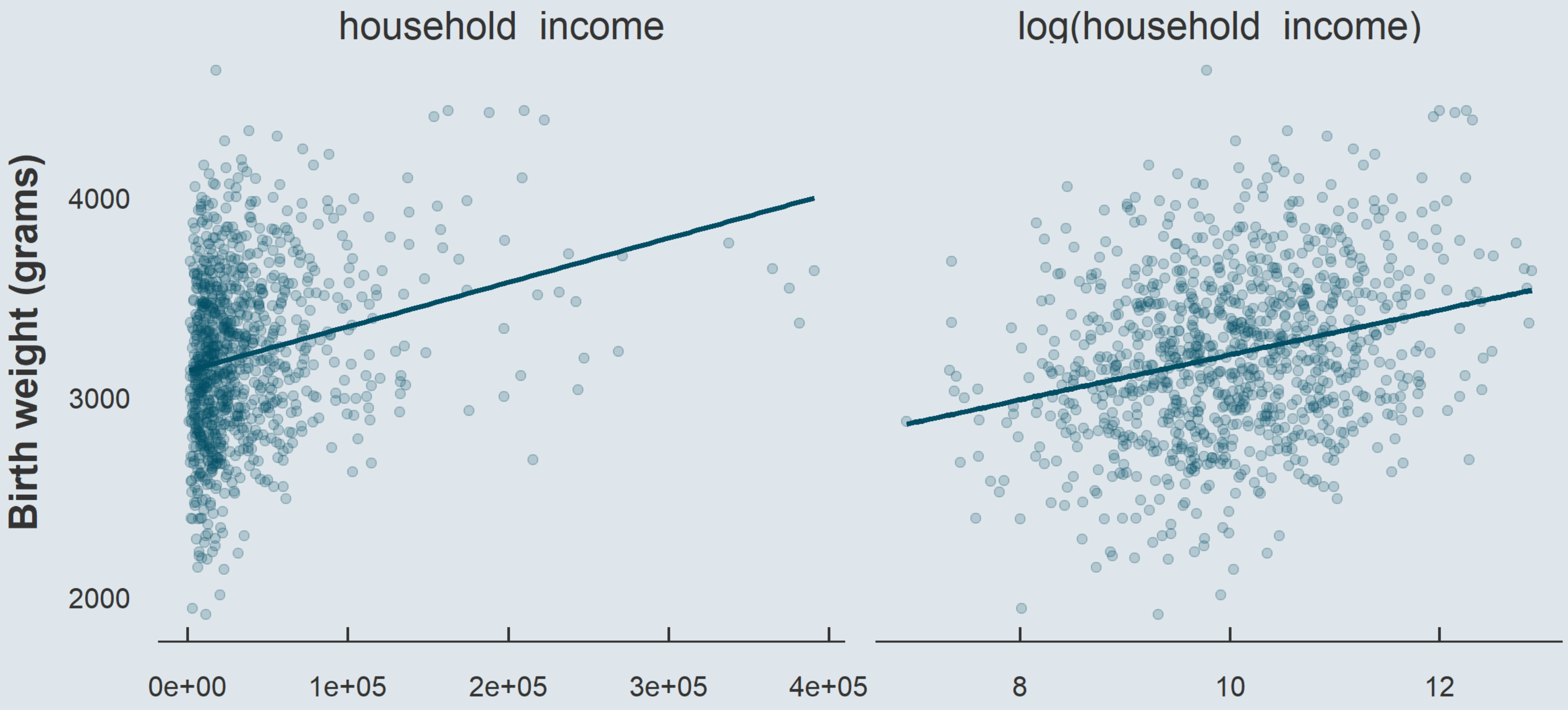
Interpretation of the regression coefficient

	y	**log(y)**
x	$\hat{\beta}$ is the unit increase in y due to a 1 unit increase in x	$\hat{\beta} \times 100$ is the % increase in y due to a 1 unit increase in x
log(x)	$\hat{\beta} \div 100$ is the unit increase in y due to a 1% increase in x	$\hat{\beta}$ is the % increase in y due to a 1% increase in x

1. Point estimates

1.3. Log vs. level

- Let's give it a try with our example on household income and birth weight
  - We've already seen that because income is log-normally distribution, it should be included in log



1. Point estimates

1.3. Log vs. level

- So what would be your interpretation of the slope estimated from the following regression?

$$\text{Birth weight}_i = \alpha + \beta \log(\text{Household income}_i) + \varepsilon$$

```
lm(birth_weight ~ log(household_income), data)$coefficients
```

```
##           (Intercept) log(household_income)
##             2091.2323              112.3234
```

- With a continuous y **in level** and a **logged** x variable, the template would be:

"Everything else equal, a 1 percent increase in [x] is associated with a [beta/100] [unit] [in/de]crease in [y] on average."

