FLS 6441 - Methods III: Explanation and Causation

Week 1 - Review of Regression

Jonathan Phillips

March 2020

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 (5th March)

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2. A Framework for Explanation (12th March)

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4. Survey and Lab Experiments (26th March)
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7. Discontinuities (23rd April)

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7. Discontinuities (23rd April)
8. Difference-in-Differences (30th April)
9. Controlling for Confounding (7th May)
10. Matching (14th May)
11. Comparative Cases and Process Tracing (21st May)

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11. Comparative Cases and Process Tracing (21st May)
12. Generalizability, Reproducibility and Mechanisms (28th May)

Course Schedule

- Wednesday 18h - Submit Replication Task

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- Thursday 14h-16h - Room 105

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- Thursday 16.15-18.00 - Lab 122

Evaluation

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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?

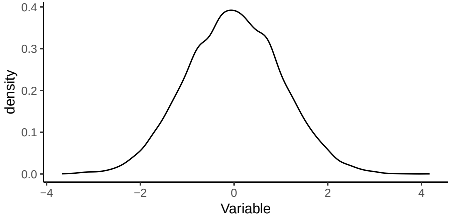
Section 1

What Does Regression Actually Do?

Data

- We work with variables, which VARY!

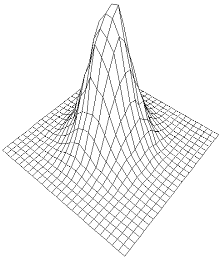
Variable
0.30
-0.67
0.39
0.03
-1.26
1.26
-1.44
0.16
0.50
0.01



Data

- We work with variables, which VARY!

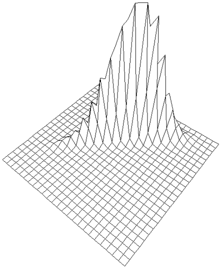
Variable_1	Variable_2
-0.44	0.63
0.06	0.68
-0.21	-0.02
0.44	-0.25
1.29	0.46
-0.38	-0.81
-1.04	0.24
-0.16	1.84
1.29	0.06
-0.10	-0.18



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

1. Regression as Least Squares

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

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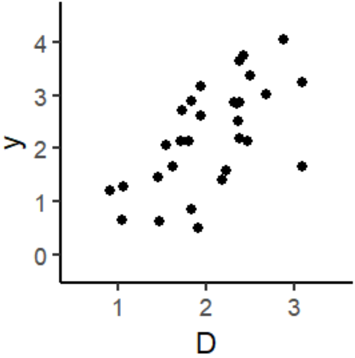

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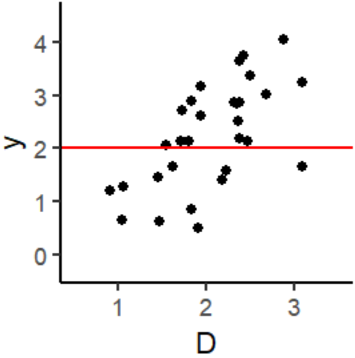

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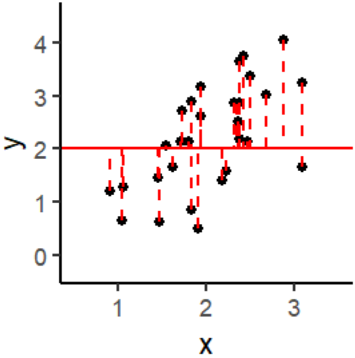
- Regression identifies the line through the data that minimizes the sum of squared vertical distances
- $y_i = \alpha + \beta D_i + \epsilon_i$

Slope = 0



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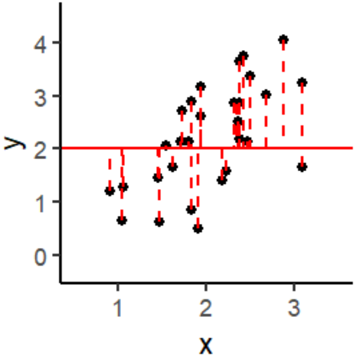
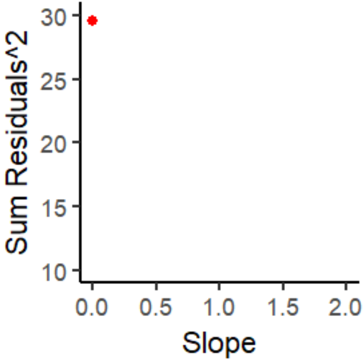


