FLS 6441 - Methods III: Explanation and Causation

Week 1 - Review of Regression

Jonathan Phillips

March 2019

Course Objectives

1. Change how you think about quantitative methods, *explaining* politics, and not just describing it

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Course Website

Course Topics

1. Review of Regression (21st March)

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2. A Framework for Explanation (28th March)

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4. Survey and Lab Experiments (11th April)
5. Randomized Natural Experiments (18th April, Semana Santa)

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6. Instrumental Variables (25th April)
7. Discontinuities (2nd May)

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8. Difference-in-Differences (9th May)
9. Controlling for Confounding (16th May)
10. Matching (23rd May)
11. Comparative Cases and Process Tracing (30th May)

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11. Comparative Cases and Process Tracing (30th May)
12. Generalizability, Reproducibility and Mechanisms (6th June)

Course Schedule

- Wednesday 18h - Submit Replication Task

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- Friday 10h-12h - Office Hours (DCP 2061)

Project

- Quality > Quantity

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- Max 15 pages, English or Portuguese

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- Submit paper and code by email to me by 30th June 2019

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- Use at least one of the methods studied in class

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- *Tip:* Pick a simple question and dataset

If you get Lost:

1. Don't panic! Everyone needs to see this content 3 or 4 times to 'get' it

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6. Ask me

Today's Objectives

1. What Does Regression Actually Do?
2. Guide to 'Smart' Regression
3. What Does Regression NOT Do?

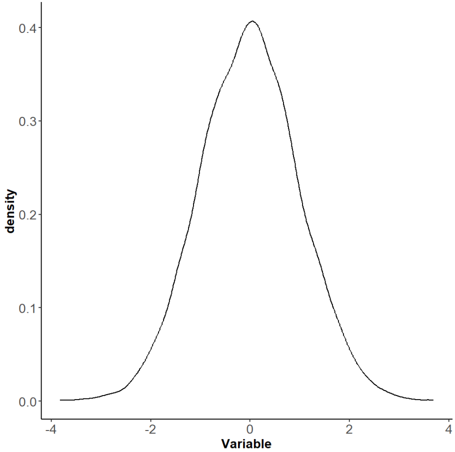
Section 1

What Does Regression Actually Do?

Data

- We work with variables, which VARY!

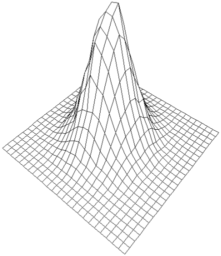
Variable
0.30
-0.67
0.39
0.03
-1.26
1.26
-1.44
0.16
0.50
0.01



Data

- We work with variables, which VARY!

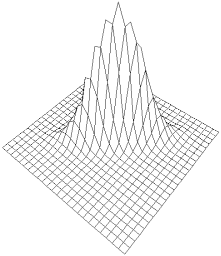
Variable_1	Variable_2
-0.44	0.63
0.06	0.68
-0.21	-0.02
0.44	-0.25
1.29	0.46
-0.38	-0.81
-1.04	0.24
-0.16	1.84
1.29	0.06
-0.10	-0.18



Data

- We work with variables, which VARY!

Variable_1	Variable_2
-0.86	-0.44
-0.35	-0.34
1.27	0.04
-0.35	-0.12
-0.43	-0.43
0.05	-0.05
0.69	0.49
1.27	0.69
0.22	-0.07
-0.28	-0.05



What Does Regression Actually Do?

1. Regression as Least Squares
2. Regression as Conditional Expectation
3. Regression as (Partial) Correlation

Regression as Least Squares

- Regression identifies the line through the data that minimizes the sum of squared vertical distances

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- $y_i = \alpha + \beta D_i + \epsilon_i$

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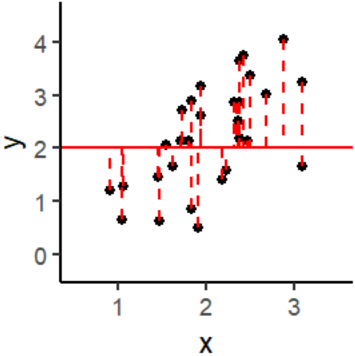
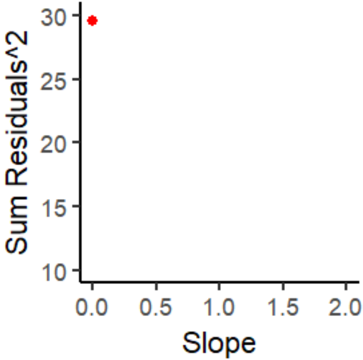
Slope = 0



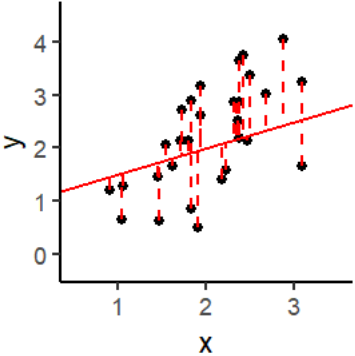
Sum of Residuals^2 = 29.6



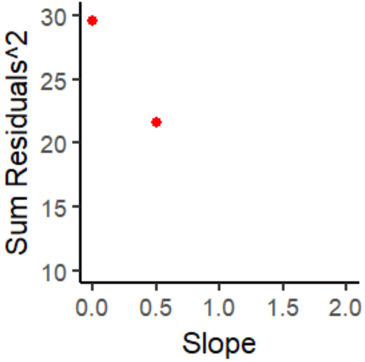
Regression as Least Squares

- Regression identifies the line through the data that minimizes the sum of squared vertical distances
- $y_i = \alpha + \beta D_i + \epsilon_i$

Slope = 0.5



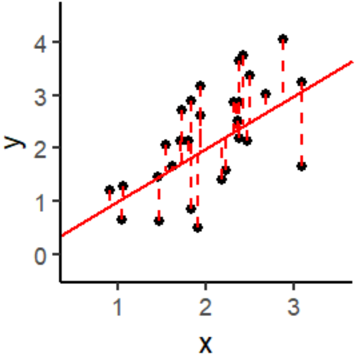
Sum of Residuals^2 = 21.6



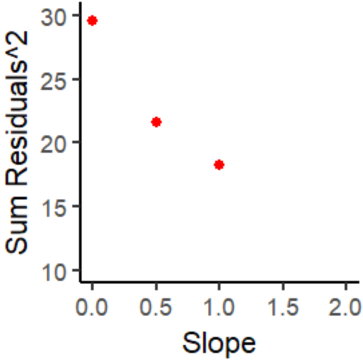
Regression as Least Squares

- Regression identifies the line through the data that minimizes the sum of squared vertical distances
- $y_i = \alpha + \beta D_i + \epsilon_i$

Slope = 1



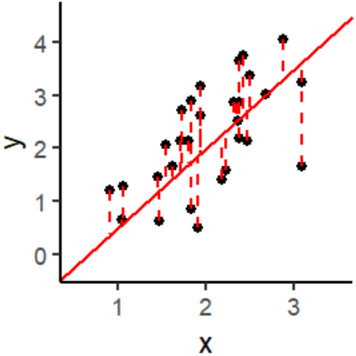
Sum of Residuals^2 = 18.3



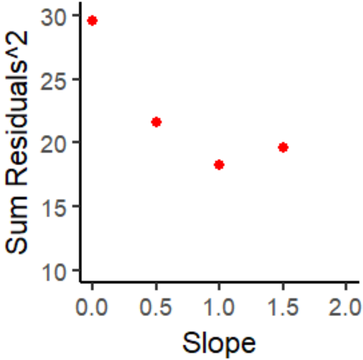
Regression as Least Squares

- Regression identifies the line through the data that minimizes the sum of squared vertical distances
- $y_i = \alpha + \beta D_i + \epsilon_i$

Slope = 1.5



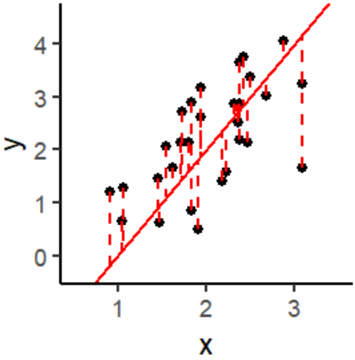
Sum of Residuals^2 = 19.6



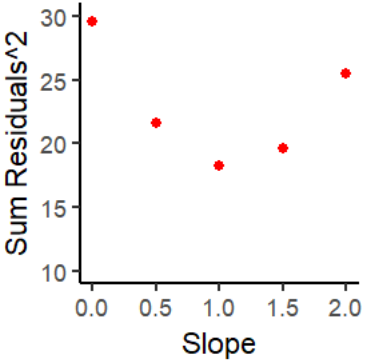
Regression as Least Squares

- Regression identifies the line through the data that minimizes the sum of squared vertical distances
- $y_i = \alpha + \beta D_i + \epsilon_i$

Slope = 2



Sum of Residuals^2 = 25.5



Regression as Least Squares

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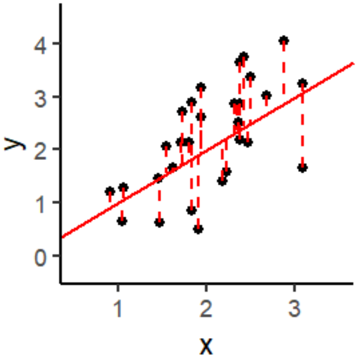
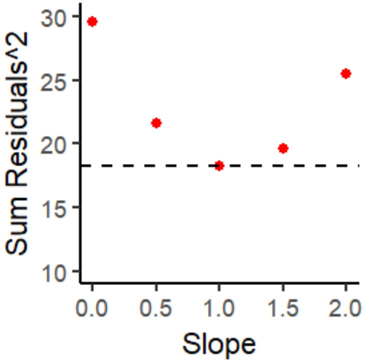
Slope = 1



