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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8. Difference-in-Differences (9th May)
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10. Matching (23rd May)
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11. Comparative Cases and Process Tracing (30th May)
12. Generalizability, Reproducibility and Mechanisms (6th June)

Course Schedule

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- Thursday 14h-16h - Class (105)

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- Thursday 16.15-17.30 - Class (105) OR Lab (122)

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- Friday 10h-12h - Office Hours (DCP 2061)
    - Or just send me an email

Evaluation

- Replication Tasks - 40%

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  - 8 best grades out of 10 tasks

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- Participation - 20%

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- Max 15 pages, English or Portuguese

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- *Tip:* Pick a simple *causal* 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?

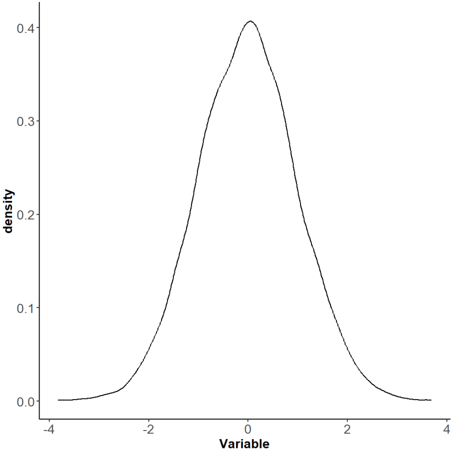
Section 1

What Does Regression Actually Do?

Data

- We work with variables, which VARY!

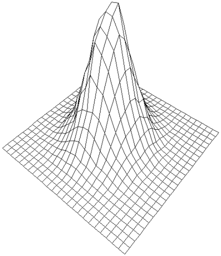
Variable
0.30
-0.67
0.39
0.03
-1.26
1.26
-1.44
0.16
0.50
0.01



Data

- We work with variables, which VARY!

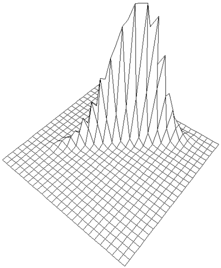
Variable_1	Variable_2
-0.44	0.63
0.06	0.68
-0.21	-0.02
0.44	-0.25
1.29	0.46
-0.38	-0.81
-1.04	0.24
-0.16	1.84
1.29	0.06
-0.10	-0.18



Data

- We work with variables, which VARY!

Variable_1	Variable_2
-0.86	-0.69
-0.35	-0.44
1.27	0.42
-0.35	-0.22
-0.43	-0.56
0.05	-0.04
0.69	0.70
1.27	1.07
0.22	-0.00
-0.28	-0.13



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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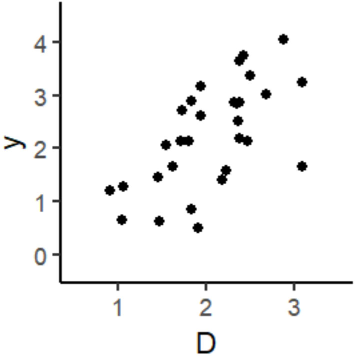

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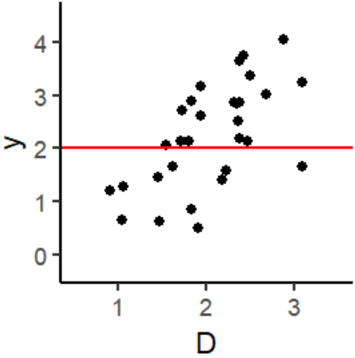

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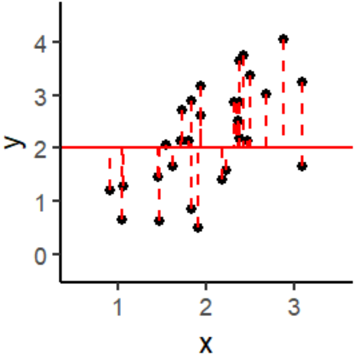
Slope = 0



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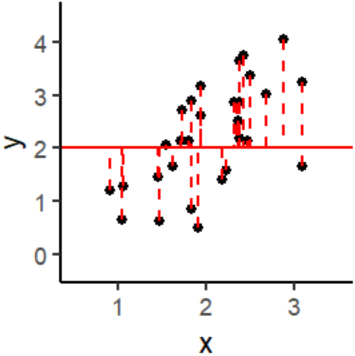
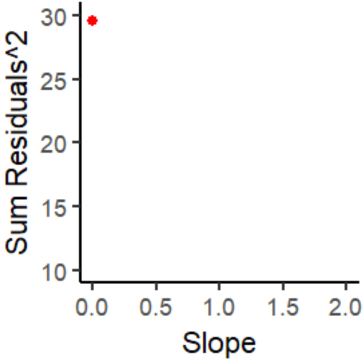


Sum of Residuals^2 = 29.6



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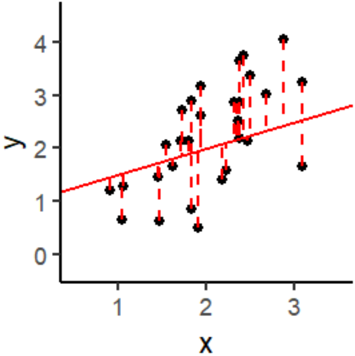
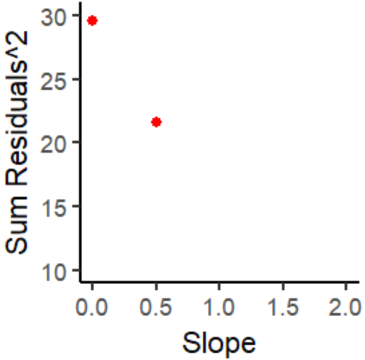
Slope = 0.5



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
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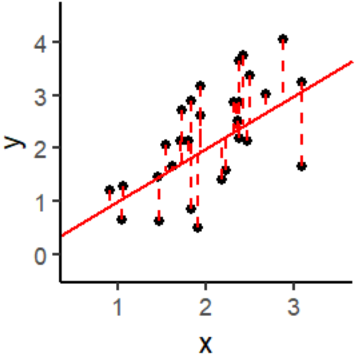
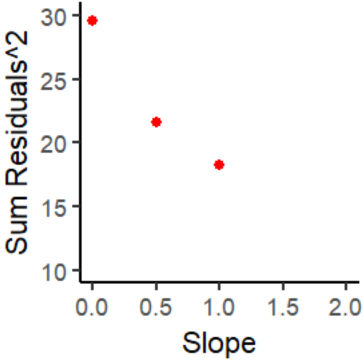
Slope = 1



Sum of Residuals^2 = 18.3



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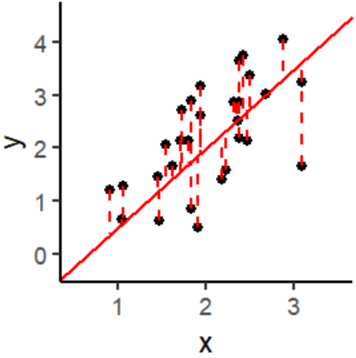
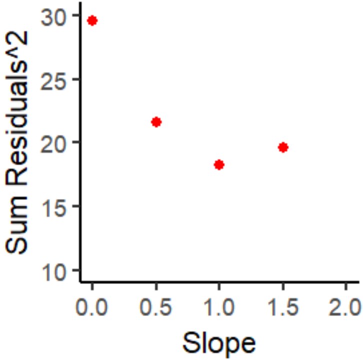
Slope = 1.5



Sum of Residuals^2 = 19.6



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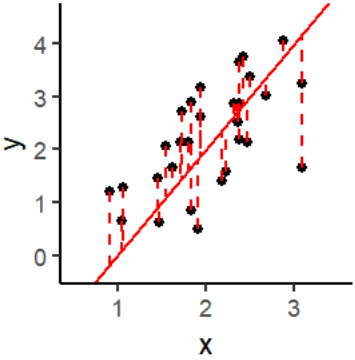
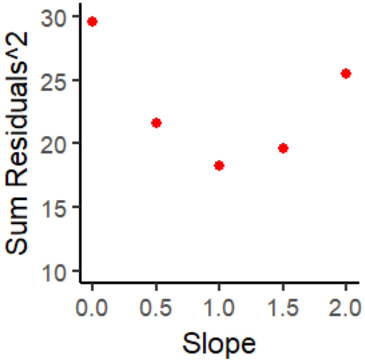
Slope = 2



Sum of Residuals^2 = 25.5



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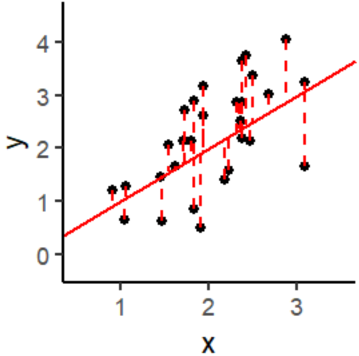

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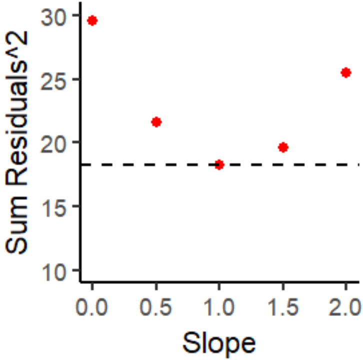

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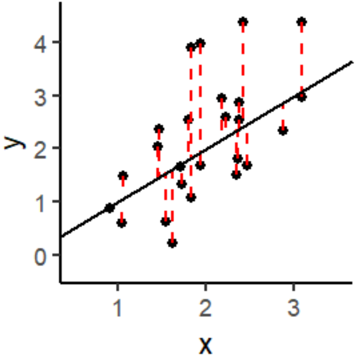