Sum of Residuals^2 = 29.6



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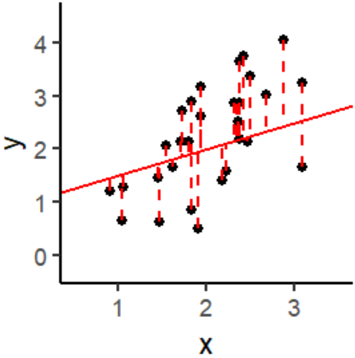
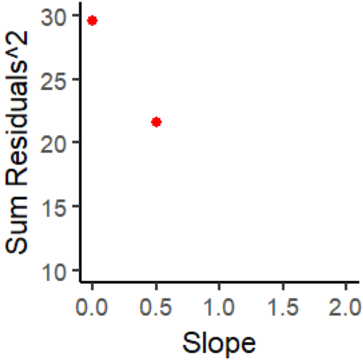
Slope = 0.5



Sum of Residuals^2 = 21.6



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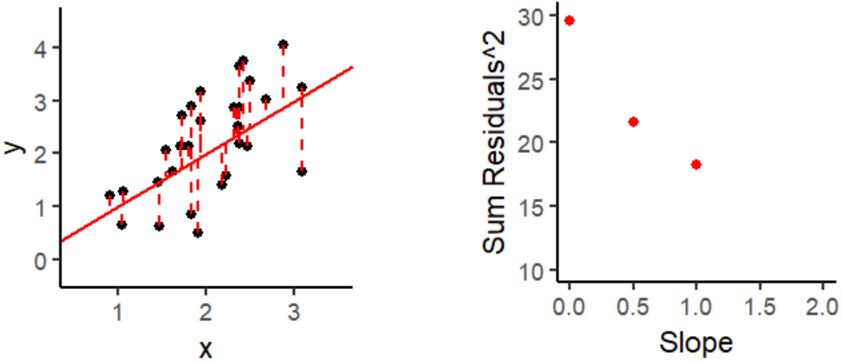
Slope = 1

Sum of Residuals^2 = 18.3



1. Regression as Least Squares

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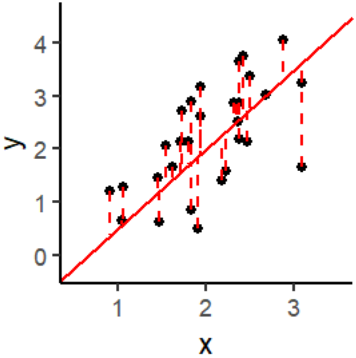
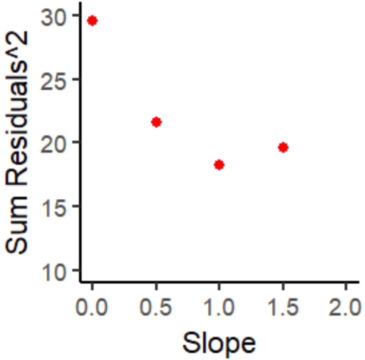
Slope = 1.5



Sum of Residuals^2 = 19.6



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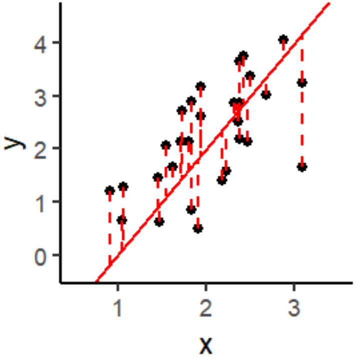
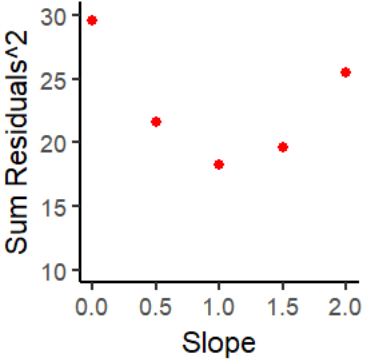
Slope = 2