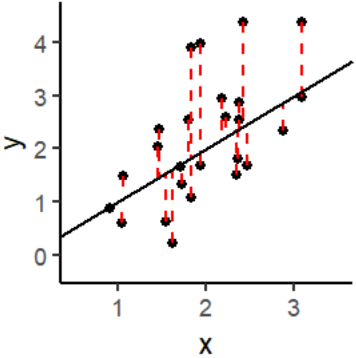
Sum of Residuals^2 = 18.3



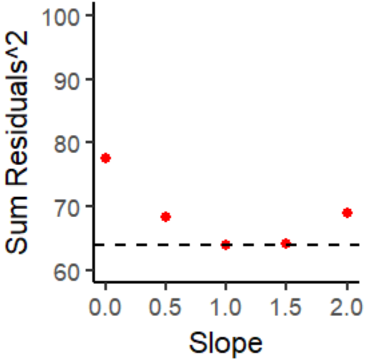
Regression as Least Squares

- If we add pure *noise* to y, our estimate of β is unchanged
  - The residual error increases
- $y_i = \alpha + \beta D_i + \epsilon_i$

Slope = 1

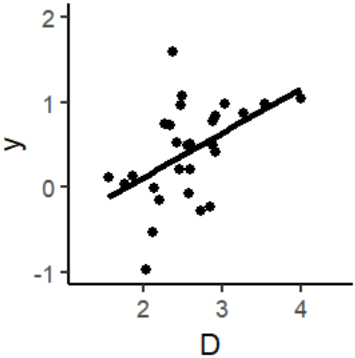


Sum of Residuals^2 = 63.9



Regression as Least Squares

- Dummy control variables *remove variation* associated with specific levels or categories
  - The same for fixed effects
- $y_{ij} = \alpha + \beta_1 D_{ij} + \epsilon_i$



Ignoring the dummy control variable, the slope coefficient is 1

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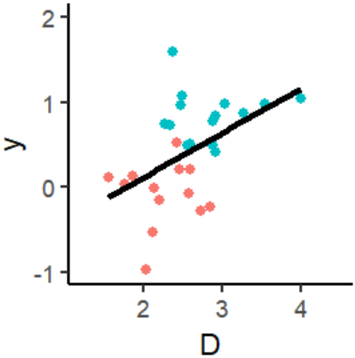

But the data points really represent two very different groups, blues and reds

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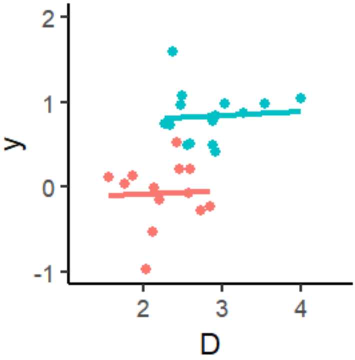

What if we treated each group *separately*?

Regression as Least Squares

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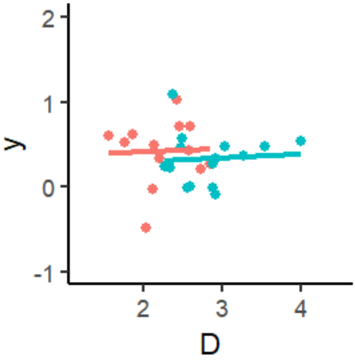

Dummy control variables *remove* the average Y differences between blues and reds

Regression as Least Squares

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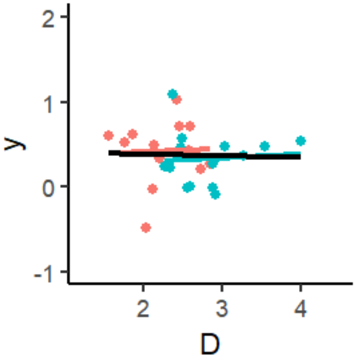

The new regression line for the full data now has a slope of zero

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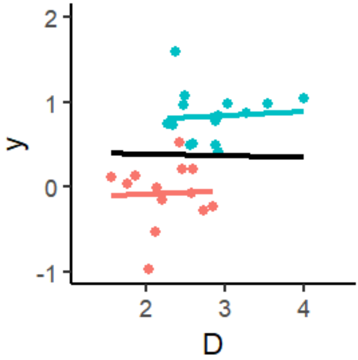
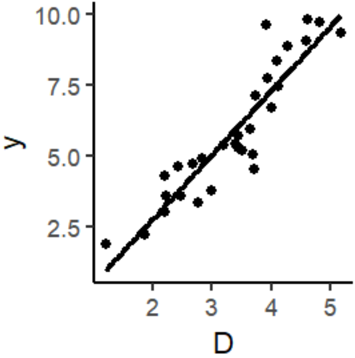


Equivalently, dummy control variables restrict comparisons to **within the same group**:

1. How much does X affect Y within the blue group? 0
2. How much does X affect Y within the red group? 0
3. What's the average of (1) and (2) (weighted by the number of units in each group)? 0

Regression as Least Squares

- Continuous control variables *remove variation* based on how much the control explains y
- $y_i = \alpha + \beta_1 D_i + \beta_2 X_i + \epsilon_i$



The coefficient β_1 is 2.267
Real effect = 1

Regression as Least Squares

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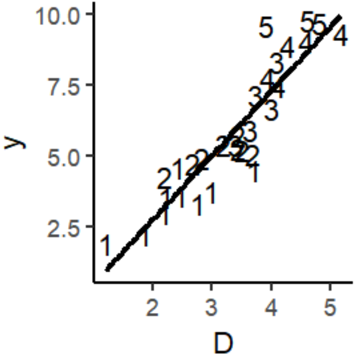
- $y_i = \alpha + \beta_1 D_i + \epsilon_i$



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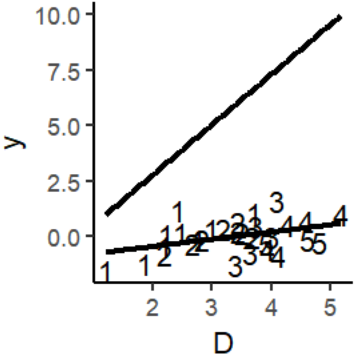

The coefficient β_1 is 1.024
Real effect = 1

Regression as Least Squares

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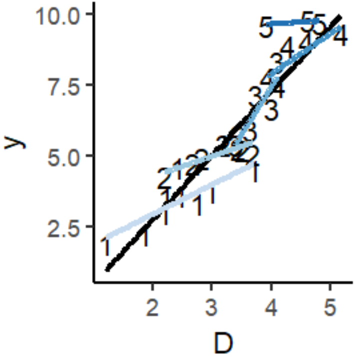

- Equivalently, we subset to each value of x, and find each slope
- Then average these slopes, $\beta_1 = 1.33$
- Impossible with truly continuous variables

Regression as Conditional Expectation

- Regression is also a **Conditional Expectation Function**

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- Regression is also a **Conditional Expectation Function**
- Conditional on x, what is our expectation (mean value) of y?

$$y_i = \alpha + \beta_1 D_i + \epsilon_i$$

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$$y_i = \alpha + \beta_1 D_i + \epsilon_i$$
$$Attitude_i = \alpha + \beta_1 Income_i + N(0, \sigma^2)$$

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$$y_i = \alpha + \beta_1 D_i + \epsilon_i$$
$$Attitude_i = \alpha + \beta_1 Income_i + N(0, \sigma^2)$$
$$Attitude_i = 2.235 - 0.000818 * Income_i + N(0, 2.38)$$

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$$Attitude_i = 2.235 - 0.000818 * Income_i + N(0, 2.38)$$

$$(Attitude_i | Income_i = 3000) = 2.235 - 0.000818 * 3000 + N(0, 2.38)$$

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$$(Attitude_i | Income_i = 3000) = 2.235 - 0.000818 * 3000 + N(0, 2.38)$$
$$(Attitude_i | Income_i = 3000) = -0.22 + N(0, 2.38)$$

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$$(Attitude_i | Income_i = 3000) = -0.22 + N(0, 2.38)$$
$$E(Attitude | Income_i = 3000) = -0.22$$

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$$Attitude_i = 2.235 - 0.000818 * Income_i + N(0, 2.38)$$

- $E(y|x)$, $E(Attitude|Income)$
  - When income is 3000, the average attitude is -0.22

Regression as Conditional Expectation

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$$y_i = \alpha + \beta_1 D_i + \epsilon_i$$
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$$Attitude_i = 2.235 - 0.000818 * Income_i + N(0, 2.38)$$

- $E(y|x)$, $E(Attitude|Income)$
  - When income is 3000, the average attitude is -0.22
  - When income is 6000, the average attitude is -2.67

Regression as Conditional Expectation

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  - When income is 3000, the average attitude is -0.22
  - When income is 6000, the average attitude is -2.67
  - When income is -1000, the average attitude is 3.05

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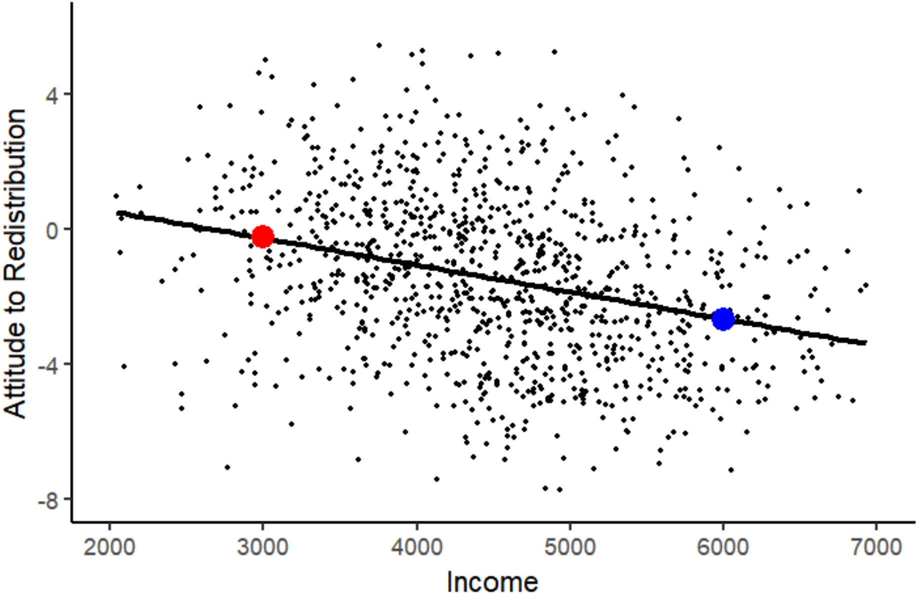
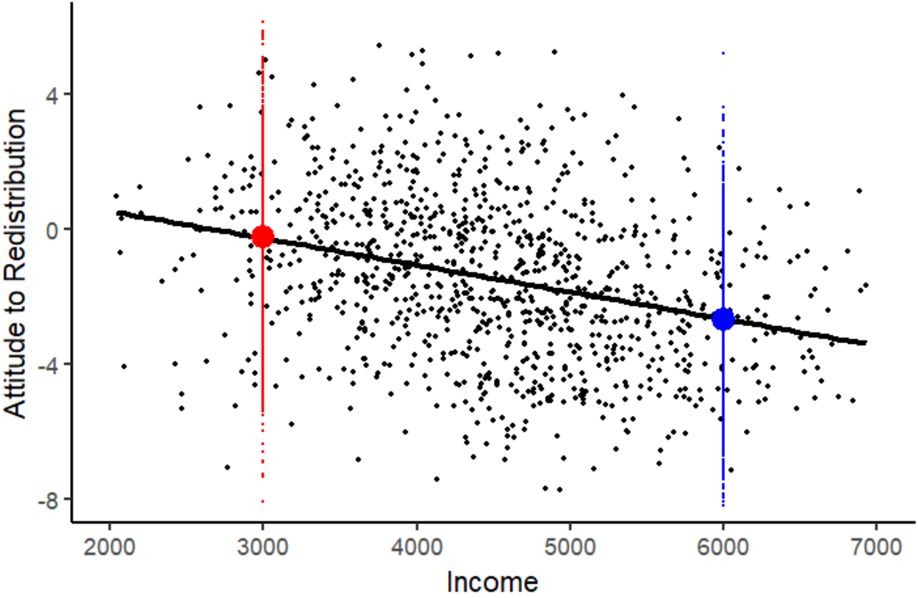
$$Attitude_i = 2.235 - 0.000818 * Income_i + N(0, 2.38)$$