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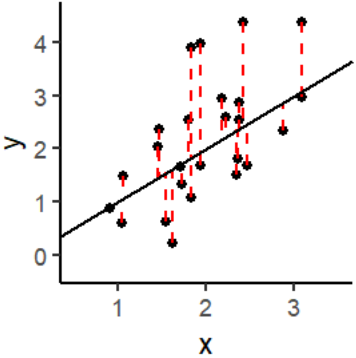
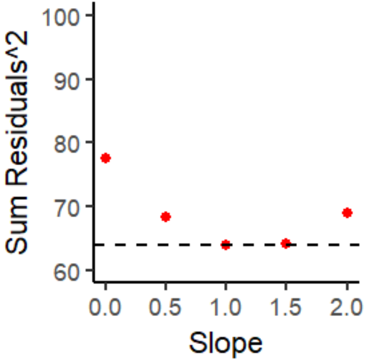


Sum of Residuals^2 = 63.9



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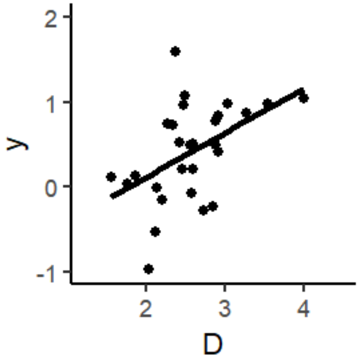

Ignoring the dummy control variable, the slope coefficient is 1

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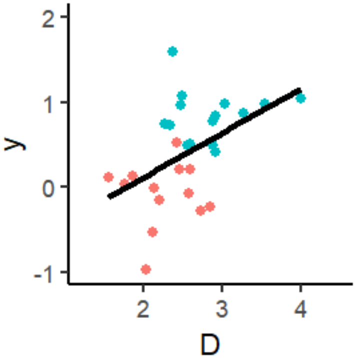

But the data points really represent two very different groups, blues and reds

Regression as Least Squares

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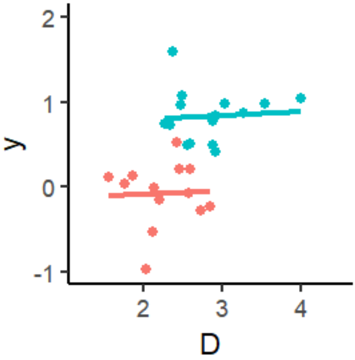

What if we ran the regression for each group *separately*?

Regression as Least Squares

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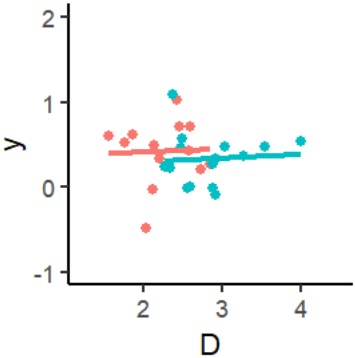

Dummy control variables *remove* the average Y differences between blues and reds

Regression as Least Squares

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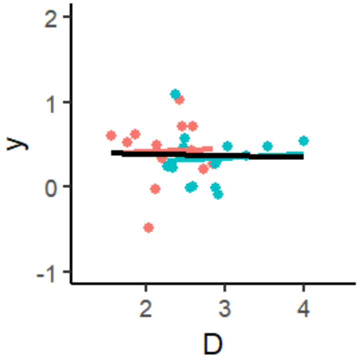

The new regression line for the full data now has a slope of zero

Regression as Least Squares

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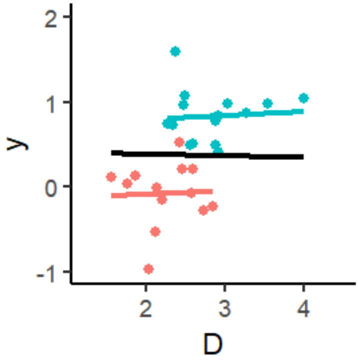

Equivalently, dummy control variables restrict comparisons to **within the same group**:

1. How much does D affect Y within the blue group? 0
2. How much does D 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

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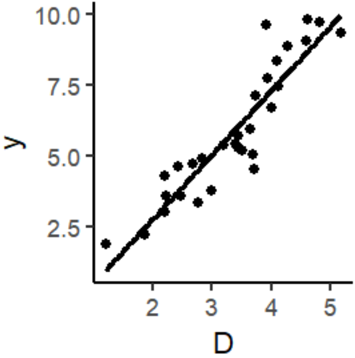

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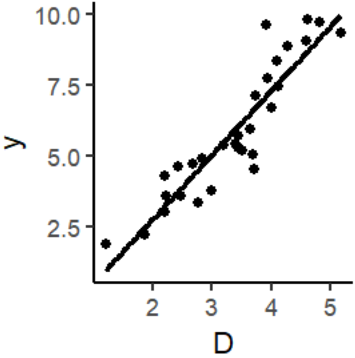

The coefficient β_1 is 2.267
Real effect = 1

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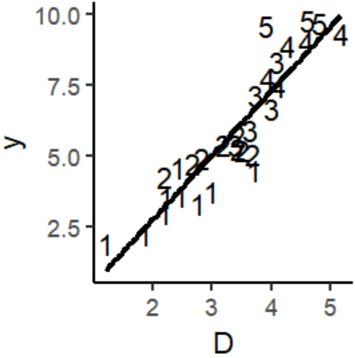

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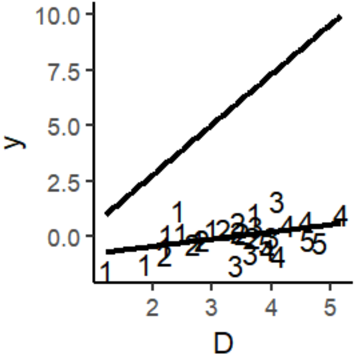

The coefficient β_1 is 1.024
Real effect = 1

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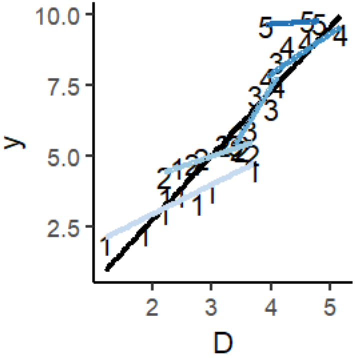

- Equivalently, we subset the data to each value of X, and find each slope

Regression as Least Squares

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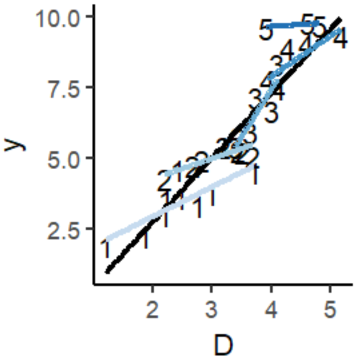

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- Then average these slopes, $\beta_1 \sim 1$

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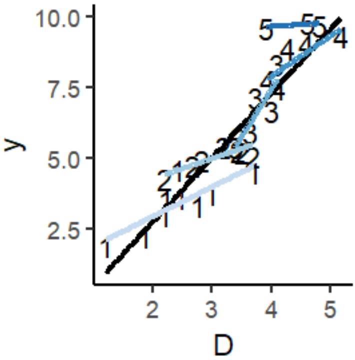

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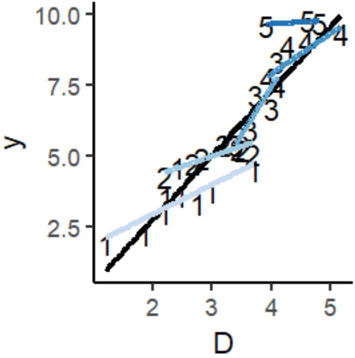

- Equivalently, we subset the data to each value of X, and find each slope
- Then average these slopes, $\beta_1 \sim 1$
- Impossible with truly continuous variables
- So regression uses linearity to fill in the gaps

Regression as Conditional Expectation

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

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- **Conditional on D,** What is our expectation (mean value) of y?

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

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- **Conditional on D,** What is our expectation (mean value) of y?

$$y_i = \alpha + \beta_1 D_i + \epsilon_i$$
$$E(y) = \alpha + \beta_1 D$$

Regression as Conditional Expectation

- **Conditional on a specific value of D,** what is our expectation (mean value) of y?

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

Regression as Conditional Expectation

- **Conditional on a specific value of D,** what is our expectation (mean value) of y?

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

Regression as Conditional Expectation

- **Conditional on a specific value of D,** what is our expectation (mean value) of y?

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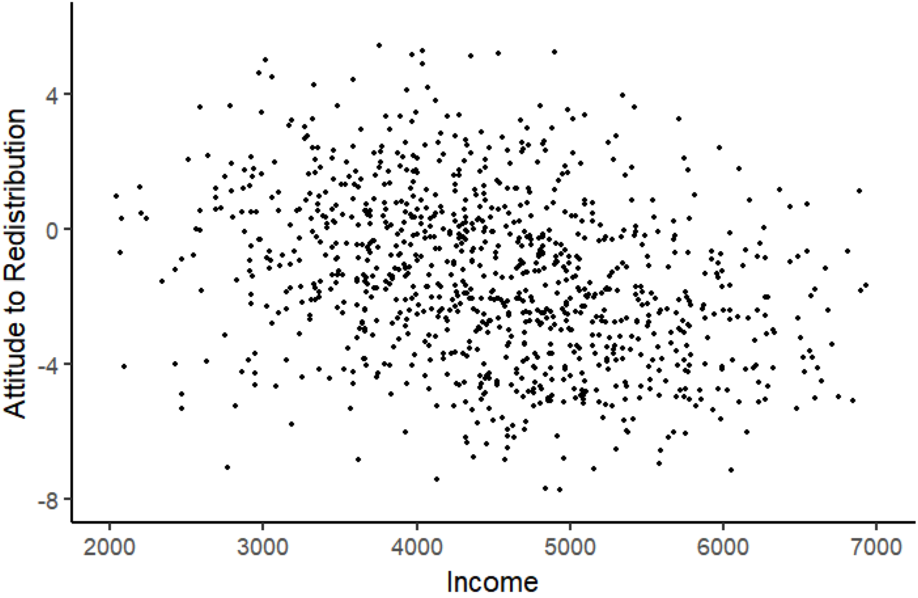
Regression as Conditional Expectation