Sum of Residuals^2 = 25.5



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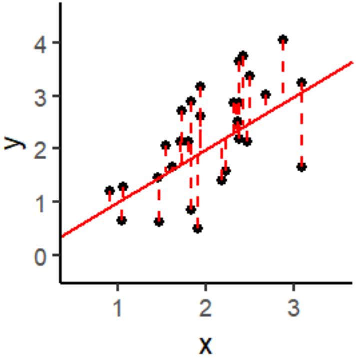
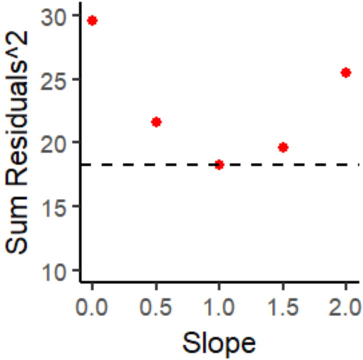
Slope = 1



Sum of Residuals^2 = 18.3



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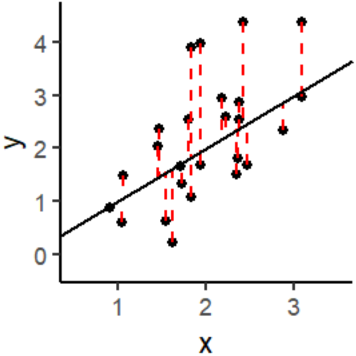
     - The residual error increases
   - $y_i = \alpha + \beta D_i + \epsilon_i$

Slope = 1



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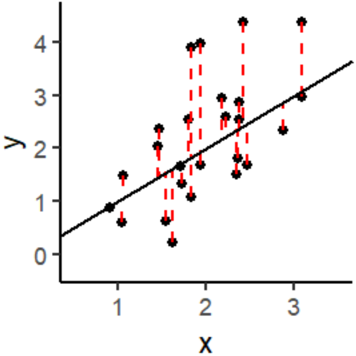
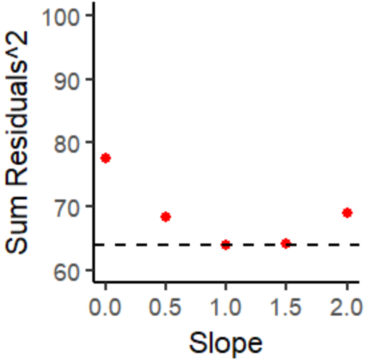


Sum of Residuals^2 = 63.9



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- Dummy control variables *remove variation* associated with specific levels or categories
  - The same as Fixed Effects

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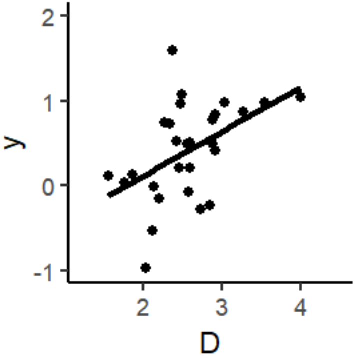
- $y_{ij} = \alpha + \beta_1 D_{ij} + \epsilon_i$



Ignoring the dummy control variable, the slope coefficient is 1

1. Regression as Least Squares

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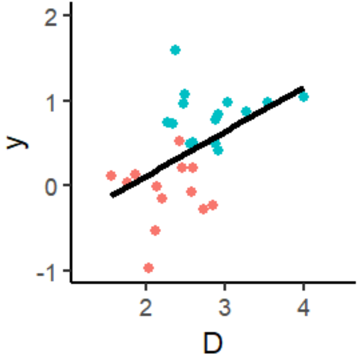

But the data points really represent two very different groups, blues and reds

1. Regression as Least Squares

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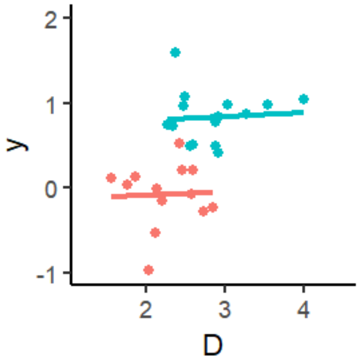
- $y_{ij} = \alpha + \beta_1 D_{ij} + \beta_2 X_j + \epsilon_i$