- So in our case, the **adequate interpretation** would be:

*"Everything else equal, a **1 percent increase in annual household income** is associated with a **1.12 grams increase in the birth weight of the newborn** on average."*

Today: Interpretation

1. Point estimates ✓
  1.1. Continuous variables
  1.2. Discrete variables
  1.3. Log vs. level

2. Practice interpretation

3. Regression tables
  3.1. Layout
  3.2. Reported significance
  3.3. R squared

4. Wrap up!

Today: Interpretation

1. **Point estimates ✓**
    1.1. Continuous variables
    1.2. Discrete variables
    1.3. Log vs. level

2. **Practice interpretation**

2. Practice interpretation

➜ Let's practice coefficient interpration with randomly generated relationships:

Relationships between department characteristics

Select inputs

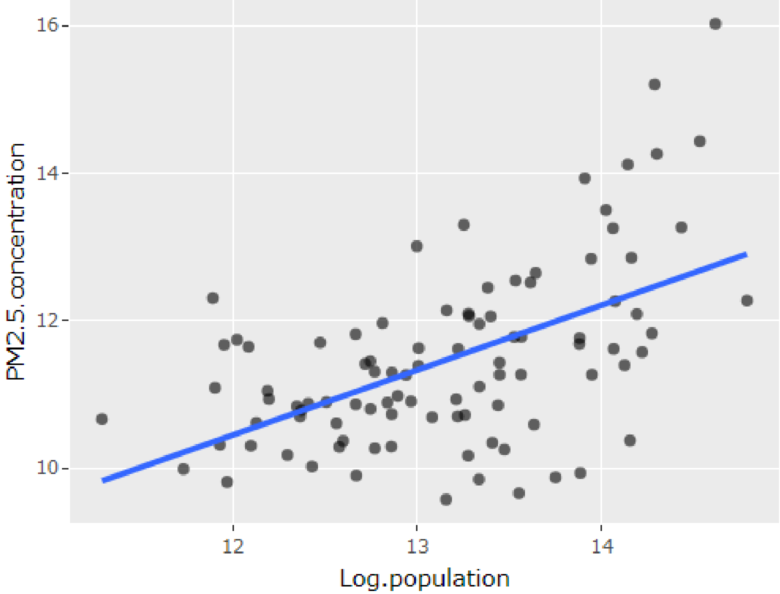
X variable: Log.population

Y variable: PM2.5.concentration

Select Year: 2012 — 2015 — 2017

Random selection

Regression results



	Dependent variable:
	PM2.5.concentration
Log.population	0.880***
	(0.141)
Constant	-0.112
	(1.855)
Observations	96
R^2	0.294
Note:	*p<0.1; **p<0.05; ***p<0.01

Today: Interpretation

1. Point estimates ✓
- 1.1. Continuous variables
- 1.2. Discrete variables
- 1.3. Log vs. level

2. Practice interpretation ✓

3. Regression tables
- 3.1. Layout
- 3.2. Reported significance
- 3.3. R squared

4. Wrap up!

Today: Interpretation

1. Point estimates ✓

- 1.1. Continuous variables
- 1.2. Discrete variables
- 1.3. Log vs. level

2. Practice interpretation ✓

3. Regression tables

- 3.1. Layout
- 3.2. Reported significance
- 3.3. R squared

3. Regression tables

3.1. Layout

- **So far** we've been **used to** regression results **displayed this way:**

```
lm(birth_weight ~ household_income, data)$coefficients
```

```
##      (Intercept) household_income
##     3.134528e+03     2.213871e-03
```

- Or with the more exhaustive **summary()** coefficients output:

```
summary(lm(birth_weight ~ household_income, data))$coefficients
```

```
##                      Estimate   Std. Error    t value     Pr(>|t|)
## (Intercept)      3.134528e+03 1.656840e+01 189.187165 0.000000e+00
## household_income 2.213871e-03 2.808507e-04   7.882732 8.355367e-15
```

→ *But in **formal** reports and academic papers, the **layout** of regression tables is **a bit different***

3. Regression tables

3.1. Layout

	Dependent variable:	
	Birth weight	
	(1)	(2)
Household income	0.002^{***}	0.002^{***}
	(0.0003)	(0.0003)
Girl (ref: Boy)		-135.218^{***}
		(34.838)
Constant	$3,134.528^{***}$	$3,246.365^{***}$
	(16.568)	(34.257)
Observations	1,000	963
Note:	*p<0.1; **p<0.05; ***p<0.01	

Regression tables often contain multiple regressions:

- With **one regression in each column**
  - Regression models are numbered
  - Dependent variable mentioned above
- And one variable in **each row**
  - With the **point estimate**
  - And a **precision measure** below
- **General info** on each model **at the bottom**
- A **symbology** for the **p-value** testing whether the coefficient is significantly different from 0 or not

3. Regression tables

3.1. Layout

	Dependent variable:	
	Birth weight	
	(1)	(2)
Household income	0.002***	0.002***
	(0.0003)	(0.0003)
Girl (ref: Boy)		-135.218***
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Constant	3,134.528***	3,246.365***
	(16.568)	(34.257)
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It makes it easy to compare the different models:

- We can **add controls progressively**
  - Check the **stability** of the main **coefficient**

→ *If it gets significantly closer to 0 it might indicate that the raw relationship was fallaciously driven by a confounding factor*

- And **compare general statistics**
  - N is lower in the second regression
  - It means that there are missing values
  - Could this induce a selection bias?