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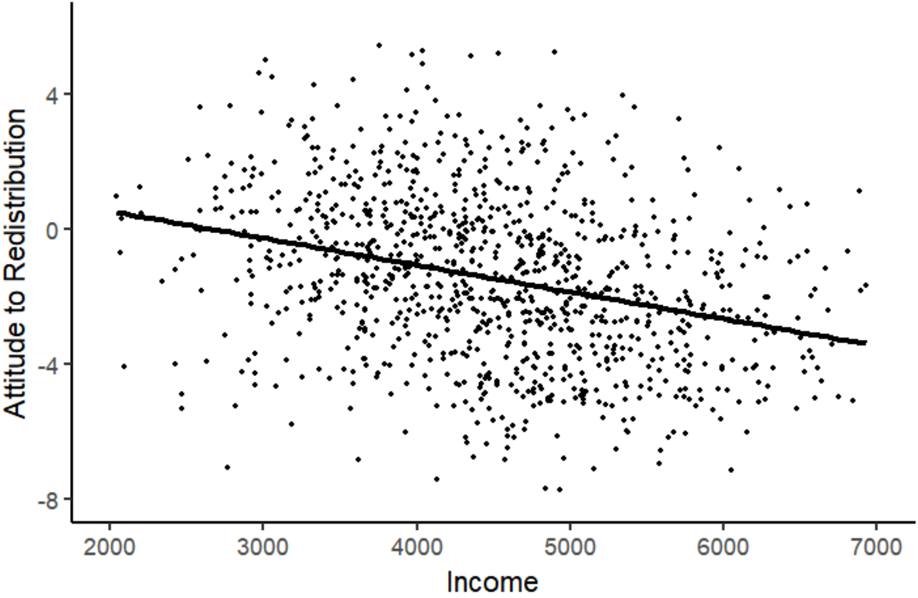

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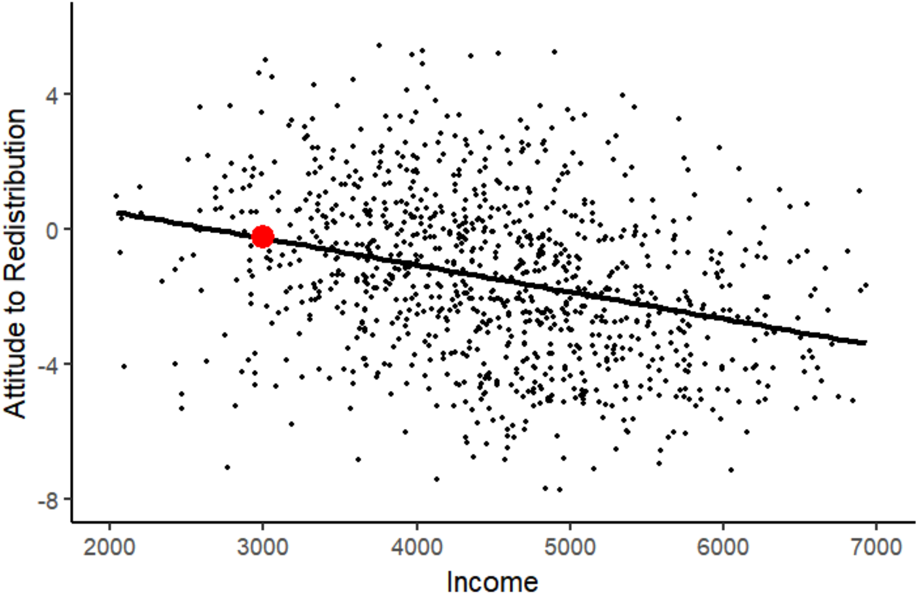

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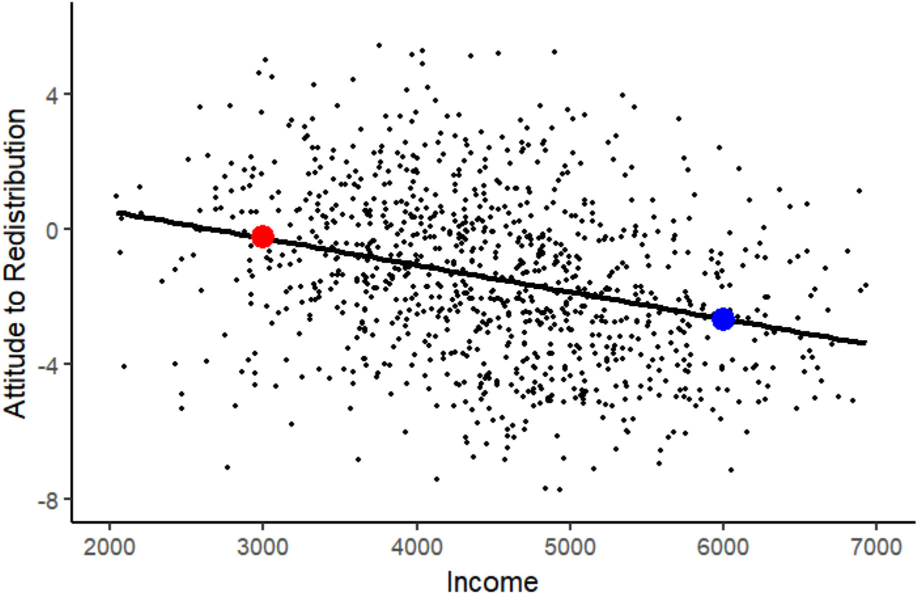

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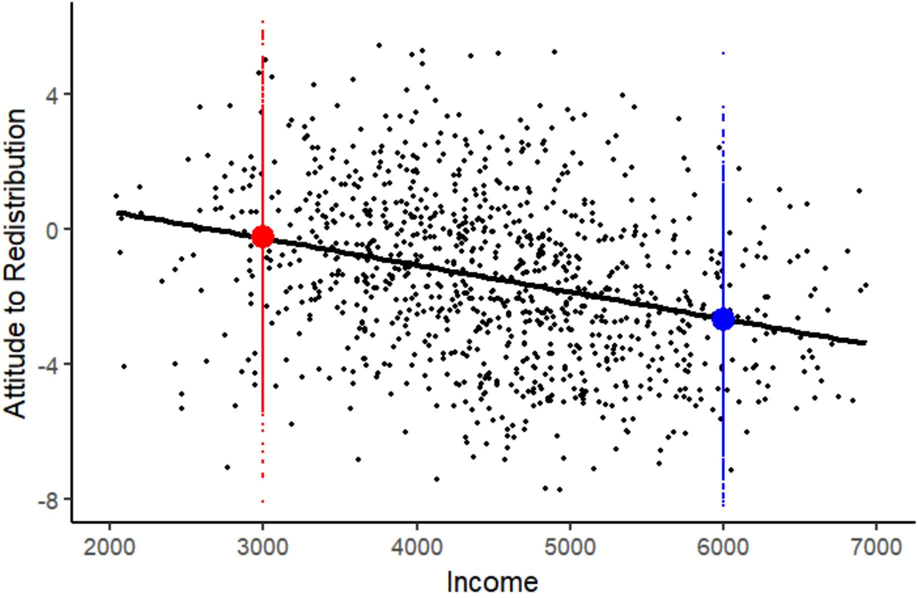

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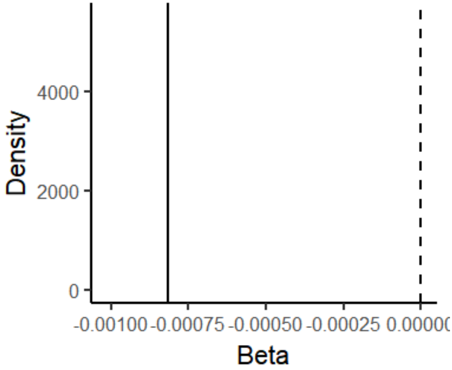
Observations	1,000
Note:	*p<0.1; **p<0.05; ***p<0.01



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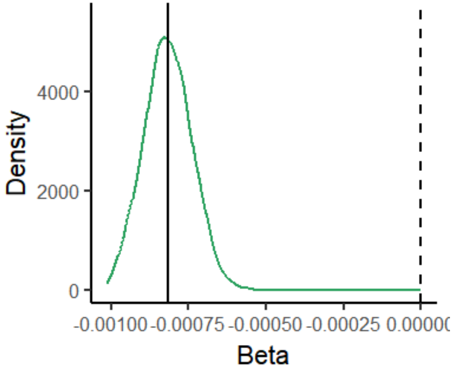

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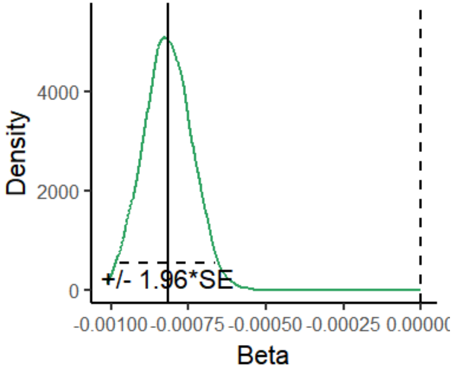

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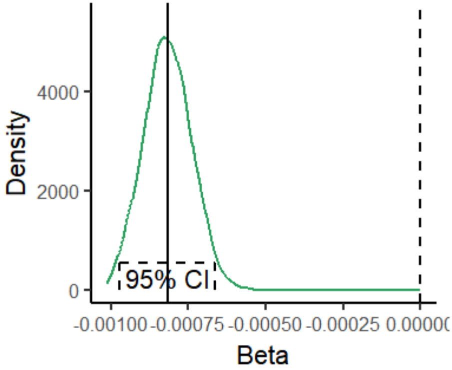