- $E(y|x)$, $E(Attitude|Income)$
  - When income is 3000, the average attitude is -0.22
  - When income is 6000, the average attitude is -2.67
  - When income is -1000, the average attitude is 3.05
- $E(attitude|income, age, gender, municipality)$

Regression as Conditional Expectation



Regression as Conditional Expectation



Regression as Conditional Expectation

- How do we work out the conditional expectation? We estimate β

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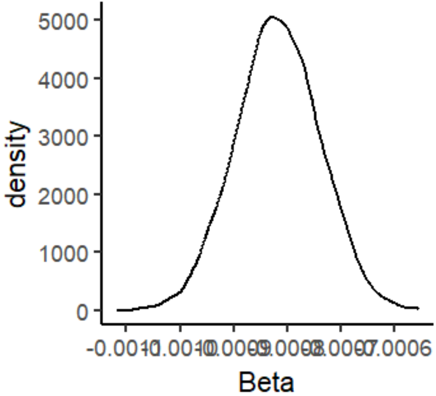
Constant	2.234719^{***} (0.361477)
Observations	1,000
Note:	*p<0.1; **p<0.05; ***p<0.01



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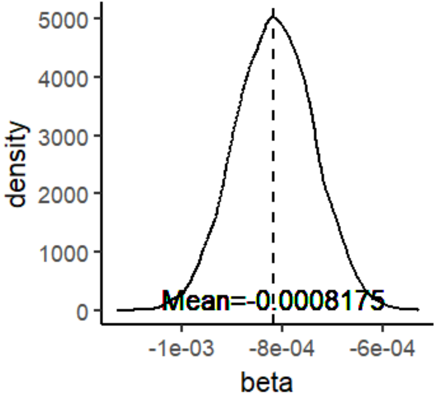

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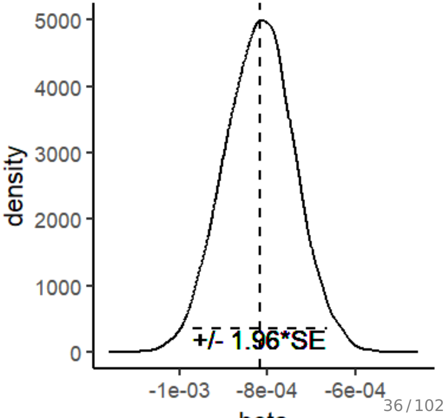

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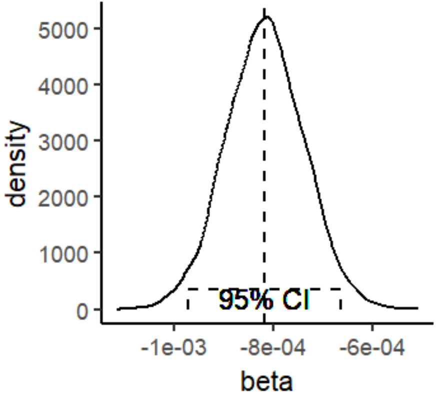

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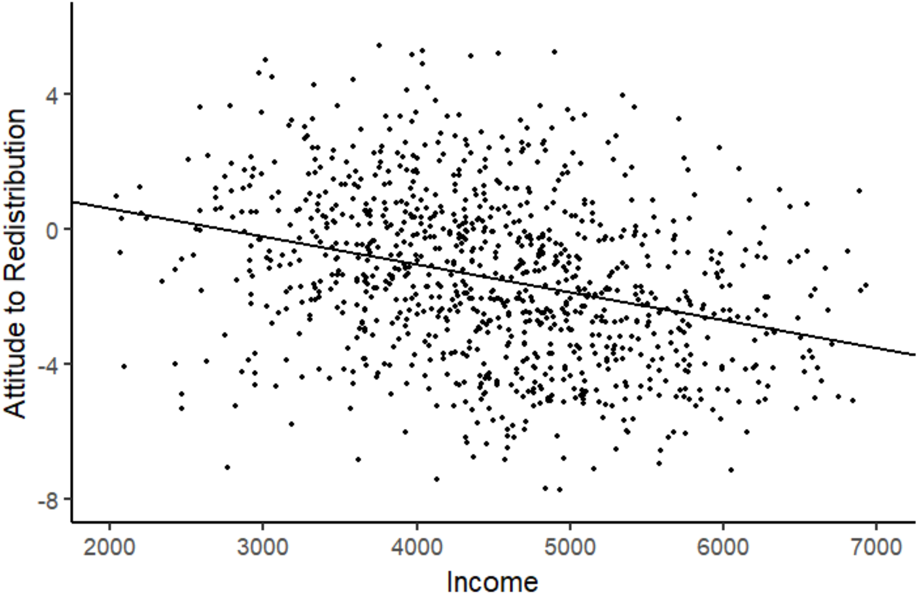

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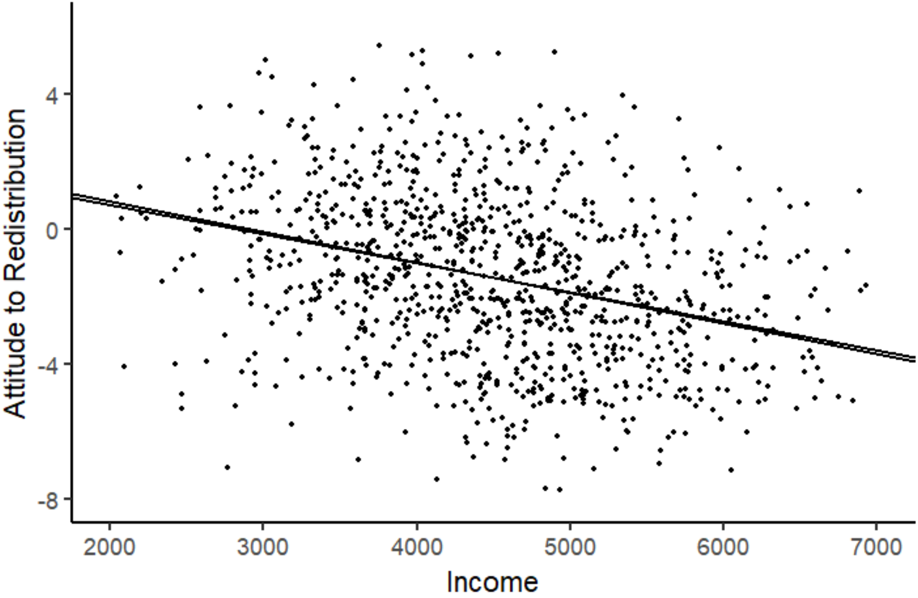

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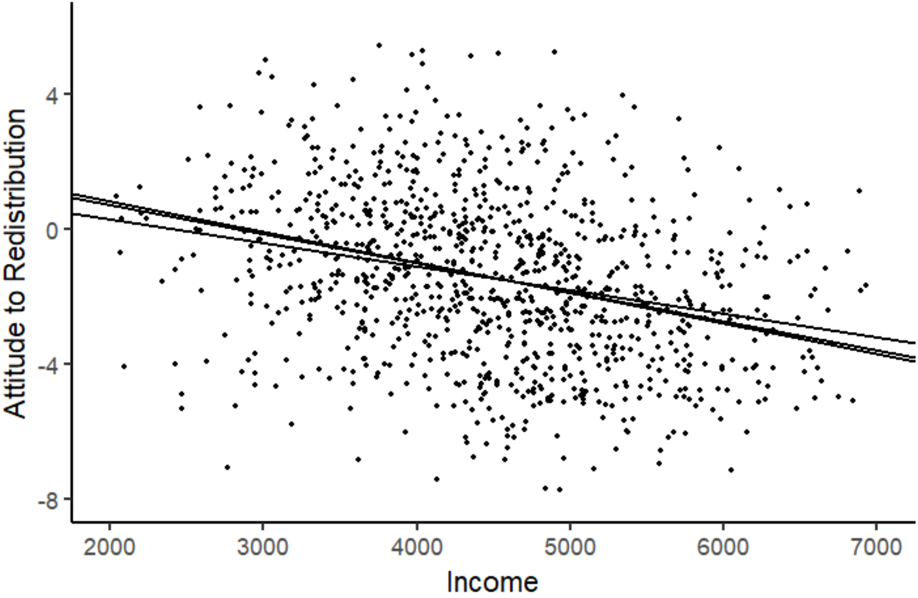