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

1. Regression as Least Squares

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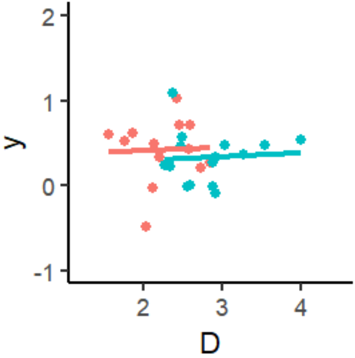

Dummy control variables *remove* the average Y differences between blues and reds

1. Regression as Least Squares

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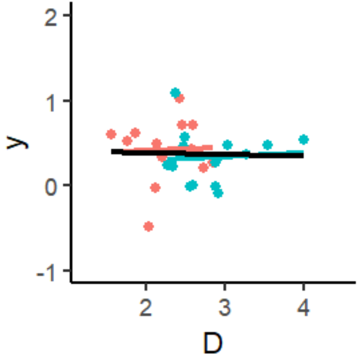

The new regression line for the full data now has a slope of zero

1. Regression as Least Squares

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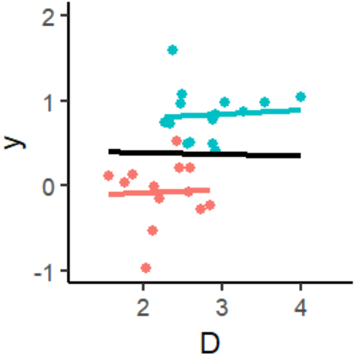

Equivalently, dummy control variables restrict comparisons to **within the same group**:

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

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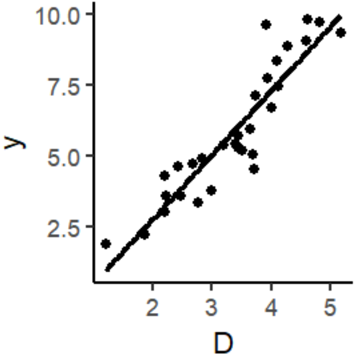

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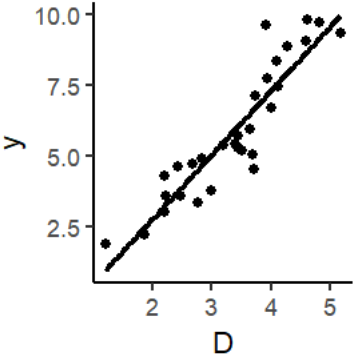

The coefficient β_1 is 2.267
Real effect = 1

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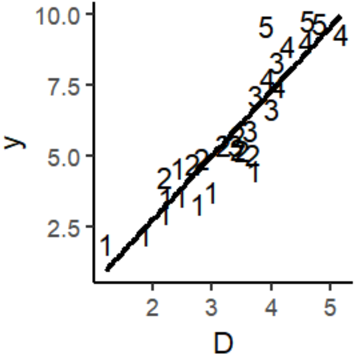

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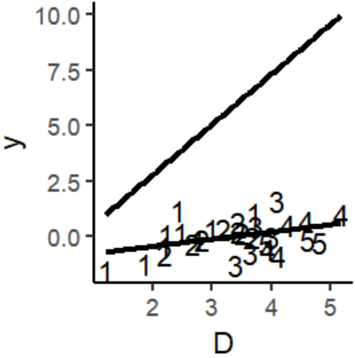

The coefficient β_1 is 1.024
Real effect = 1

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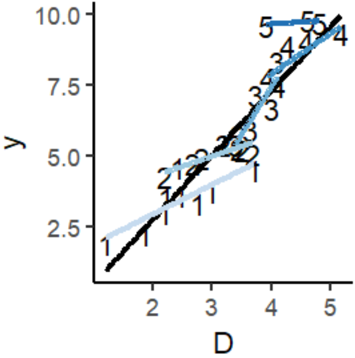

- Equivalently, we subset the data to each value of X, and find each slope

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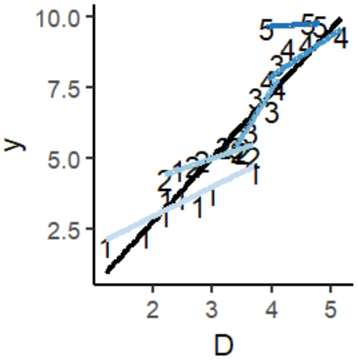