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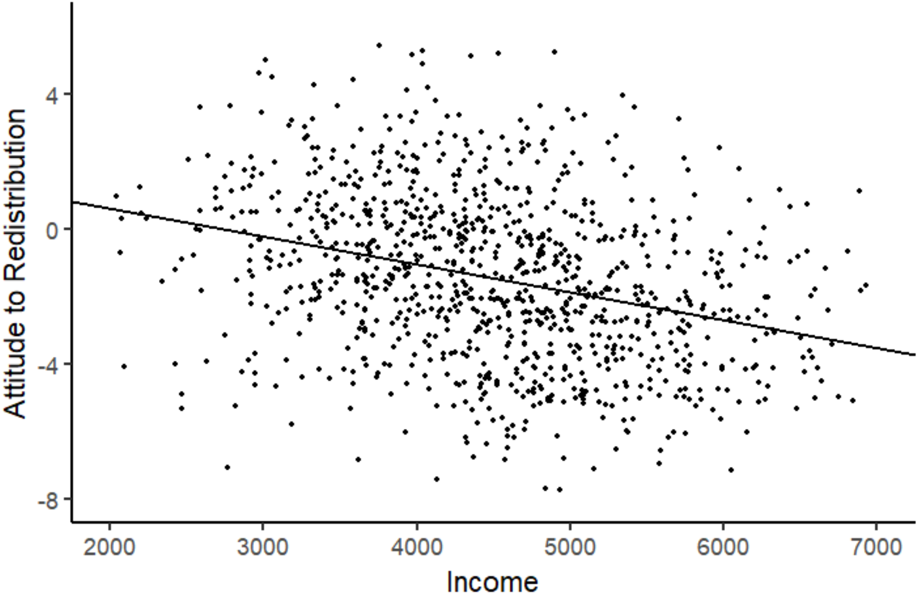

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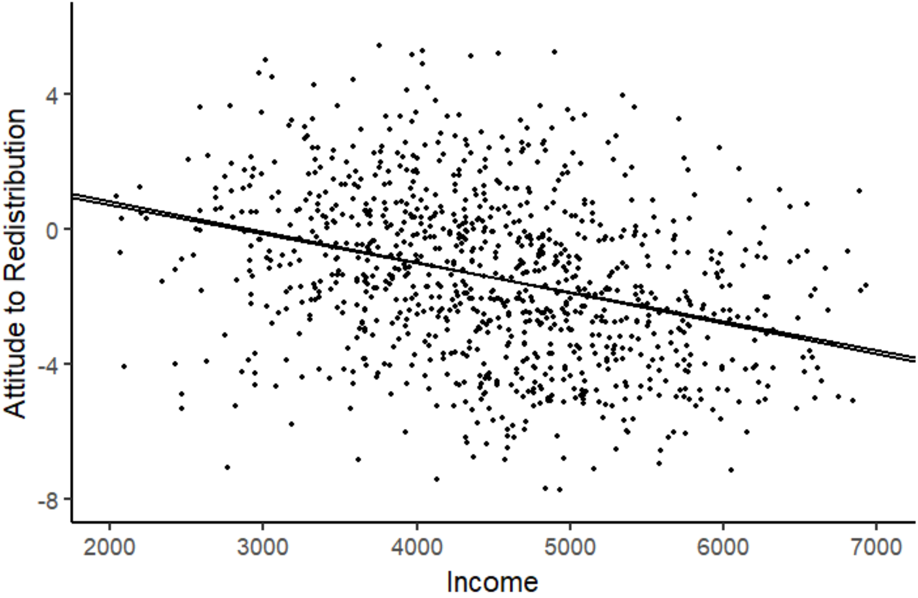

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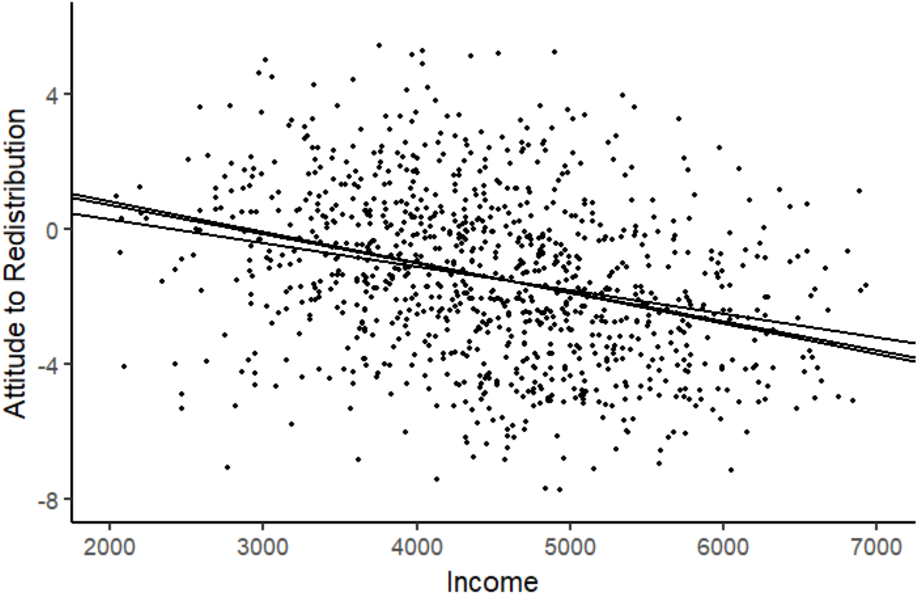

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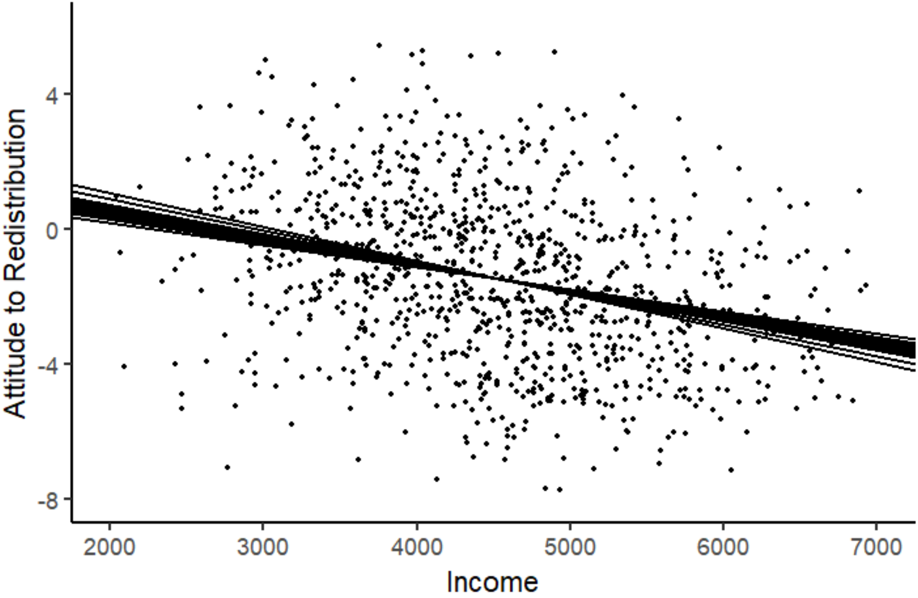

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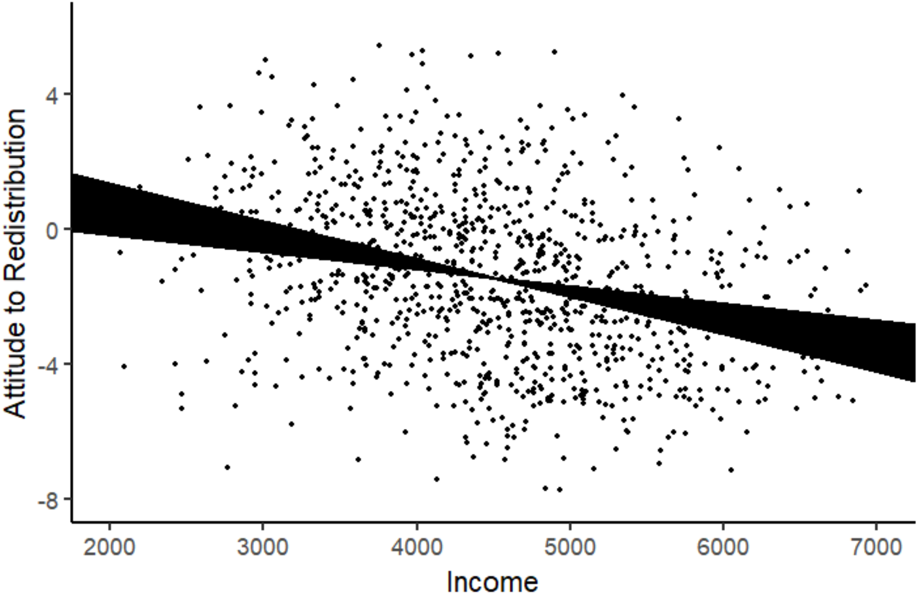

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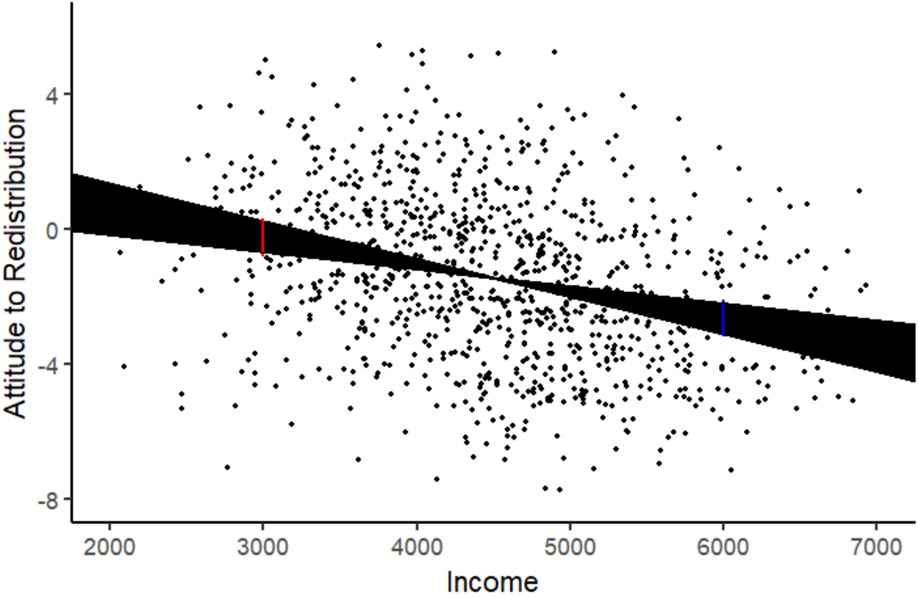