3. Regression tables

3.2. Reported significance

	Dependent variable:	
	Birth weight	
	(1)	(2)
Household income	0.002***	0.002***
	(0.0003)	(0.0003)
Girl (ref: Boy)		-135.218***
		(34.838)
Constant	3,134.528***	3,246.365***
	(16.568)	(34.257)
Observations	1,000	963
Note:	*p<0.1; **p<0.05; ***p<0.01	

It makes it easy to compare the different models:

- The **evolution** of the **significance** matters as well
  - The main coefficient should stay significant
- But don't rely too much on the **symbology**
  - Thresholds are **not always the same**
  - **Sometimes** there are **none**
- Instead, keep in mind this **rule of thumb:**

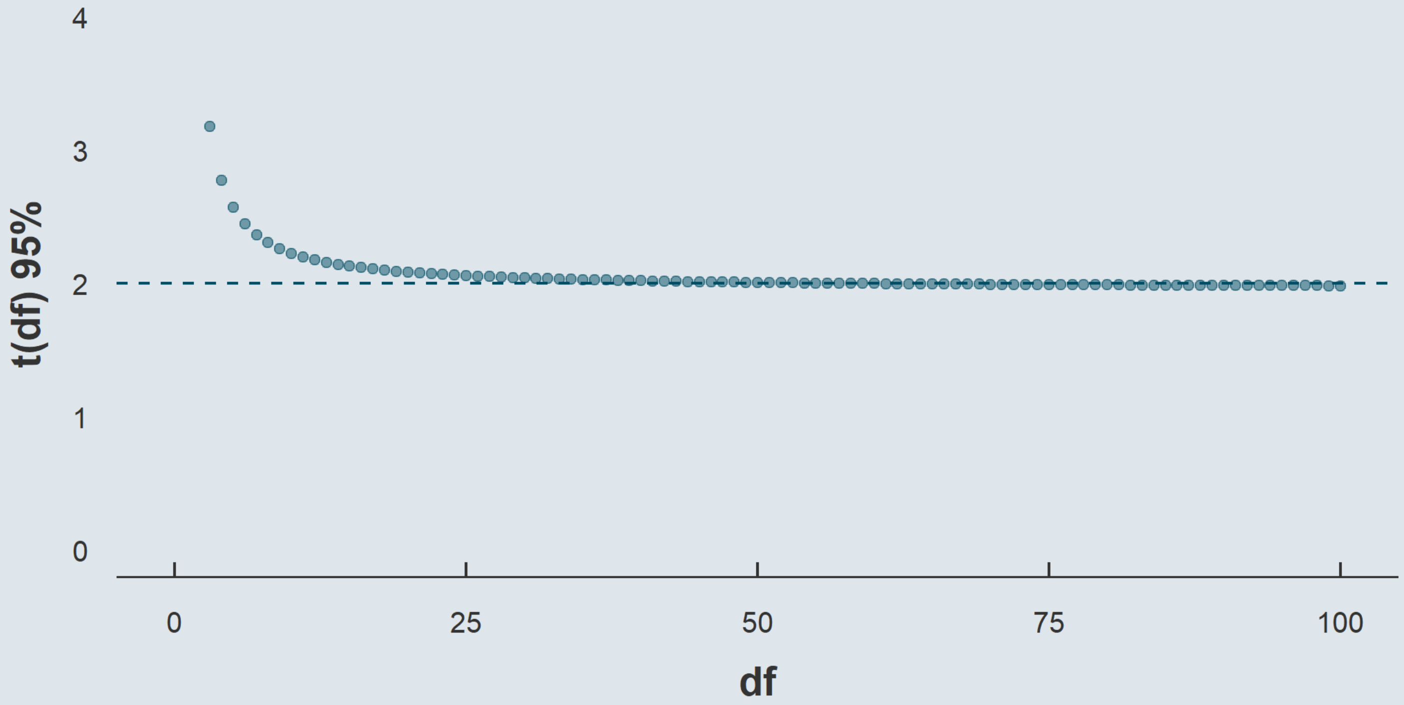
→ ***A coefficient $\approx$ twice larger than its standard error has a p-value of $\approx$ 5%***

3. Regression tables

3.2. Reported significance

- Remember the formula for the **confidence interval:**
  - We can **fix** the **confidence level** $1-\alpha$ to 95% and check **how** t **varies with** df

$$\hat{\beta} \pm t(\mathrm{df})_{1-\frac{\alpha}{2}} \times \mathrm{se}(\hat{\beta})$$



3. Regression tables

3.2. Reported significance

- **As soon as** you have **about 20 observations more than** you have **parameters** to estimate:
  - The t **value** gets very **close to 2**
  - And as df increases it quickly converges to $\approx$ 2

- The coefficient is statistically significant if the lower bound of its (absolute) confidence interval is larger than 0
  - Which is an easy calculation if we **approximate the t value by 2**
  - A reasonable approximation for a back of the envelope calculation unless there are very few observations