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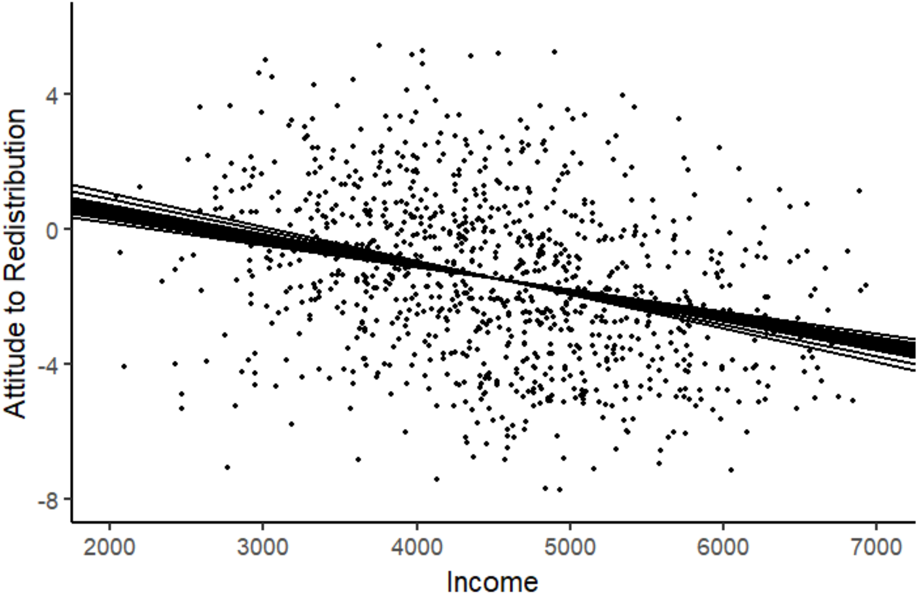

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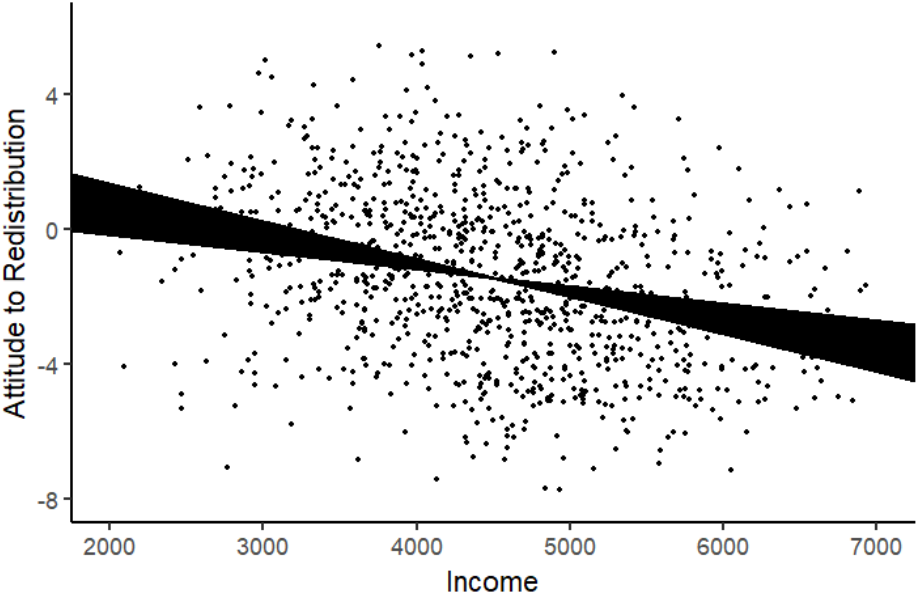

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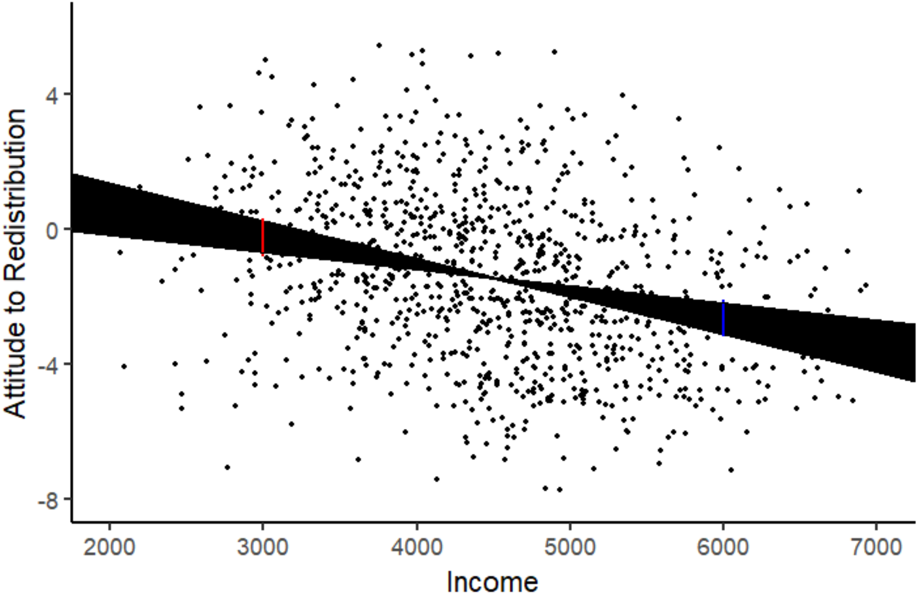

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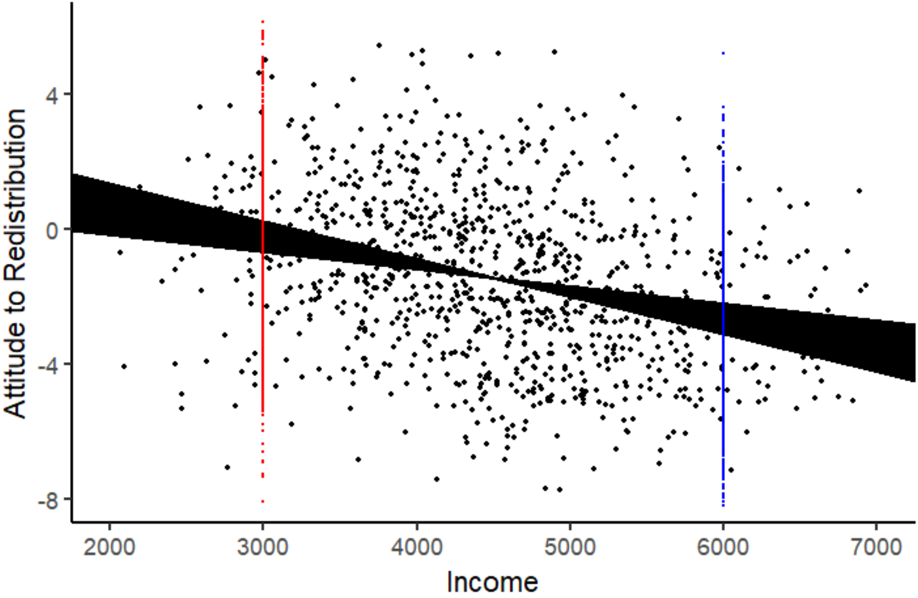

Regression as (Partial) Correlation

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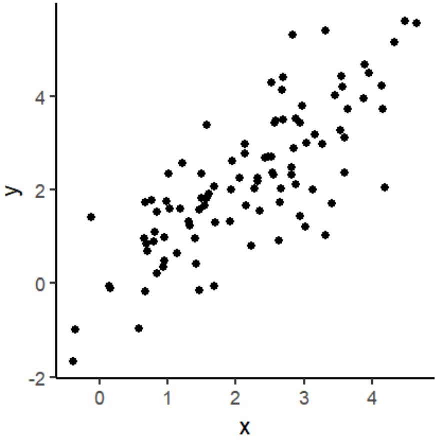

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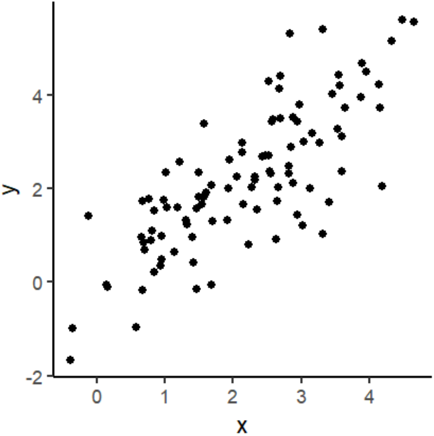

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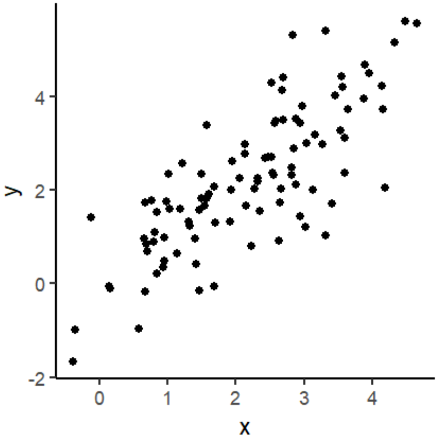

- Correlation is 0.781
- Regression Results:

	term	estimate
1	(Intercept)	0.006
2	x	1.008

Regression as (Partial) Correlation

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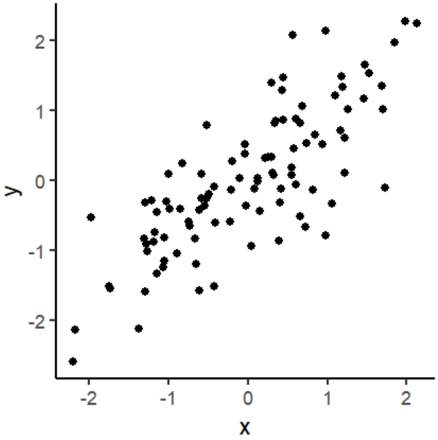
- $\hat{\beta} = cor(x, y) * \frac{\sigma_Y}{\sigma_X}$



- Correlation is 0.781
- It's *identical* if we standardize both variables first ($\frac{(x - \bar{x})}{\sigma_x}$)
- Standardized Regression Results:

	term	estimate
1	(Intercept)	0.000
2	x	0.781

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$$\beta_{x_1} = \frac{r_{yx_1} - r_{yx_2} r_{x_1x_2}}{1 - r^2_{x_1x_2}}$$

$$r_{yx_1|x_2} = \frac{r_{yx_1} - r_{yx_2} r_{x_1x_2}}{\sqrt{(1 - r^2_{yx_2})(1 - r^2_{x_1x_2})}}$$

- **There is no magic in regression, it's just 'extra' correlation**

Section 2

Guide to ’Smart’ Regression

Regression Guide

1. We will use regression throughout this course

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2. But in a very **precise** way for each methodology

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2. But in a very **precise** way for each methodology
3. There are fundamental best practices that apply to all the methodologies

Regression Guide

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8. **Predict Meaningful Comparisons:** To communicate your findings

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- What measure of income should we use?
  - Pre-tax, post-tax, after government benefits?
- It depends on the theory we are testing

2. Data Sample

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- We include a control for country
- But everyone in Qatar earns exactly \$1m - no variation in income!
- We may as well throw the Qatar data away

3. Regression Models

The Regression Model reflects the data type of the outcome variable:

- Continuous -> Ordinary Least Squares
  - Pick a precise number that reflects your attitude to redistribution
- Binary -> Logit
  - Do you support redistribution, yes or no?
- Unordered categories -> Multinomial logit
  - Do you think redistribution is a western, oriental or african concept?
- Ordered categories -> Ordered logit
  - Do you want a lot more, more, the same, less, or a lot less redistribution?
- Count -> Poisson
  - In the past year, how many times have you complained about redistribution?