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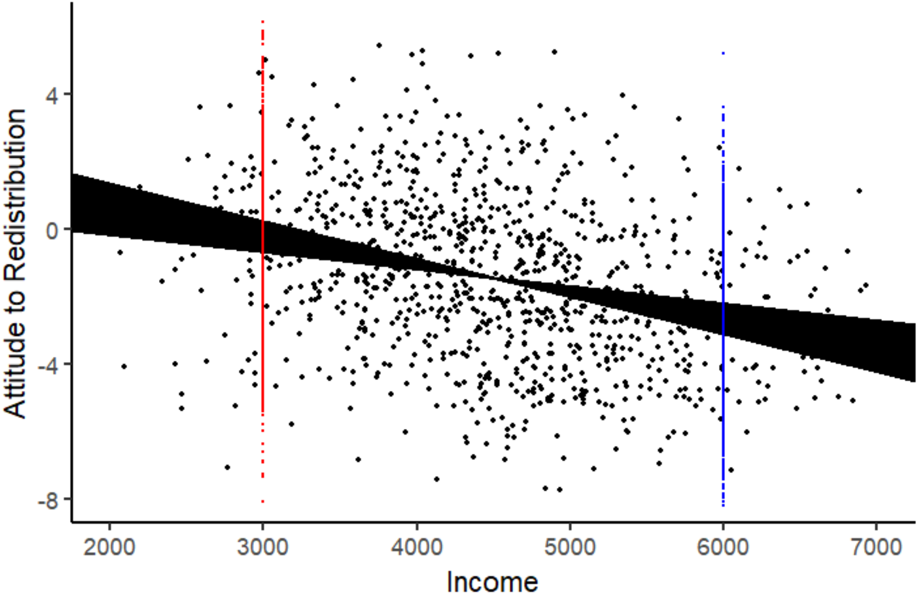

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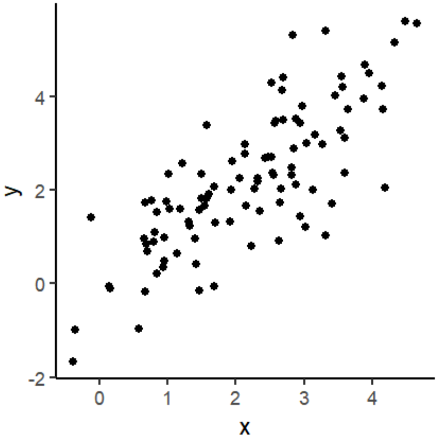

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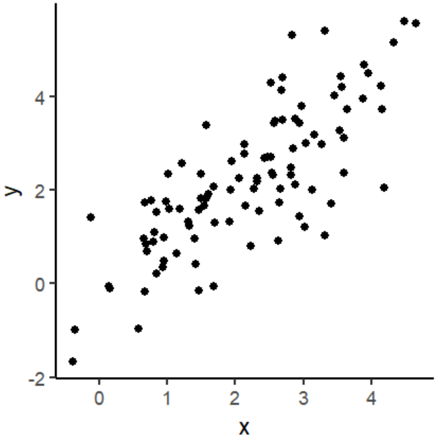

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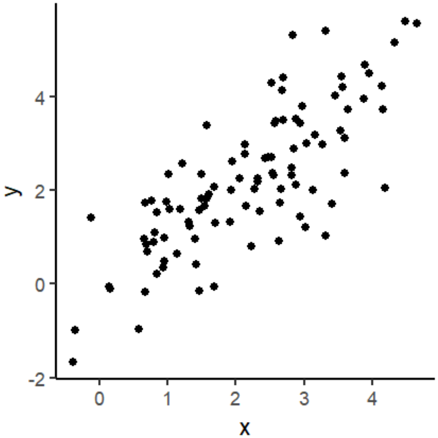

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	term	estimate
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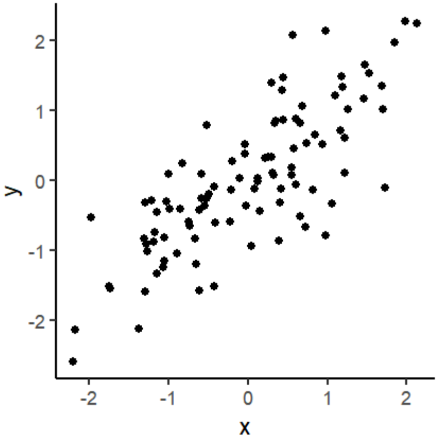

- Correlation is 0.781
- It's **identical** if we standardize both variables first ($\frac{(x_i - \bar{x})}{\sigma_x}$)
- Standardized Regression Results:

	term	estimate
1	(Intercept)	0.000
2	x	0.781

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$$\beta_{x_1} = \frac{r_{yx_1} - r_{yx_2} r_{x_1 x_2}}{1 - r^2_{x_1 x_2}}$$

$$r_{yx_1|x_2} = \frac{r_{yx_1} - r_{yx_2} r_{x_1 x_2}}{\sqrt{(1 - r^2_{yx_2})(1 - r^2_{x_1 x_2})}}$$

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

Section 2

Guide to ’Smart’ Regression

Regression Guide

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3. There are fundamental best practices that apply to all the methodologies

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  - Pre-tax, post-tax, after government benefits?
- It depends on the theory we are testing

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- Count -> Poisson
  - In the past year, how many times have you complained about redistribution?

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  - 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?

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- 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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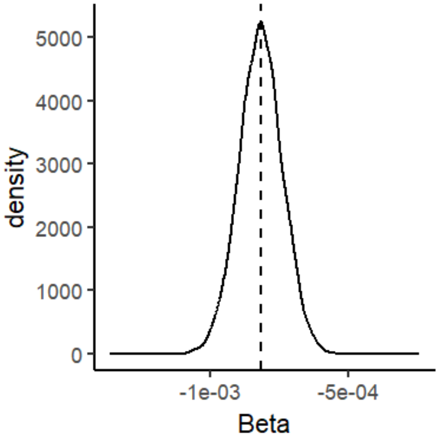

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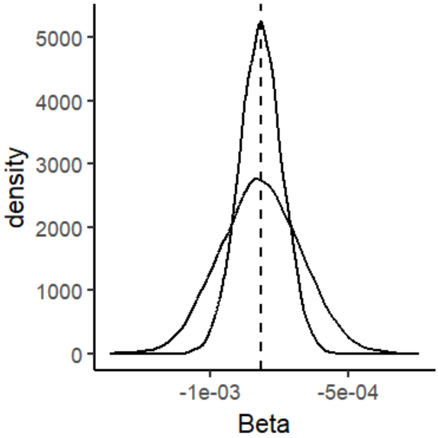

- With clustered SEs, the wider distribution of our betas suggests we're *less* confident β is close to -0.0008175

7. Interpreting Regression Results

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    1. The scale of the explanatory variable

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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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- Basic OLS **with log treatment**: $y_i = \alpha + \beta log(D_i) + \epsilon$
  - A 1% change in the explanatory variable is associated with a $\beta * log(\frac{101}{100})$ 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

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- Difficult! It depends on:
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  3. The regression model we used
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- **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

7. Interpreting Regression Results

OLS with Interaction:

$Redist_i = \alpha + \beta_1 Gender_i + \beta_2 Income_i$
$+ \beta_3 Gender_i * Income_i + \epsilon_i$

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	Dependent variable:
	redist
gender1	-2.942614^{***} (0.700510)
income	0.079980^{***} (0.000110)
gender1:income	0.000986^{***} (0.000152)
Constant	0.112903 (0.454926)
Observations	1,000
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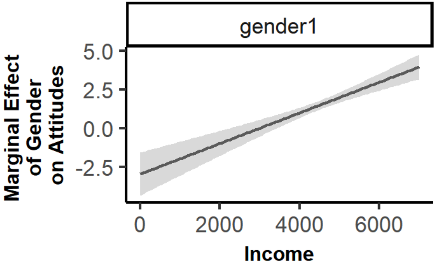

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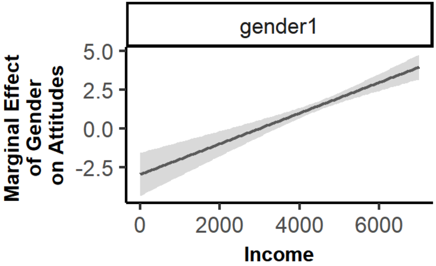

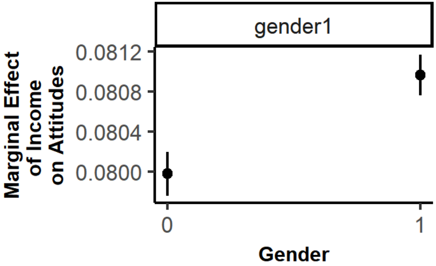

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- The coefficient on the regression of income on attitude to redistribution is -0.000818
  - So??? What do we learn from this?
  - Coefficients are hard to interpret, and depend on how we measure each variable
  - And p-values are arbitrary
- Better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