- The *(absolute)* lower bound of the CI writes:

$$|\hat{\beta}| - t(\text{df})_{1-\frac{\alpha}{2}} \times \text{se}(\hat{\beta})$$

$$|\hat{\beta}| - 2 \times \text{se}(\hat{\beta}) > 0$$

$$|\hat{\beta}| > 2 \times \text{se}(\hat{\beta})$$

*So if the **coefficient** is clearly more than **twice larger** than it's **standard error**, it must be **statistically significant** at the **5% significance** level*

➜ But sometimes the p-value or the confidence interval is reported instead of the standard error

3. Regression tables

3.2. Reported significance

	Dependent variable:	
	Birth weight	
	(1)	(2)
Household income	0.002^{***}	0.002^{***}
	p = 0.000	p = 0.000
Girl (ref: Boy)		-135.218^{***}
		p = 0.0002
Constant	$3,134.528^{***}$	$3,246.365^{***}$
	p = 0.000	p = 0.000
Observations	1,000	963
Note:	*p<0.1; **p<0.05; ***p<0.01	

	Dependent variable:	
	Birth weight	
	(1)	(2)
Household income	0.002^{***}	0.002^{***}
	(0.002, 0.003)	(0.002, 0.003)
Girl (ref: Boy)		-135.218^{***}
		(-203.500, -66.936)
Constant	$3,134.528^{***}$	$3,246.365^{***}$
	(3,102.055, 3,167.002)	(3,179.223, 3,313.507)
Observations	1,000	963
Note:	*p<0.1; **p<0.05; ***p<0.01	

3. Regression tables

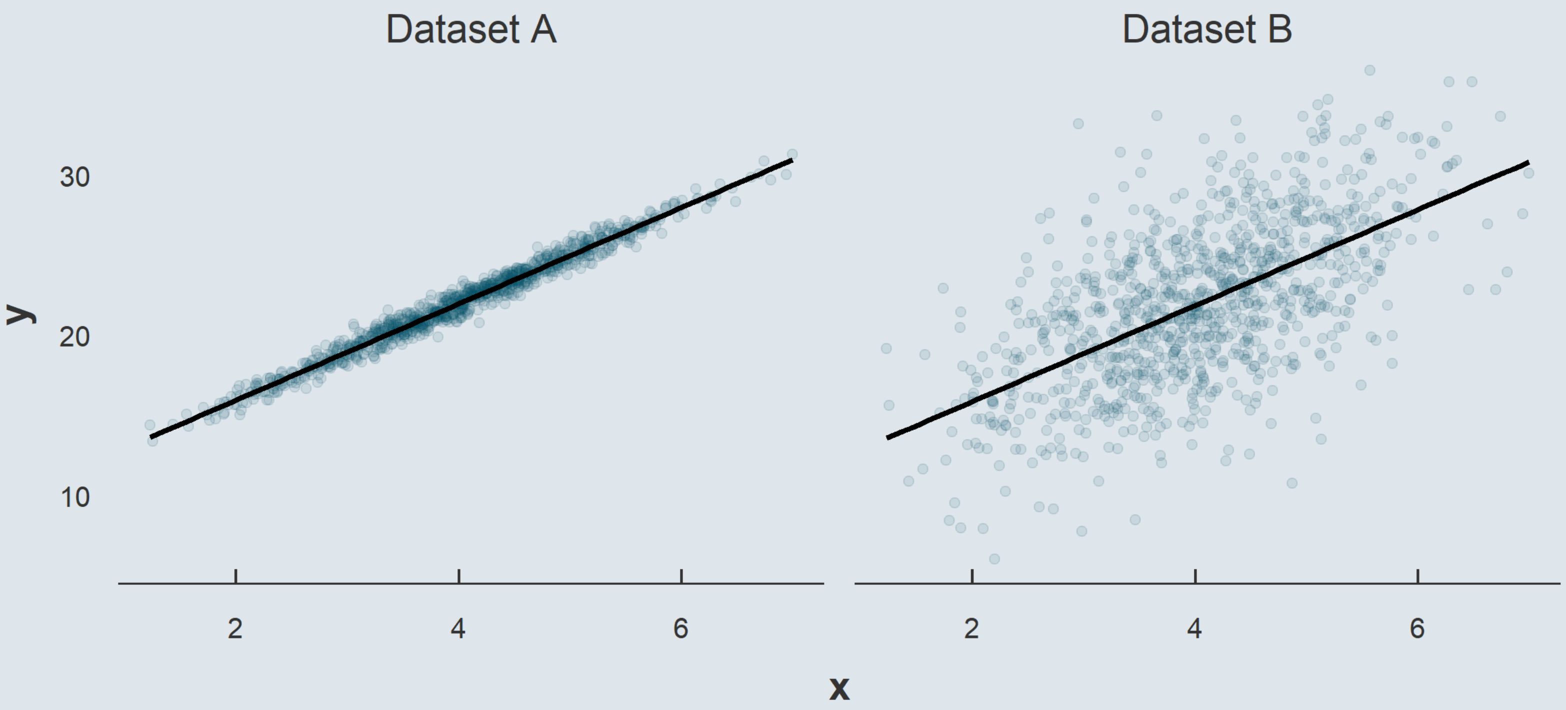
3.3. R squared

- In **regression tables**, the $\mathbf{R^2}$ of the model is **always reported** below the number of observations
    - The R^2 captures how well the **model fits the data**
    -