4. Covariates

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- Only include where there is theory or evidence that this variable could be an **omitted variable**

5. Fixed Effects

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- Removing *ALL* the variation between countries
  - If rich *countries* have stronger attitudes to redistribution, we control for this
  - So we can ask whether richer *people* have stronger attitudes
- Our question becomes: How do variations within income in the same country affect attitudes to redistribution?

6. Errors Structure

- An assumption of regression analysis is that the errors are independent
  - Knowing the value of one error tells you *nothing* about the value of the next error
- But your attitudes to redistribution are probably very similar to everyone you live with, even after controlling for income etc. due to 'unobservable' variables (conversations over dinner...)

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- So we don't really have 2 observations, we have closer to 1 'independent' observation
- So the standard errors for our β's are *over-confident* (too small)
- We need to adjust for these dependencies with clustered standard errors
  - Created by the underlying structure of the data
  - Or by our data sampling process

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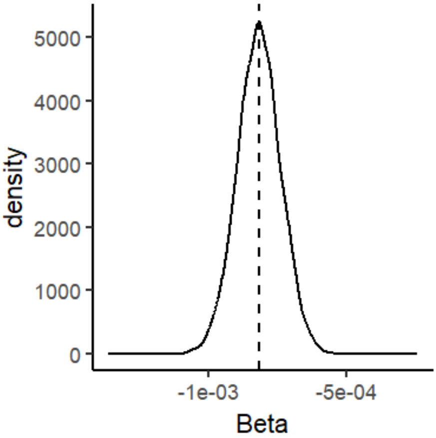

- The distribution of our estimated betas suggests we're pretty confident β is close to -0.0008175

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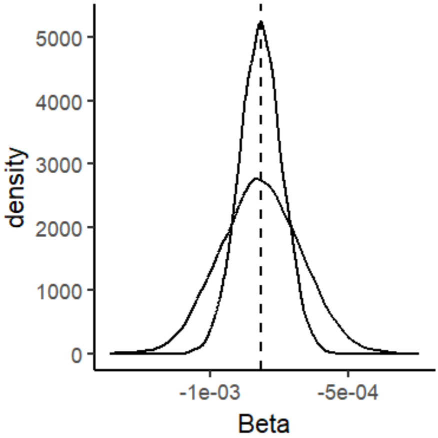

- With clustered SEs, the wider distribution of our betas suggests we're *less* confident β is close to -0.0008175

7. Interpreting Regression Results

- Difficult! It depends on:
  1. The scale of the explanatory variable
  2. The scale of the outcome
  3. The regression model we used
  4. The presence of any interaction
- Basic OLS: $y_i = \alpha + \beta D_i + \epsilon$
  - A 1 [unit of D] change in the explanatory variable is associated with a β [unit of y] change in the outcome, holding other variables constant

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- Basic OLS **with log outcome**: $log(y_i) = \alpha + \beta D_i + \epsilon$
  - A 1 [unit of D] change in the explanatory variable is associated with a $100 * (e^{\beta} - 1)\%$ change in the outcome, holding other variables constant

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  - A 1% change in the explanatory variable is associated with a $\beta * ln(\frac{101}{100})$ change in the outcome, holding other variables constant

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- **Logit:** $Pr(y_i = 1) = logit^{-1}(\alpha + \beta D_i + \epsilon)$
  - A 1 [unit of D] change in the explanatory variable is associated with a β change in the log-odds of $y_i = 1$, holding other variables constant

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- **Multinomial:** $Pr(y_i = C) = \alpha + \beta D_i + \epsilon$
  - A 1 [unit of D] change in the explanatory variable is associated with a $100 * (e^{\beta_C} - 1)\%$ change in the odds (relative probability, $\frac{p}{1-p}$) of moving from the baseline category to the outcome category C, holding other variables constant

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- **Ordered Multinomial:** $Pr(y_i = C) = \alpha + \beta D_i + \epsilon$
  - A 1 [unit of D] change in the explanatory variable is associated with a $100 * (e^{\beta_C} - 1)\%$ change in the odds (relative probability, $\frac{p}{1-p}$) of moving up one unit on the outcome scale, holding other variables constant

7. Interpreting Regression Results

- Difficult! It depends on:
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  2. The scale of the outcome
  3. The regression model we used
  4. The presence of any interaction
- **OLS with Interaction:** $y_i = \alpha + \beta_1 D_i + \beta_2 X_i + \beta_3 D_i * X_i + \epsilon$
  - $$\frac{\partial y}{\partial D} = \beta_1 + \beta_3 X$$
  - β_1 is the effect of D when $X = 0$ - *May not make sense!*
  - Insert values for X and see how the marginal effect changes

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- The coefficient on the regression of income on attitude to redistribution is -0.000818
  - So??? What do we learn from this?
  - Coefficients are hard to interpret, and depend on how we measure each variable
  - And p-values are arbitrary
- Better to make specific *predictions* of how changes in *D* produce changes in *Y*

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If Income is 3000:

$$Attitude_i = 2.235 - 0.000818 * 3000 + N(0, 2.378)$$

$$Attitude_i = -0.219 + N(0, 2.378)$$

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$$Attitude_i = \alpha + \beta_1 \text{ Income}_i + \epsilon_i$$

$$Attitude_i = 2.235 - 0.000818 \text{ Income}_i + N(0, 2.378)$$

If Income is 6000:

$$Attitude_i = 2.235 - 0.000818 * 6000 + N(0, 2.378)$$

$$Attitude_i = -2.673 + N(0, 2.378)$$

8. Predictions from Regressions

$$Attitude_i = \alpha + \beta_1 \text{ Income}_i + \epsilon_i$$

$$Attitude_i = 2.235 - 0.000818 \text{ Income}_i + N(0, 2.378)$$

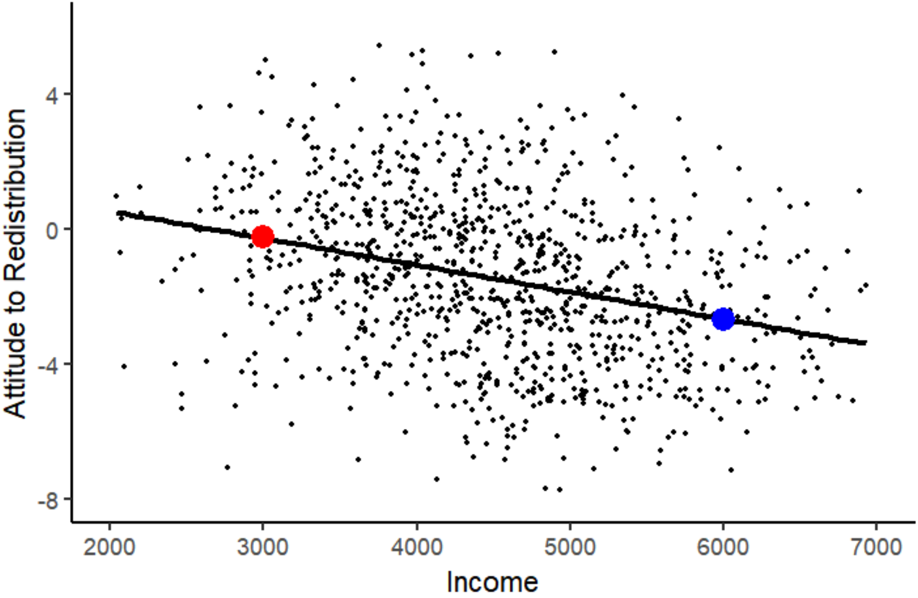
Increasing Income from 3000 to 6000:

$$\Delta Attitude_i = (2.235 - 0.000818 * 6000) - (2.235 - 0.000818 * 3000$$

$$\Delta Attitude_i = -2.673 - -0.219$$

$$\Delta Attitude_i = -2.454$$

8. Predictions from Regressions



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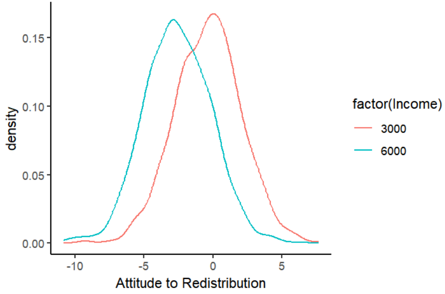
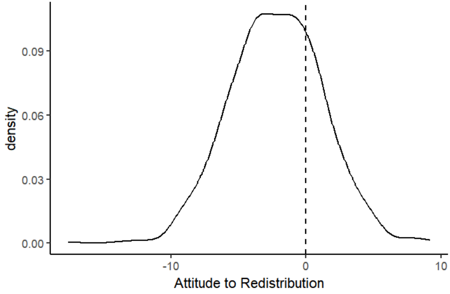
Predicted Values:



First Differences:



8. Predictions from Regressions

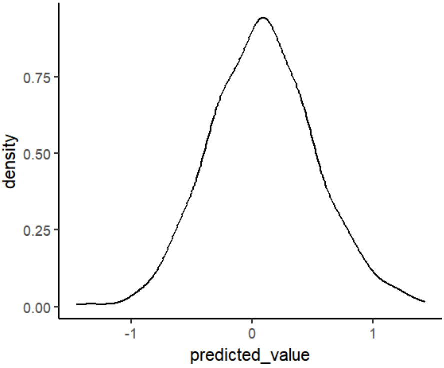
- The regression model matters because the wrong model makes non-sensical predictions
- Consider a binary outcome: $Gender_i = \alpha + \beta Income_i + \epsilon_i$
- Compare the OLS and Logit regression tables:

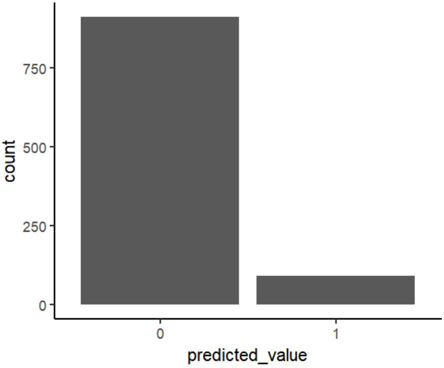
	Dependent variable:
	as.numeric(as.character(gender))
income	0.0003*** (0.00001)
Constant	−0.696*** (0.066)
Observations	1,000
Note:	*p<0.1; **p<0.05; ***p<0.01

	Dependent variable:
	as.numeric(as.character(gender))
income	0.001*** (0.0001)
Constant	−6.360*** (0.457)
Observations	1,000
Note:	*p<0.1; **p<0.05; ***p<0.01

8. Predictions from Regressions

- The regression model matters because the wrong model makes non-sensical predictions
- Consider a binary outcome: $Gender_i = \alpha + \beta Income_i + \epsilon_i$
- Compare the OLS and Logit **predictions** of gender for an income of R$3000:





Section 3

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  - Due to complex social patterns...
  - But we cannot conclude that D causes or explains Y
- *More* data will not help
- The problem is the *type* of data; it does not allow us to answer the causal question

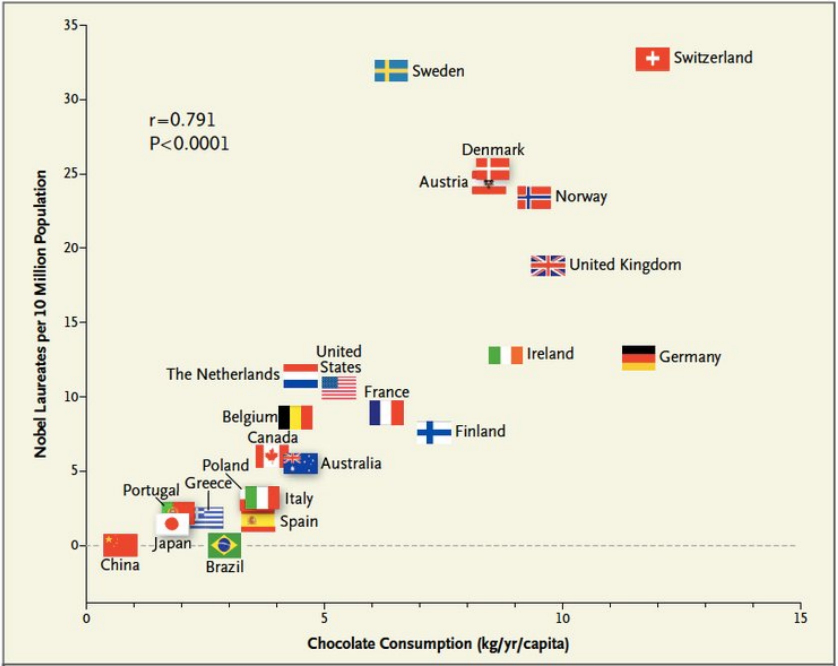
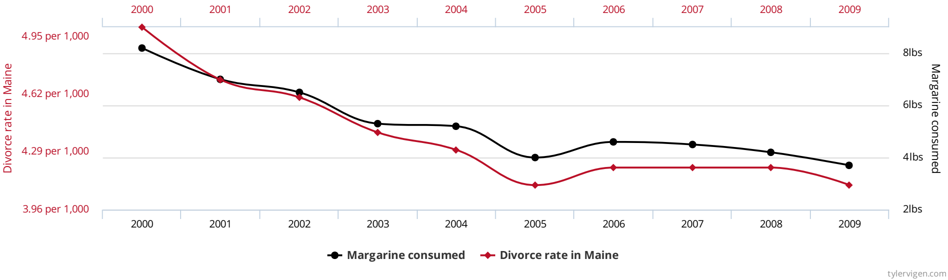
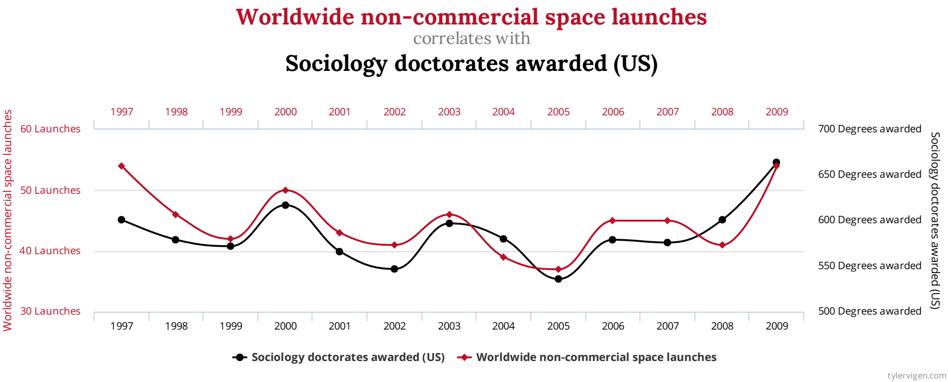


Figure 1. Correlation between Countries' Annual Per Capita Chocolate Consumption and the Number of Nobel

Divorce rate in Maine
correlates with
Per capita consumption of margarine





Worldwide non-commercial space launches
correlates with
Sociology doctorates awarded (US)
60 Launches
50 Launches
40 Launches
30 Launches
Worldwide non-commercial space launches
700 Degrees awarded
650 Degrees awarded
600 Degrees awarded
550 Degrees awarded
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Sociology doctorates awarded (US)
1997
1998
1999
2000
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2002
2003
2004
2005
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2007
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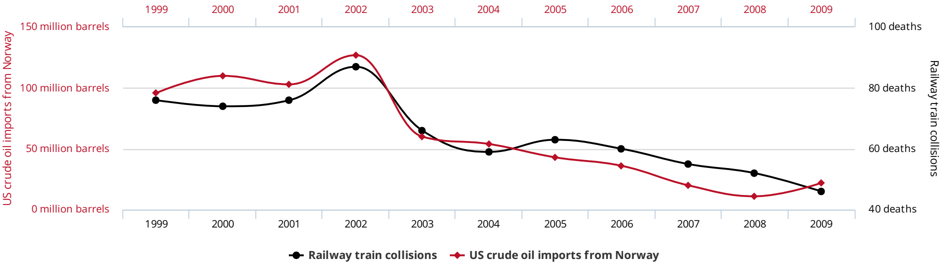
Worldwide non-commercial space launches
tylervigen.com

US crude oil imports from Norway
correlates with
Drivers killed in collision with railway train

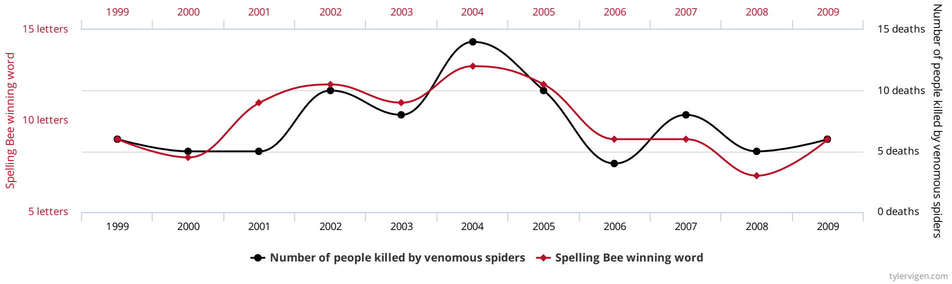


tylervigen.com

Letters in Winning Word of Scripps National Spelling Bee

correlates with

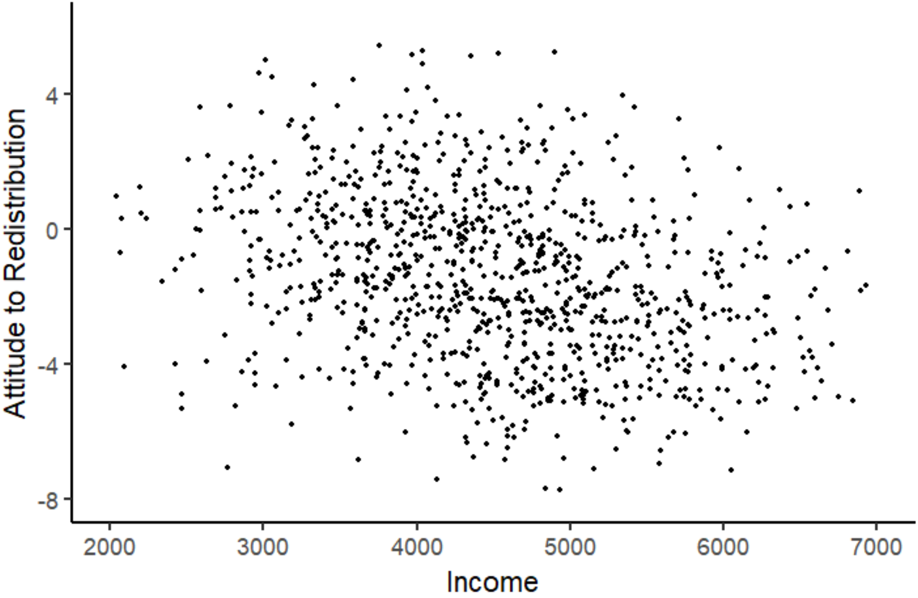
Number of people killed by venomous spiders



What Does Regression NOT Do?