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

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

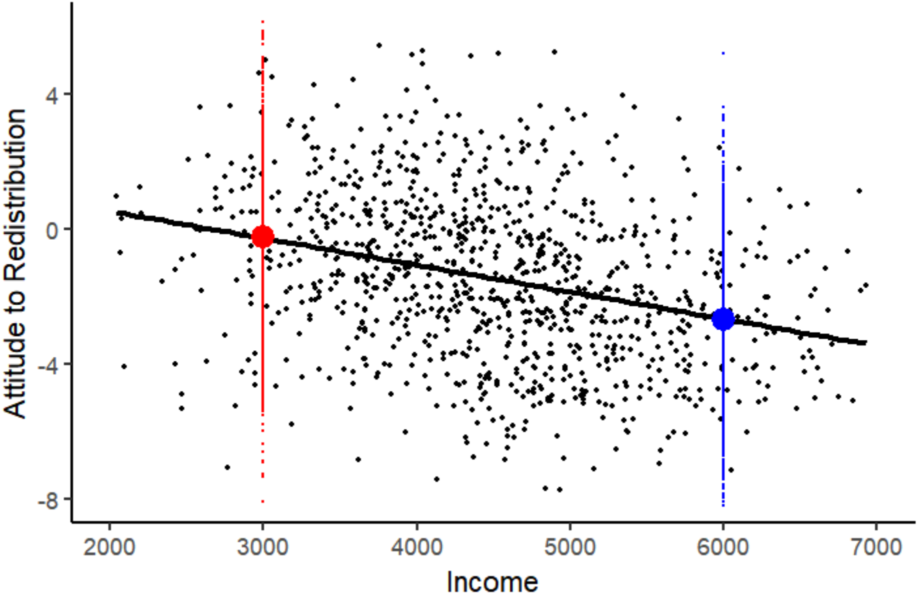
Increasing Income from 3000 to 6000:

$$\Delta Attitude_i = (2.235 - 0.000818 * 6000) - (2.235 - 0.000818 * 300$$

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

$$\Delta Attitude_i = -2.454$$

8. Predictions from Regressions



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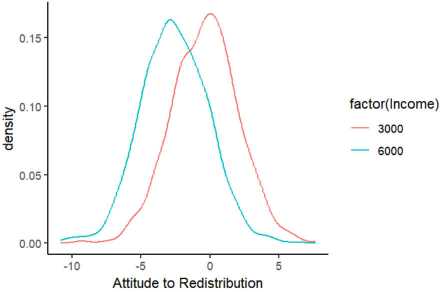

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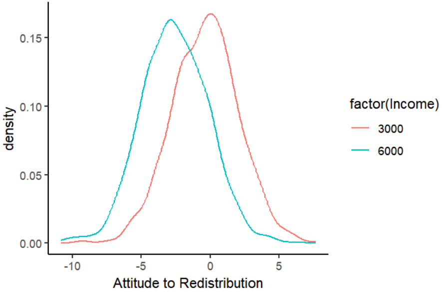
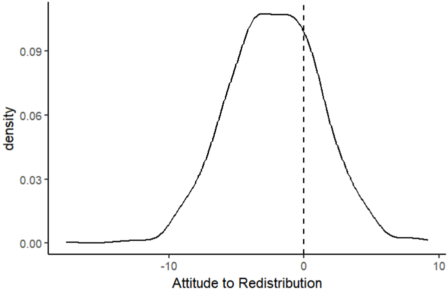


First Differences:



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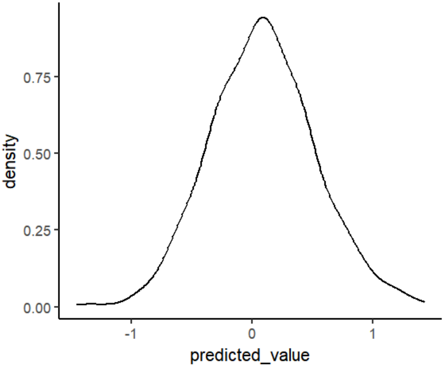
- Compare the OLS and Logit regression tables:

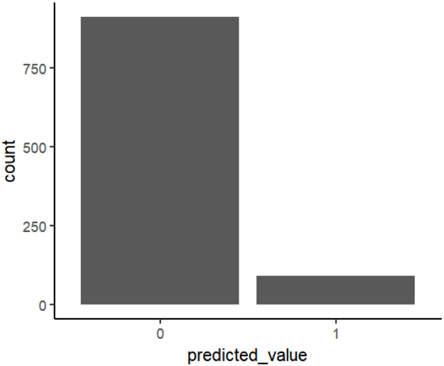
	Dependent variable:
	gender
income	0.0003*** (0.00001)
Constant	−0.696*** (0.066)
Observations	1,000
Note:	*p<0.1; **p<0.05; ***p<0.01

	Dependent variable:
	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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- These all require **research design**, **theory** and **assumptions**

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- The problem is the *content* of data; it does not allow us to answer the causal question

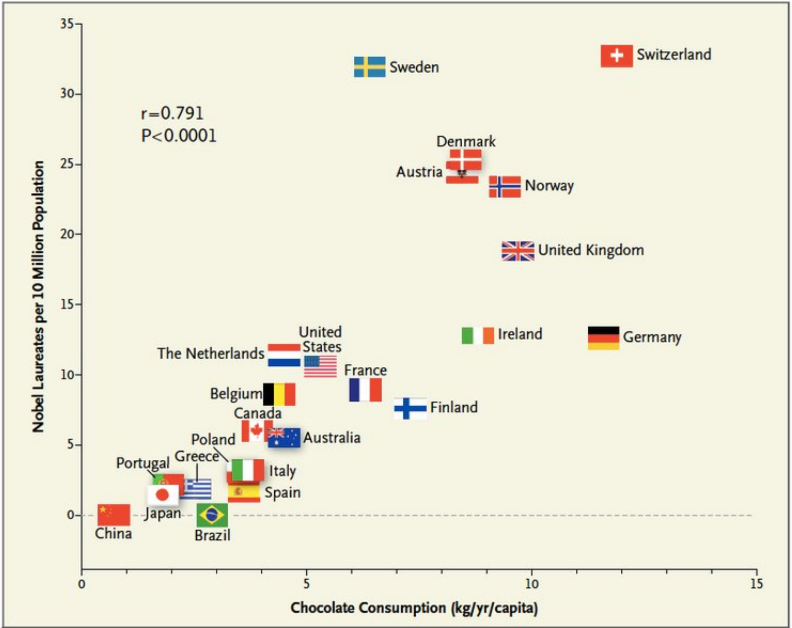
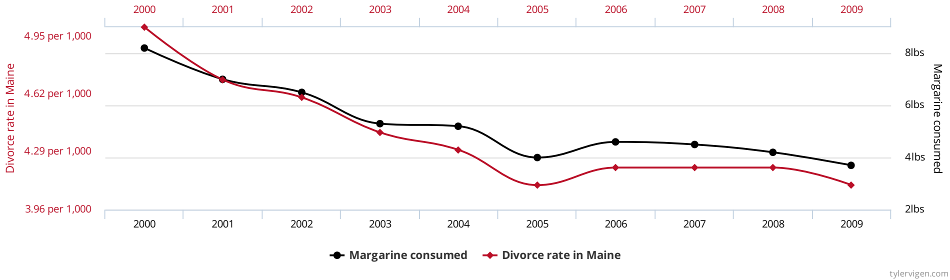
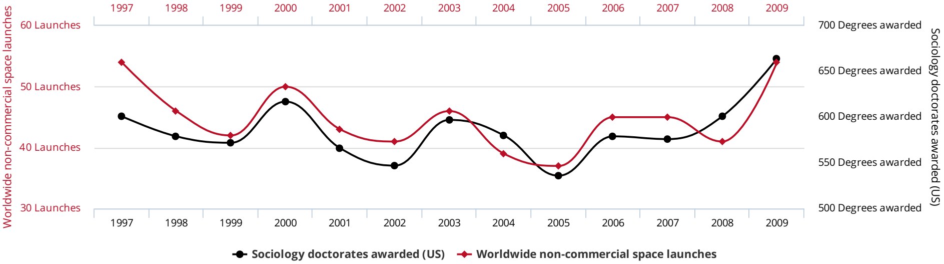


Figure 1. Correlation between Countries' Annual Per Capita Chocolate Consumption and the Number of Nobel Laureates per 10 Million Population.

Divorce rate in Maine
correlates with
Per capita consumption of margarine



Worldwide non-commercial space launches
correlates with
Sociology doctorates awarded (US)

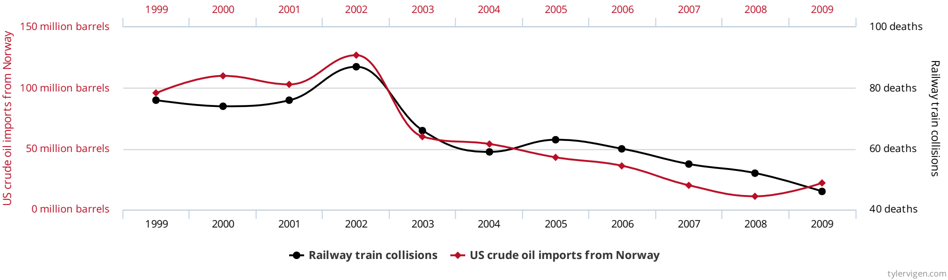


tylervigen.com

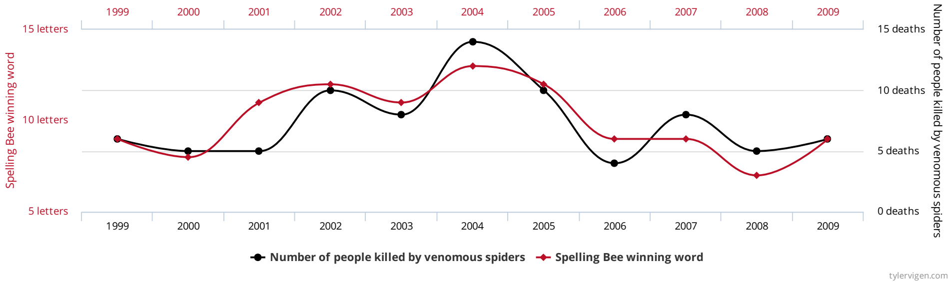
US crude oil imports from Norway

correlates with

Drivers killed in collision with railway train



Letters in Winning Word of Scripps National Spelling Bee
correlates with
Number of people killed by venomous spiders