3. Regression tables

3.3. R squared

- In **regression tables**, the **R^2** of the model is **always reported** below the number of observations
  - The R^2 captures how well the **model fits the data**
  - The model has a **good fit (high R^2)** on dataset A but a **poor fit (low R^2)** on dataset B



3. Regression tables

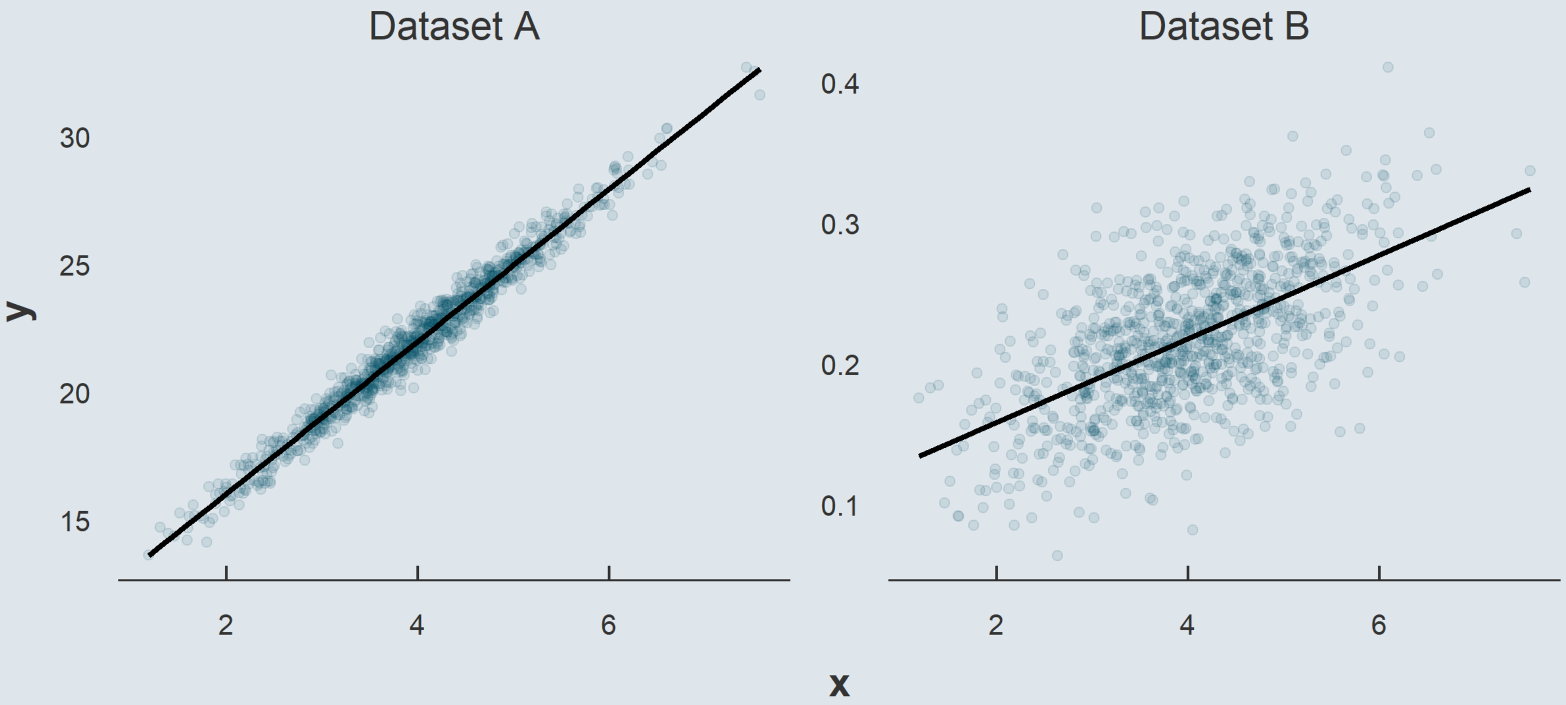
3.3. R squared

- The **standard error** already gives an idea on the goodness of the fit, but it is expressed in the **same unit as** y
  - So we **cannot compare** two different models based on that statistic
  -