- Why is correlation (regression) not causation?
    1. Omitted Variable Bias
    2. Reverse Causation
    3. Selection Bias
    4. Measurement Bias
    5. Lack of Overlap, Model Dependence

1. Omitted Variable Bias



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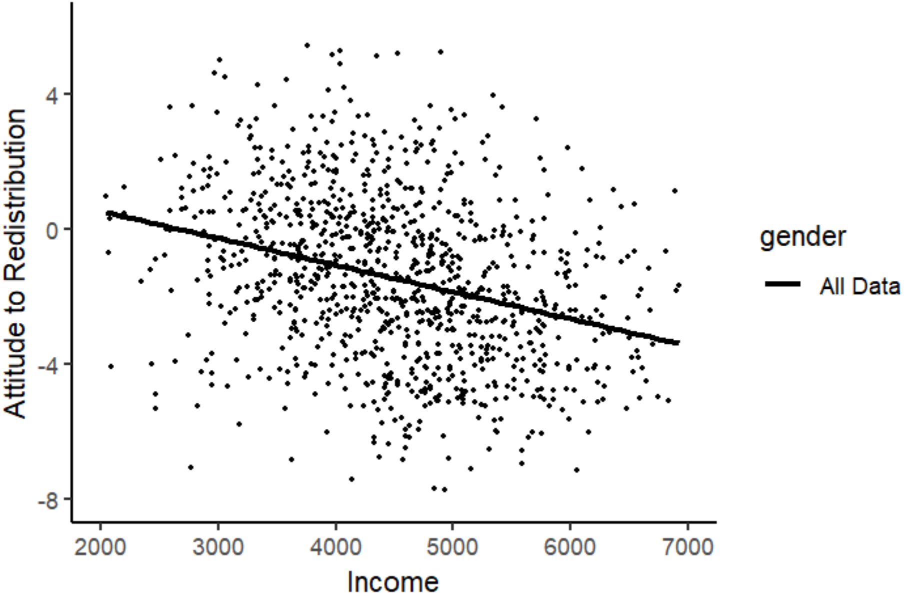

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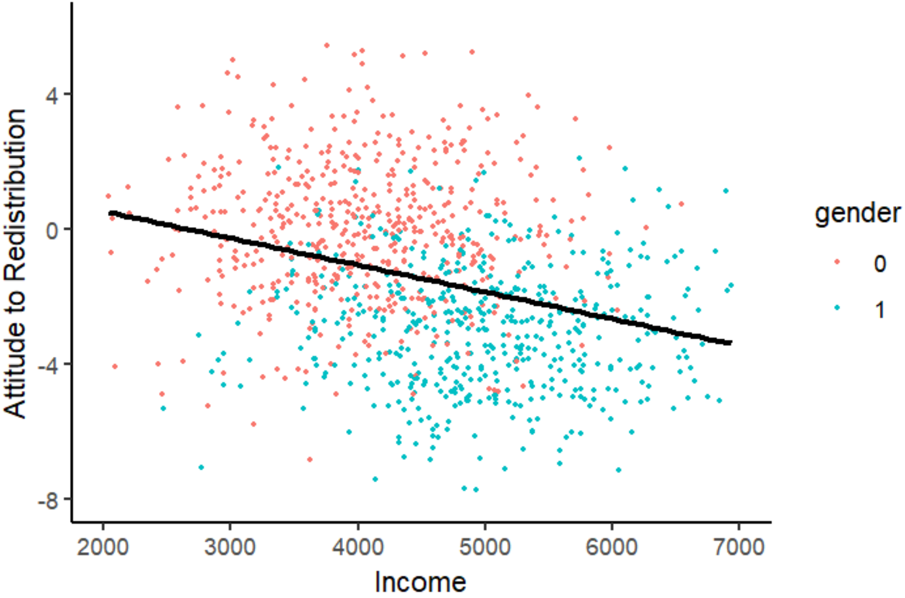

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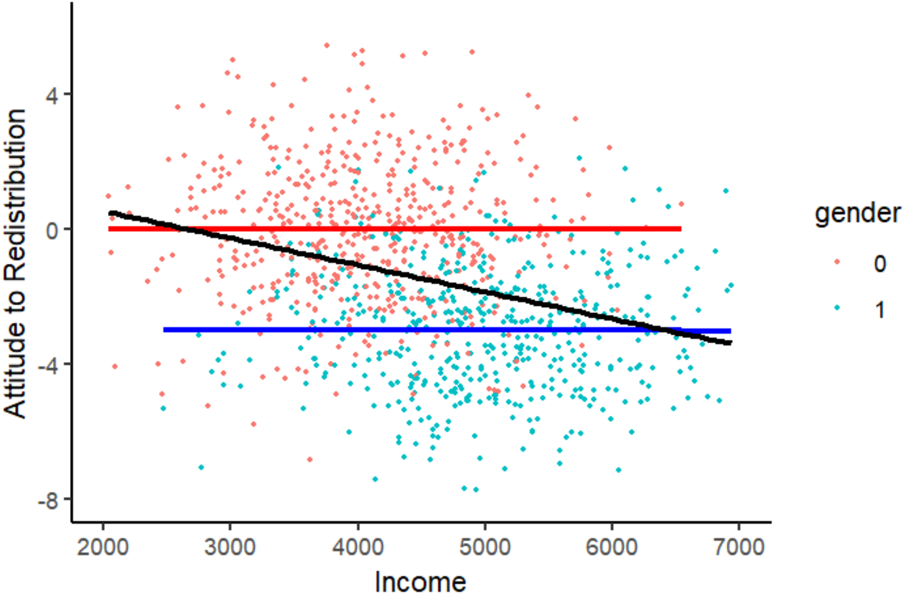

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- Significant regression coefficients just reflect the values in our dataset moving together
- Does the 'direction' of regression matter? I.e. Does regression treat D and Y differently? Yes!

	Dependent variable:
	redist
income	−0.011 (0.029)
gender1	−1.201*** (0.058)
Constant	0.589*** (0.038)
Observations	1,000
Note:	*p<0.1; **p<0.05; ***p<0.01

	Dependent variable:
	income
redist	−0.013 (0.034)
gender1	0.993*** (0.069)
Constant	−0.487*** (0.043)
Observations	1,000
Note:	*p<0.1; **p<0.05; ***p<0.01

- Remember, regression measures the *vertical* (not diagonal) distances to the regression line
  - It minimizes the *prediction errors* for Y
- But that doesn't mean it identifies the direction of causation!

2. Reverse Causation

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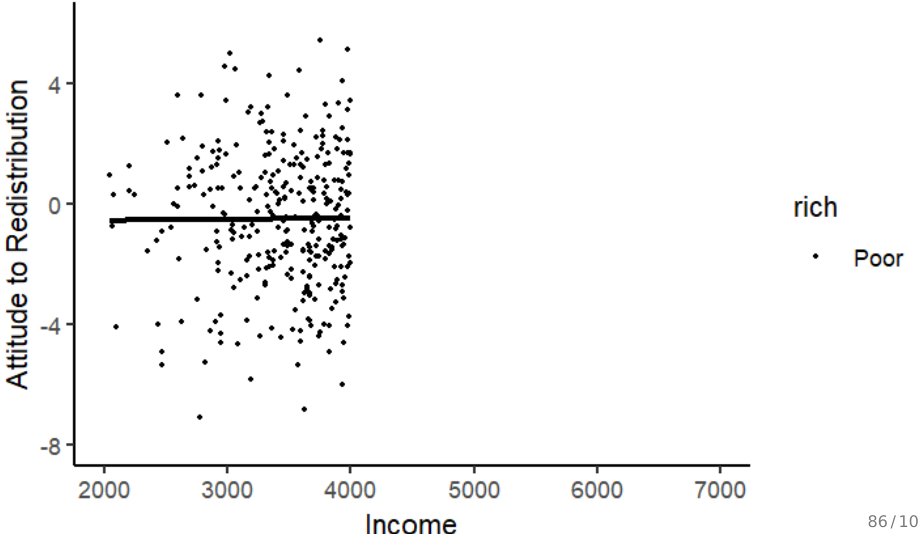
2. Reverse Causation

- Higher income may lead to higher tax rates and therefore cause more negative attitudes to redistribution
- But negative attitudes to redistribution might also make you more likely to work in the private sector and cause you to receive a higher salary
- Both would look the same in a regression
- We cannot *explain* the relationship with a regression

3. Selection Bias

- Imagine we do not see ’rich’ units with high income (above R$4000)



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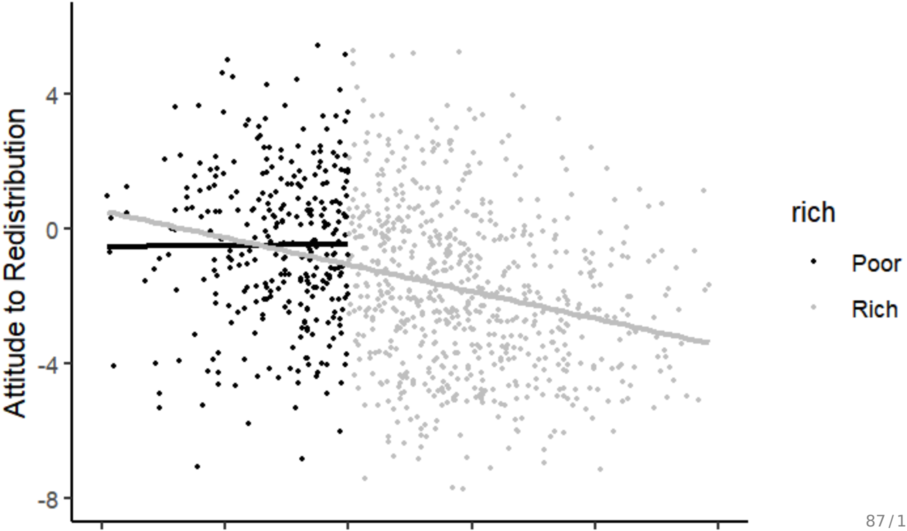


3. Selection Bias

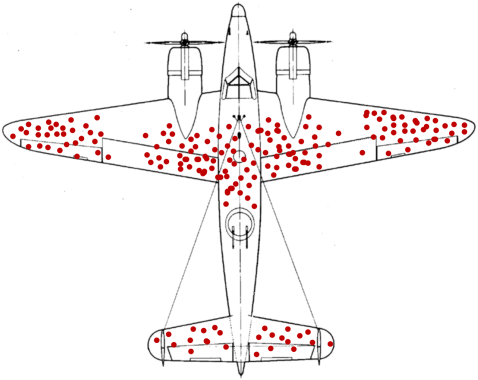
- There are four selection risks:
    1. **Selection into existence**
    2. **Selection into survival**
    3. **Selection into the dataset**
    4. **Selection into treatment**
- In each case, we don't see the *full* relationship between D and Y
- So our regression estimates are biased

3. Selection Bias

- There are four selection risks:
  1. **Selection into existence:**
     - Where do units (eg. political parties) come from?
     - Probably only parties that have a chance of success are formed
     - Does forming a party cause electoral success? Not for most people!