- Equivalently, we subset the data to each value of X, and find each slope
- Then average these slopes, $\beta_1 \sim 1$

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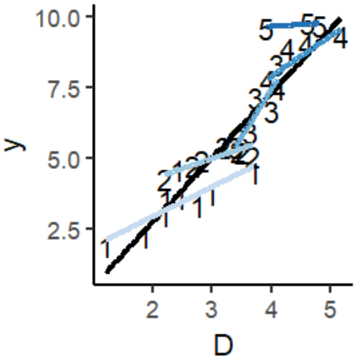

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- Impossible with truly continuous variables

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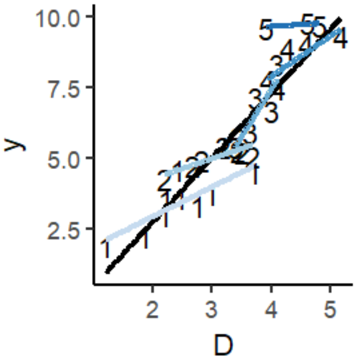

- Equivalently, we subset the data to each value of X, and find each slope
- Then average these slopes, $\beta_1 \sim 1$
- Impossible with truly continuous variables
- So regression uses linearity to fill in the gaps

2. 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?

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

2. Regression as Conditional Expectation

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

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

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

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

2. Regression as Conditional Expectation

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

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

2. Regression as Conditional Expectation

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

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

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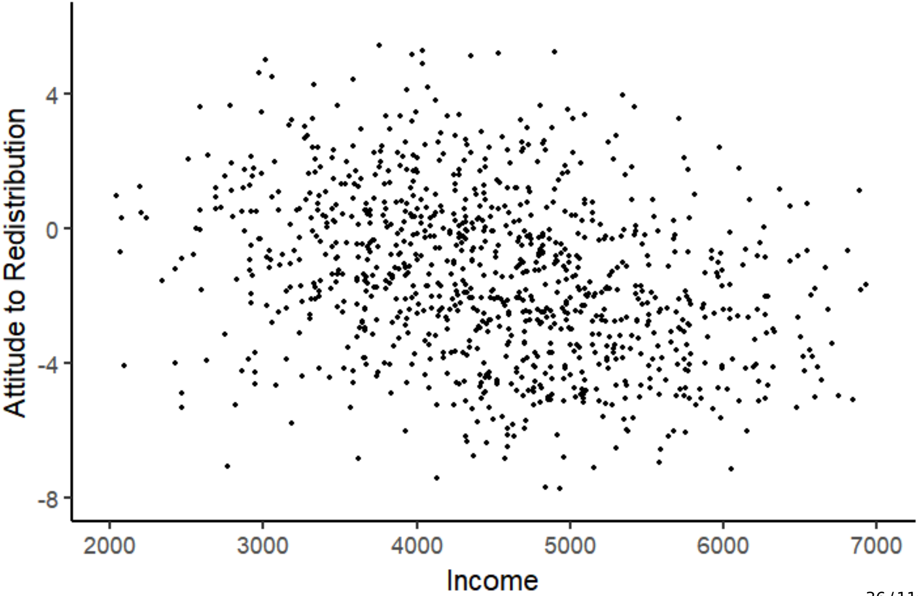