3. Regression tables

3.3. R squared

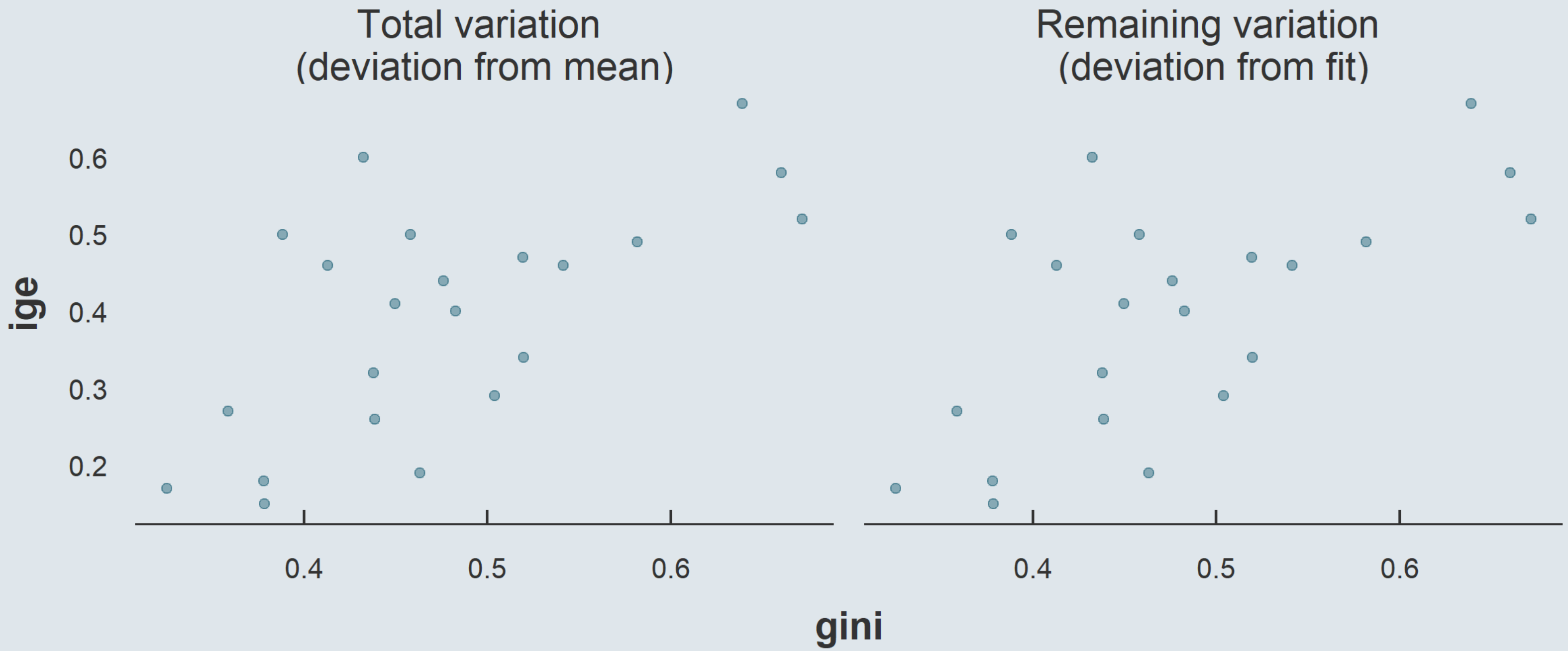
- The **standard error** already gives an idea on the goodness of the fit, but it is expressed in the **same unit as** y
  - So we **cannot compare** two different models based on that statistic
  - The standard error of the slope would be larger on dataset A than on dataset B



3. Regression tables

3.3. R squared

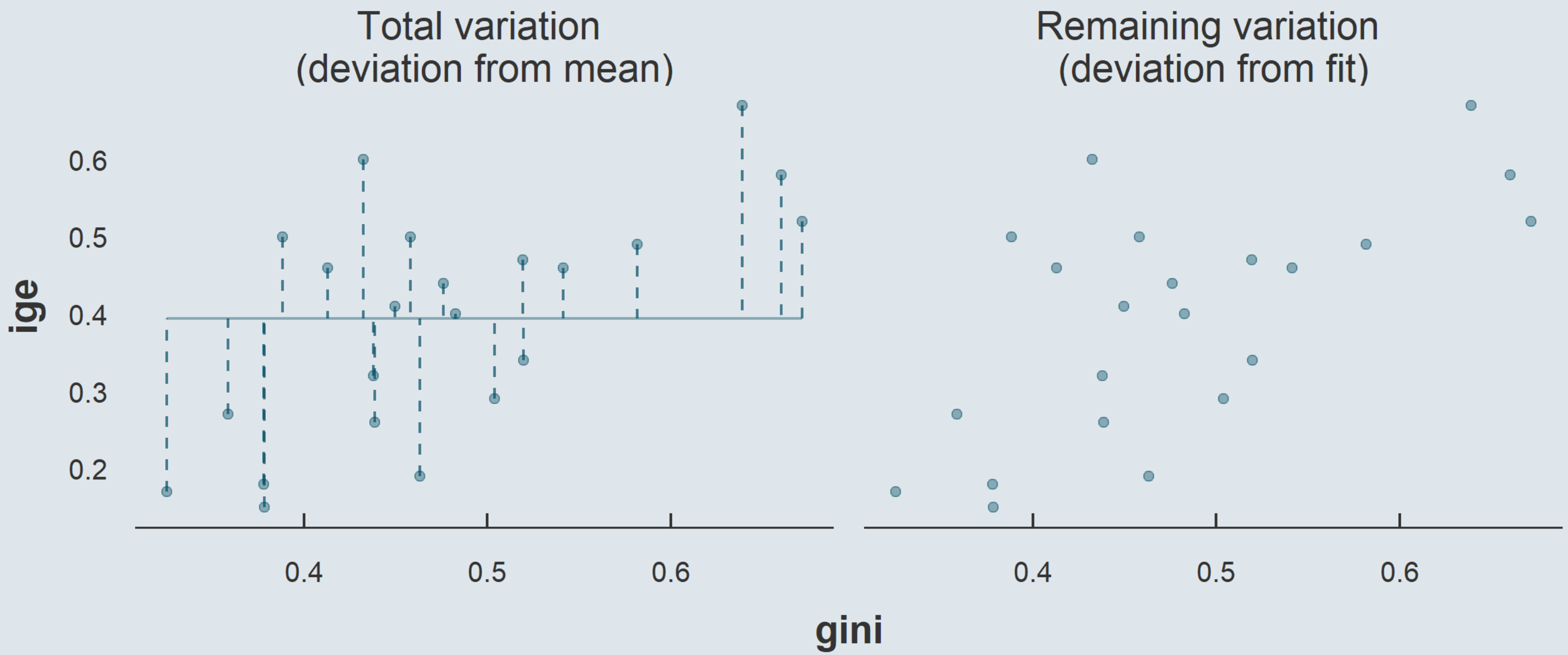
- The $\mathbf{R^2}$ captures the **goodness of fit** as the **percentage** of the y variation captured by the model, from:
  -
  -