3. Selection Bias

- There are four selection risks:
  2. **Selection into survival:**
     - Certain types of units disappear, so the units we see don't tell the full story



- Where would additional armour protect bombers?
- Returned bombers got hit
- But we do not know where *bombers that did not return* got hit

3. Selection Bias

- There are four selection risks:
  3. **Selection into the dataset:**
     - Our dataset may not be representative
     - Only units with particular values of X and Y enter the dataset
     - Eg. If survey respondents who refuse are different from those who respond - the anti-redistribution poor may dislike answering surveys

3. Selection Bias

- There are four selection risks:
  4. **Selection into treatment:**
     - All units are in our dataset, but they *choose* their treatment value
     - Who chooses treatment? Those with the most to benefit, i.e. depending on Y!
     - Applying treatment to the others would probably have a very different effect

4. Measurement Bias

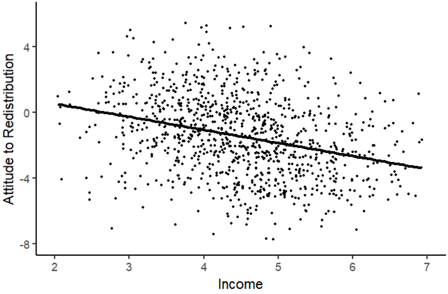
- What happens if we measure our variables wrongly?

Effects of Measurement Error

	Measured with Bias	Measured with Random Noise
Outcome Variable	Effect biased	No bias but wider standard errors
Treatment Variable	Effect biased	Effect biased to zero

4. Measurement Bias

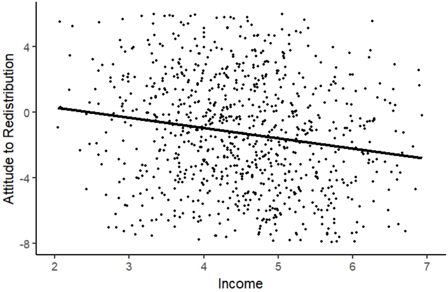
- What happens if we measure our variables wrongly?
- No extra noise:



	Dependent variable:
	redist
income	−0.818*** (0.078)
Constant	2.235*** (0.361)
Observations	1,000
Note:	*p<0.1; **p<0.05; ***p<0.01

4. Measurement Bias

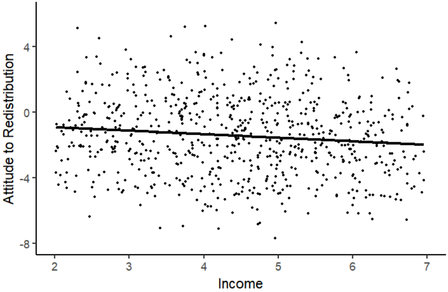
- What happens if we measure our variables wrongly?
- Noise in the **outcome variable**:



	Dependent variable:
	redist
income	−0.831*** (0.144)
Constant	2.272*** (0.665)
Observations	1,000
Note:	*p<0.1; **p<0.05; ***p<0.01

4. Measurement Bias

- What happens if we measure our variables wrongly?
- Noise in the **explanatory** variable:



	Dependent variable:
	redist
income	-0.187^{***} (0.037)
Constant	-0.620^{***} (0.183)
Observations	1,000
Note:	*p<0.1; **p<0.05; ***p<0.01

5. Lack of Overlap

- Regression normally helps us pick appropriate comparisons
  - Eg. Controlling for gender, what is the effect of income on attitudes to redistribution?
- But what if there are no women with high income?
- Regression *creates* comparisons for us
  - How? Using the functional form of the regression
  - A linear regression interpolates/extrapolates *linearly* to 'create' comparison cases
- Lack of overlap probably means we *cannot* explain outcomes with this data

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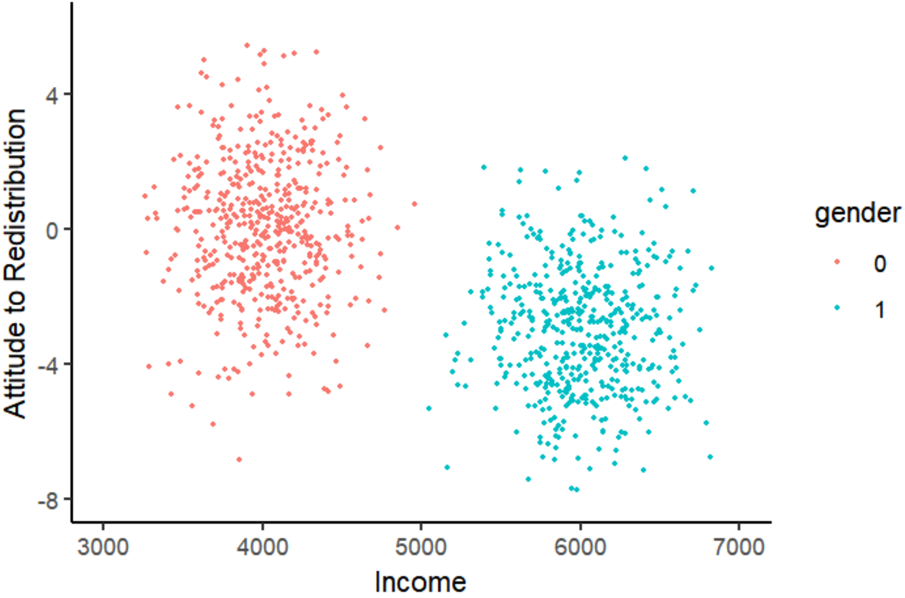

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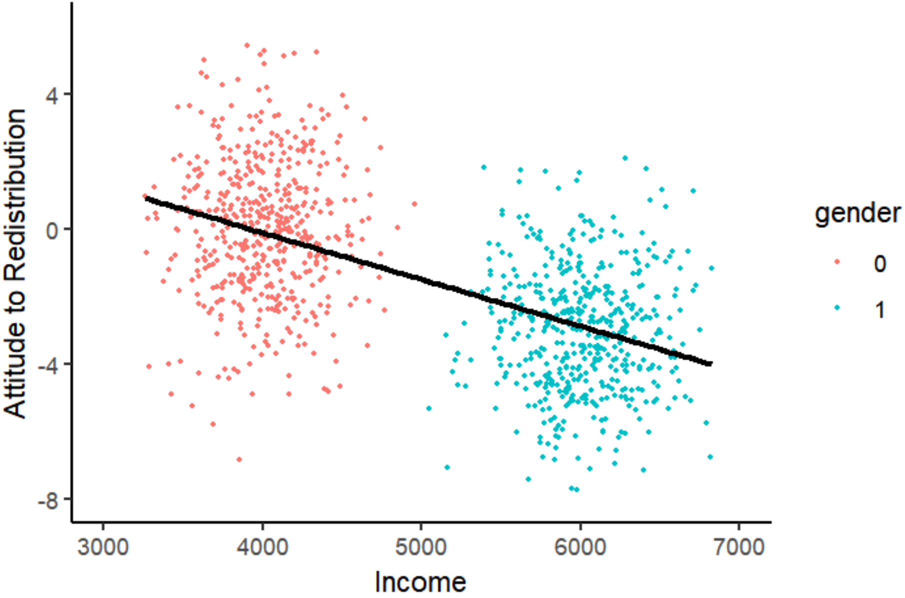

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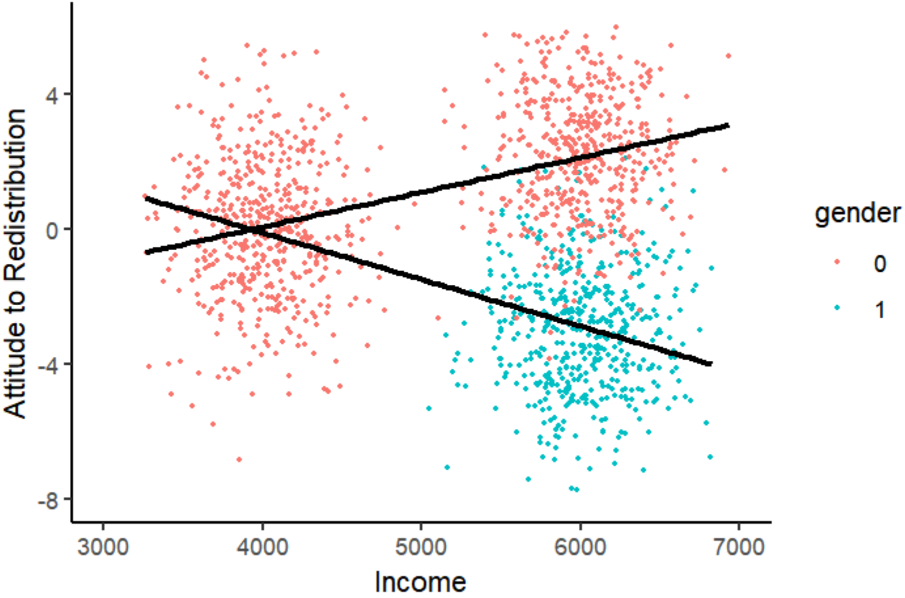

5. Lack of Overlap

- With more than a few variables, lack of overlap is *guaranteed*
- 6 variables with 10 categories each = $10^6 = 1,000,000$ possibilities
- Common datasets have 0% counterfactuals present in the data (King 2006)
  - How many 45 year-old female accountants with a PhD and a cat who live in Centro are there?
  - And we need some that are low-income and some that are high-income
- A problem of **multi-dimensionality**
- And of **model dependence** - our results depend on the functional form in our regression model

Summary

1. Regression is just fancy correlation
   - A **conditional expectation**
2. 'Smart' regression pays more attention to what **comparisons** you want to make than to statistical tests
   - And to **interpretation/prediction** rather than p-values
3. Regression **cannot explain** relationships
   - **Correlation is not causation**
   - We need to understand better **how the data were produced**