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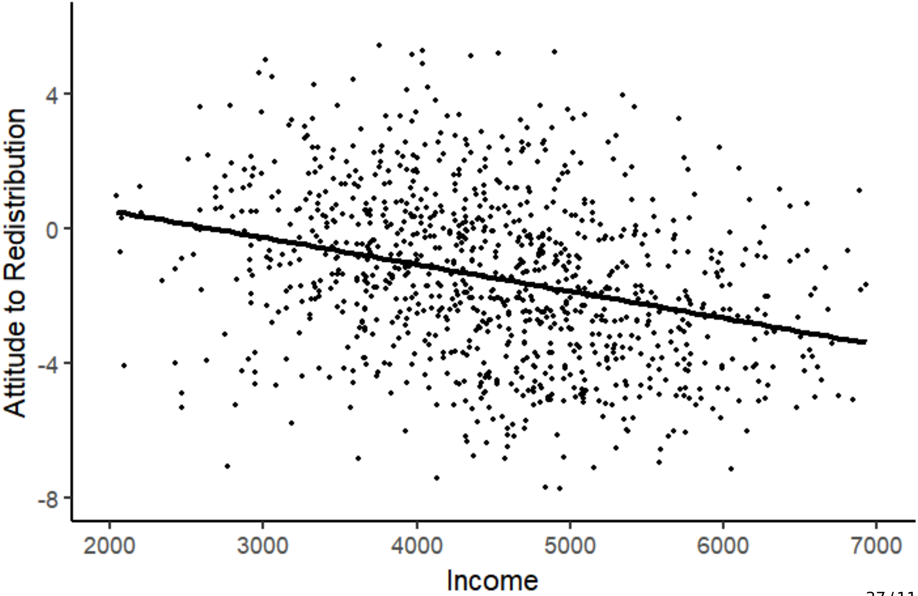

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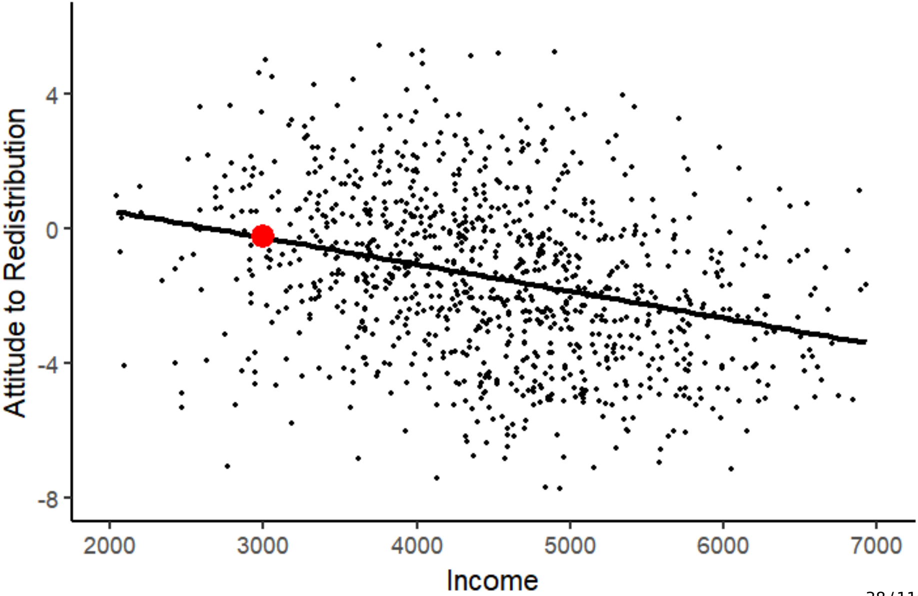

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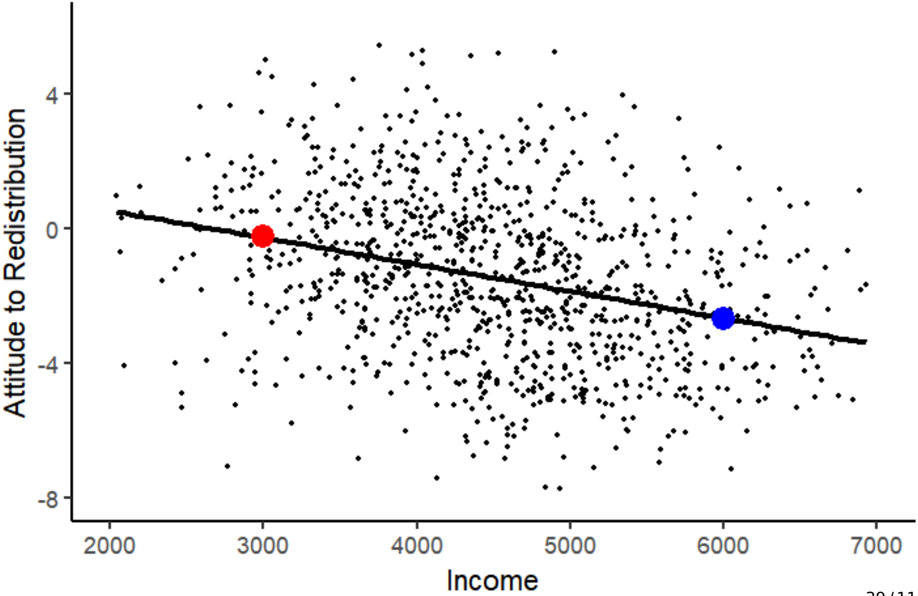