3. Regression tables

3.3. R squared

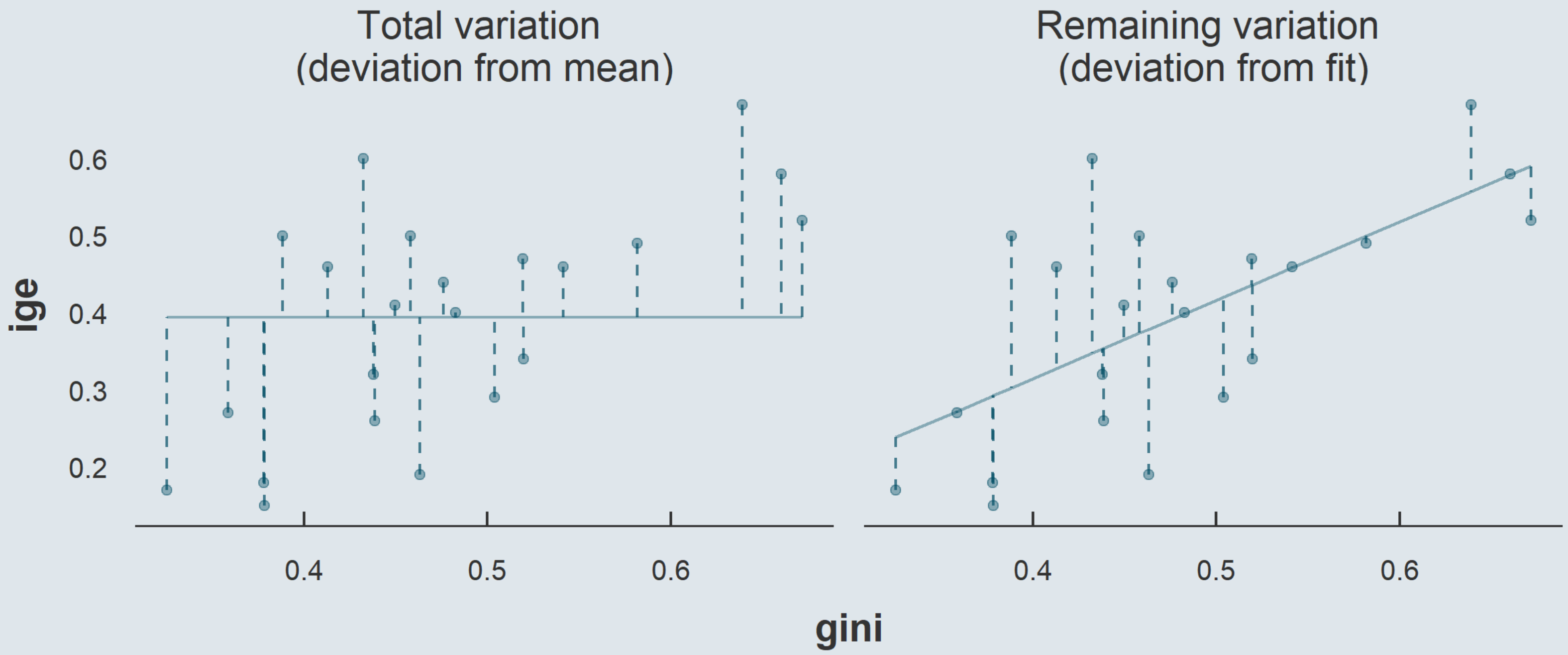
- The $\mathbf{R^2}$ captures the **goodness of fit** as the **percentage** of the y variation captured by the model, from:
  - The **total variation** of the y variable (its variance $\sum_{i=1}^{n}(y_i - \bar{y})^2$)
  -