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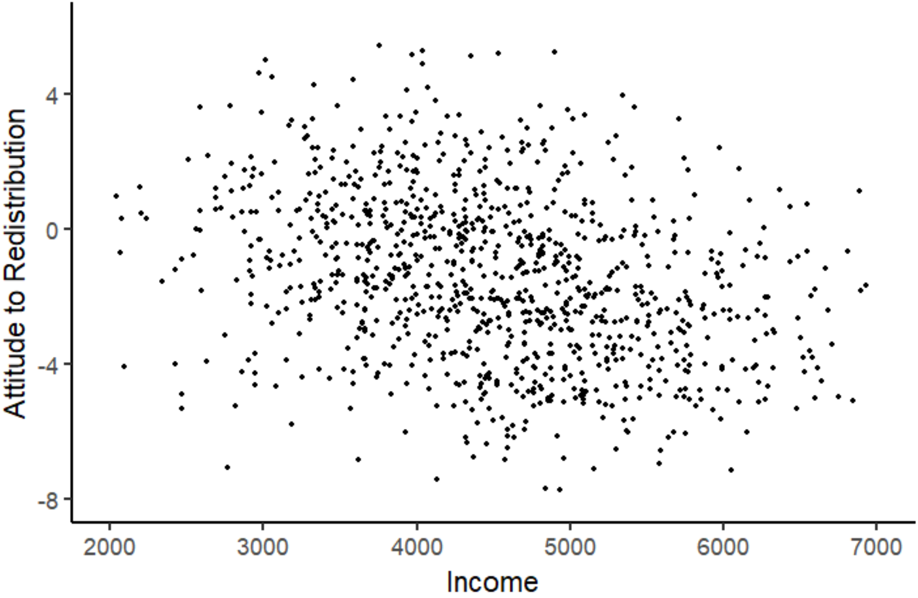

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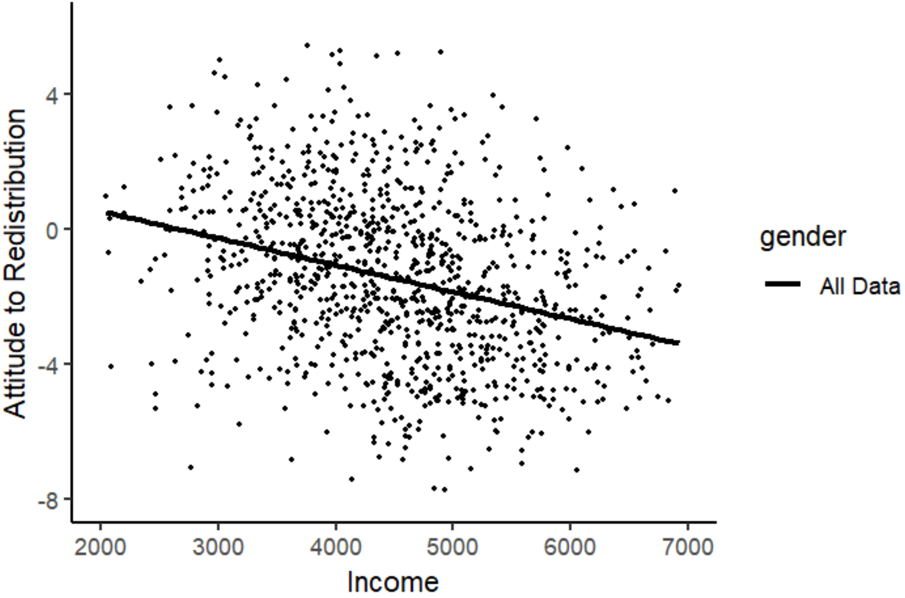

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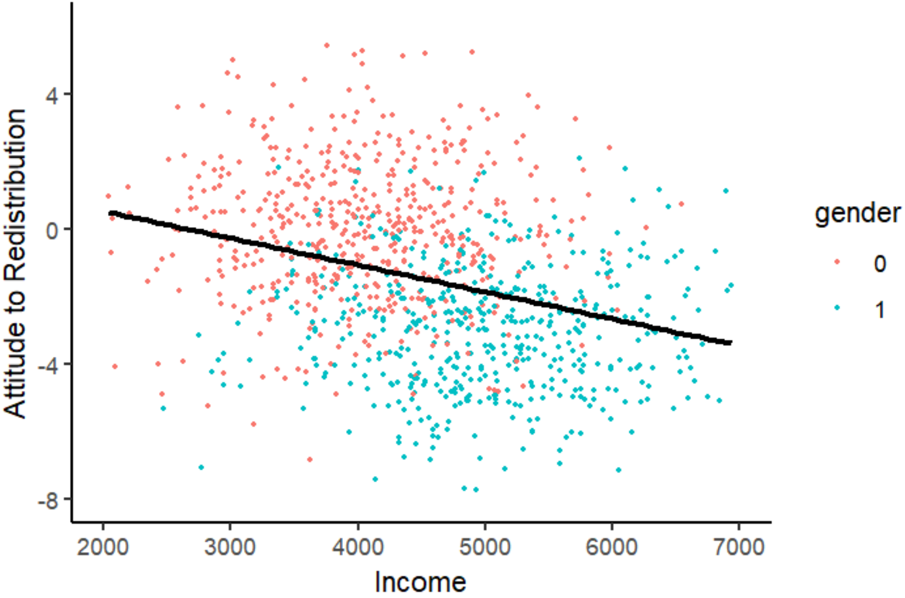

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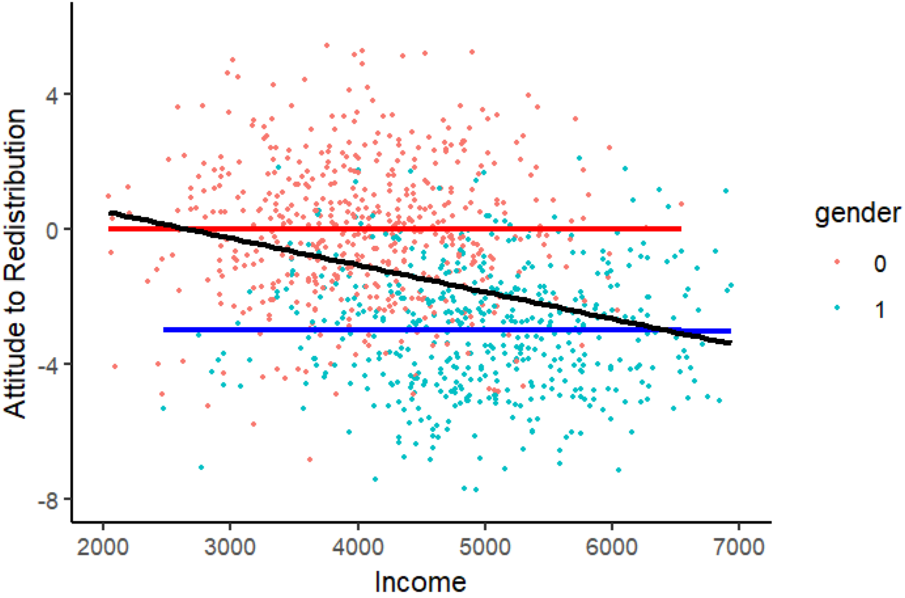

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	Dependent variable:
	redist
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gender1	−1.201*** (0.058)
Constant	0.589*** (0.038)
Observations	1,000
Note:	*p<0.1; **p<0.05; ***p<0.01

	Dependent variable:
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- 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!

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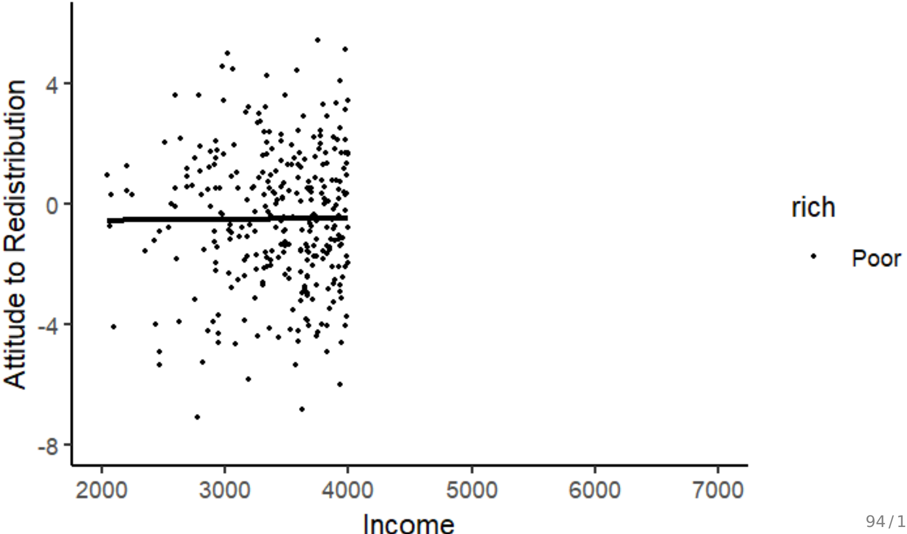
- But negative attitudes to redistribution might also make you more likely to work in the private sector and cause you to receive a higher salary
- Both would look the same in a regression
- We cannot *explain* the relationship with a regression

3. Selection Bias

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



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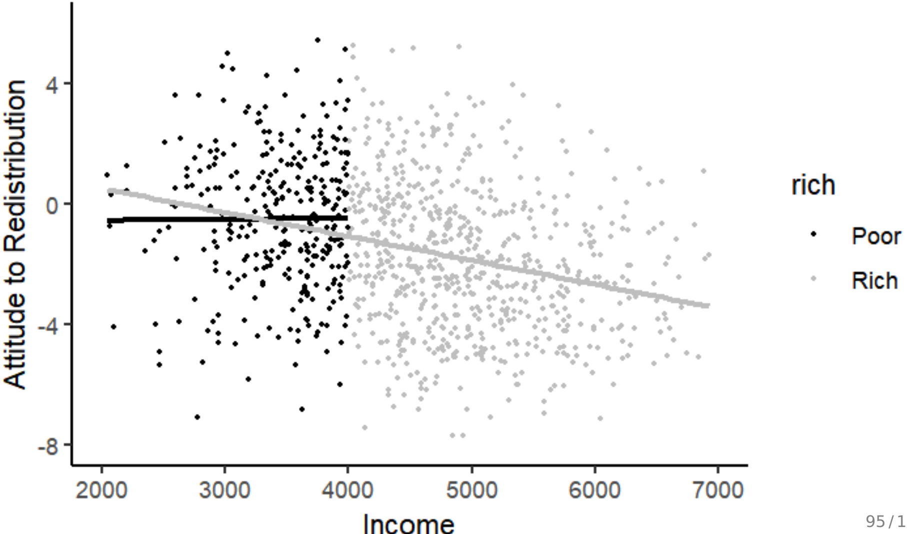

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- In each case, we don't see the *full* relationship between D and Y
- So our regression estimates are biased

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     - Probably only parties that have a chance of success are formed

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!