3. Regression tables

3.3. R squared

- The **R^2** captures the **goodness of fit** as the **percentage** of the y variation captured by the model, from:
  - The **total variation** of the y variable (its variance $\sum_{i=1}^{n}(y_i - \bar{y})^2$)
  - The **remaining variation** of the y variable once its modeled (the sum of squared residuals $\sum_{i=1}^{n} \hat{\varepsilon_i}^2$)



3. Regression tables

3.3. R squared

- We can then obtain a proper formula from the following reasoning

$$\text{Total variation} = \text{Explained variation} + \text{Remaining variation}$$

$$\frac{\text{Explained variation}}{\text{Total variation}} = 1 - \frac{\text{Remaining variation}}{\text{Total variation}}$$

$$\frac{\text{Explained variation}}{\text{Total variation}} = 1 - \frac{\sum_{i=1}^{n} \hat{\varepsilon}_i{}^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \equiv \text{R}^2$$

- Because all the terms are sums of squares, we usually talk about:
  - **Total Sum of Squares** (TSS)
  - **Explained Sum of Squares** (ESS)
  - **Residual Sum of Squares** (RSS)

3. Regression tables

3.3. R squared

- Note that the **TSS** is actually the **variance of y:**
  - So the **R^2** is interpreted as the **share of the variance of y** which is **explained** by the model
  - And as such, the R^2 is always comprised **between 0 and 1**

$$\text{R}^2 = 1 - \frac{\sum_{i=1}^n \hat{\varepsilon}_i{}^2}{\sum_{i=1}^n (y_i - \bar{y})^2} = \frac{\text{Explained variation}}{\text{Total variation}}$$

- An undesirable property of the **R^2** is that it **mechanically increases** with the number of **dependent variables**
  - Such that with many variables the R^2 tends to overestimate the goodness of the fit
  - This is why you will sometimes see some **Adjusted R^2**

$$\text{Adjusted R}^2 = 1 - \frac{(1 - \text{R}^2)(n-1)}{n - \#\text{parameters}}$$

Today: Interpretation

1. Point estimates ✓
- 1.1. Continuous variables
- 1.2. Discrete variables
- 1.3. Log vs. level

2. Practice interpretation ✓

3. Regression tables ✓
- 3.1. Layout
- 3.2. Reported significance
- 3.3. R squared

4. Wrap up!

4. Wrap up!

Standard interpretations

- When both x and y are continuous, the **general** template for the **interpretation** of $\hat{\beta}$ is:

"Everything else equal, a 1 [unit] increase in [x] is associated with an [in/de]crease of [beta] [units] in [y] on average."

- With a discrete x, the interpretation of the coefficient must be **relative to the reference category:**

"Everything else equal, belonging to the [x category] is associated with a [beta] [unit] [higher/lower] average [y] relative to the [reference category]."

- With a **binary y variable**, the coefficient must be interpreted in **percentage points:**

"Everything else equal, a 1 [unit] increase in [x] is associated with a [beta] percentage point [in/de]crease in the probability that [y equals 1] on average."

4. Wrap up!

Interpretations with variable transformation

Standardization

- To standardize a variable is to **divide it by its SD**
  - The variation of a standardized variable should not be **interpreted** in units but **in SD**
  - For instance if x and y are continuous and x is standardized, the interpretation becomes:

"Everything else equal, a 1 ***standard deviation*** *increase in [x] is associated with an [in/de]crease of [beta] [units] in [y] on average."*

- If both x and y are standardized, the slope is the correlation coefficient between x and y

Log-transformation

- The log transformation allows to interpret the coefficient in percentage terms:

Interpretation of the regression coefficient

	y	log(y)
x	$\hat{\beta}$ is the unit increase in y due to a 1 unit increase in x	$\hat{\beta} \times 100$ is the % increase in y due to a 1 unit increase in x
log(x)	$\hat{\beta} \div 100$ is the unit increase in y due to a 1% increase in x	$\hat{\beta}$ is the % increase in y due to a 1% increase in x

4. Wrap up!

Regression table layout

	Birth weight	
	(1)	(2)
Household income	0.002***	0.002***
	(0.0003)	(0.0003)
Girl (ref: Boy)		-135.218***
		(34.838)
Constant	3,134.528***	3,246.365***
	(16.568)	(34.257)
Observations	1,000	963
R^2	0.059	0.074
Note:	*p<0.1; **p<0.05; ***p<0.01	

Regression tables often contain multiple regressions:

- With **one regression in each column**
- And one variable in **each row**
  - With the **point estimate**
  - And a **precision measure** below
- **General info** on each model **at the bottom**
  - Number of observations
  - $\mathrm{R}^2 = 1 - \frac{\sum_{i=1}^{n} \hat{\varepsilon}_i^{\,2}}{\sum_{i=1}^{n}(y_i - \bar{y})^2}$
- A **symbology** for the **p-value** testing whether the coefficient is significantly different from 0 or not