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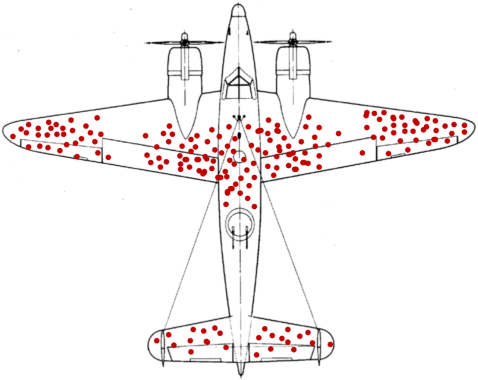

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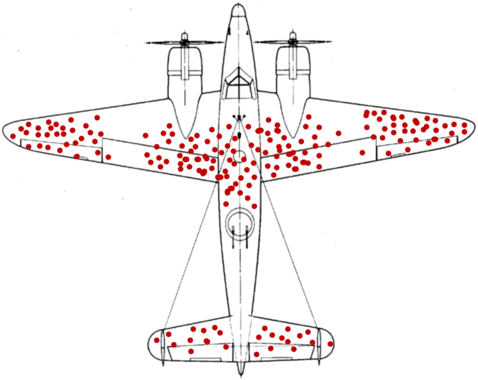

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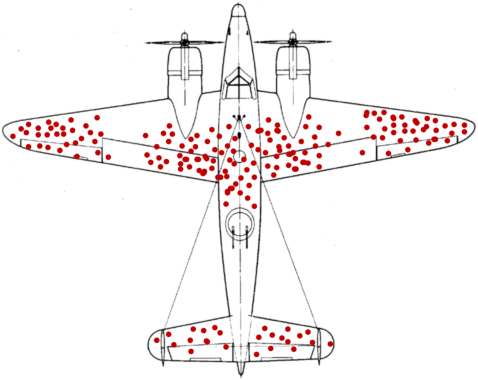

- Where would additional armour protect bombers?
- Returned bombers got hit
- But we do not know where *bombers that did not return* got hit

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     - Eg. If survey respondents who refuse are different from those who respond - the anti-redistribution poor may dislike answering surveys

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     - Applying treatment to the others would probably have a very different effect

4. Measurement Bias

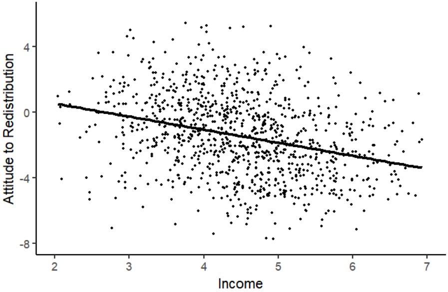
- What happens if we measure our variables wrongly?

Effects of Measurement Error

	Measured with **Bias**	Measured with **Random Noise**
Outcome Variable	Coefficient biased	No bias but wider standard errors
Treatment Variable	Coefficient biased	Effect biased towards 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

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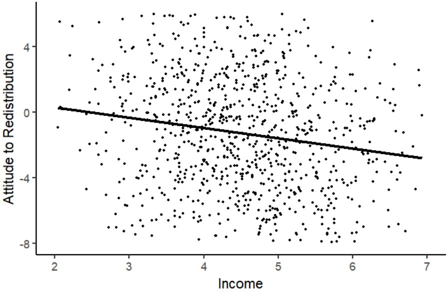

	Dependent variable:
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income	−0.831*** (0.144)
Constant	2.272*** (0.665)
Observations	1,000
Note:	*p<0.1; **p<0.05; ***p<0.01

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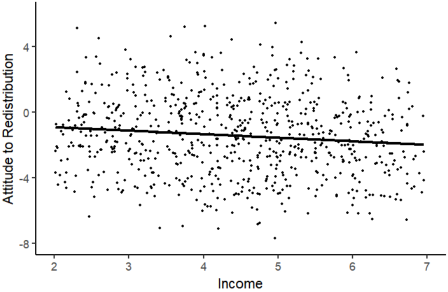

	Dependent variable:
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income	−0.187*** (0.037)
Constant	−0.620*** (0.183)
Observations	1,000
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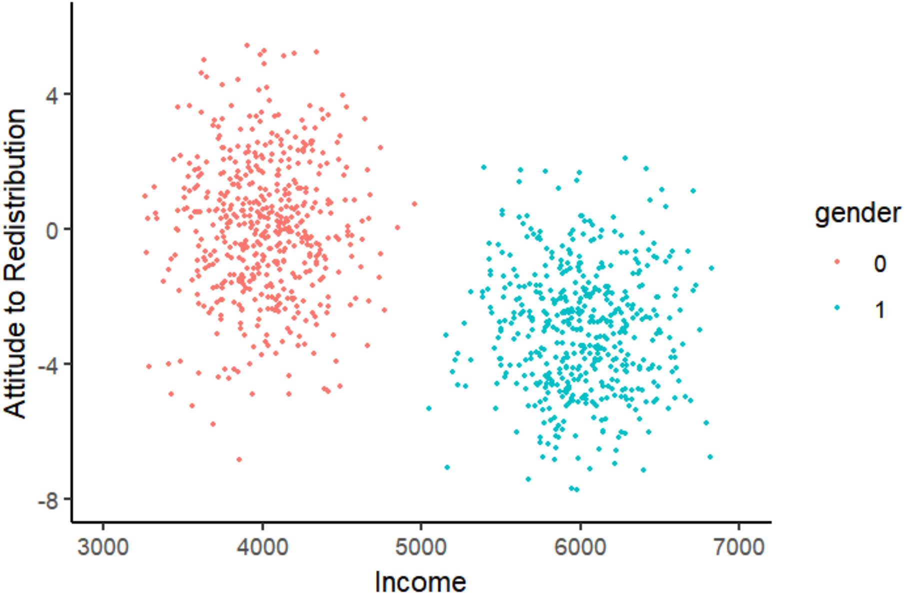

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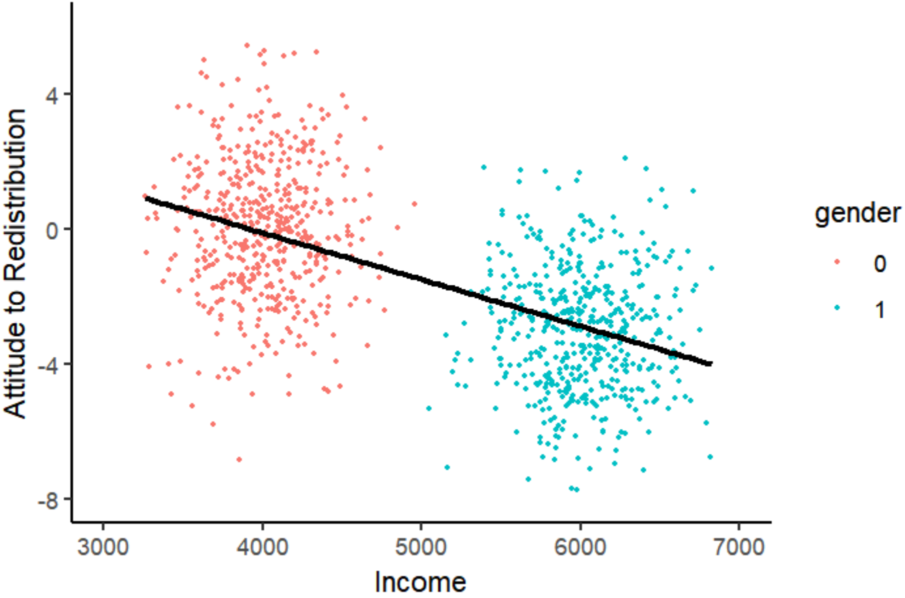

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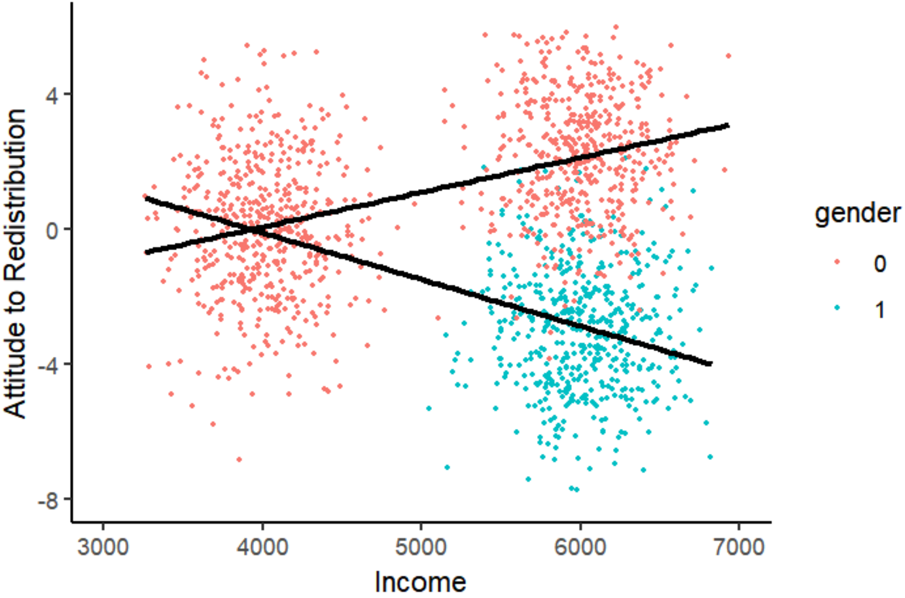

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- And of **model dependence** - our results depend on the functional form in our regression model

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