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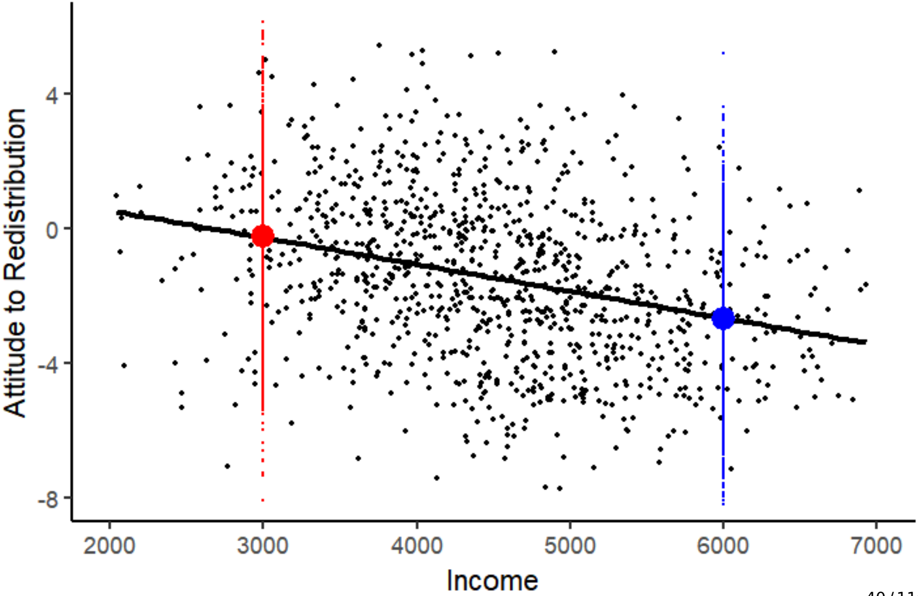

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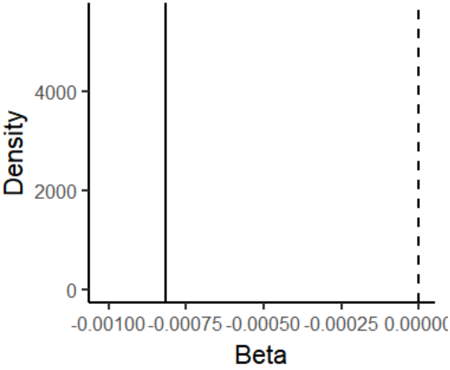
Observations	1,000
Note:	*p<0.1; **p<0.05; ***p<0.01



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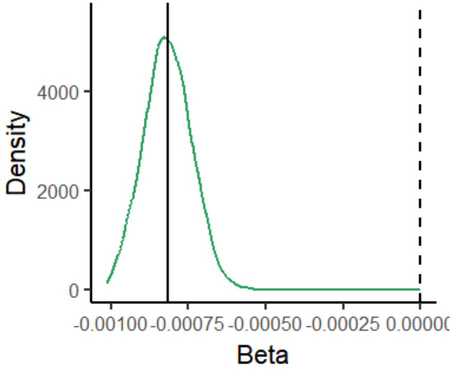

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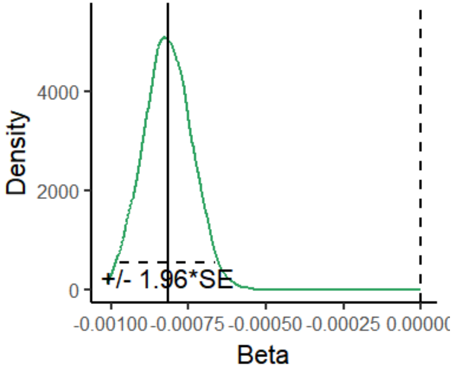

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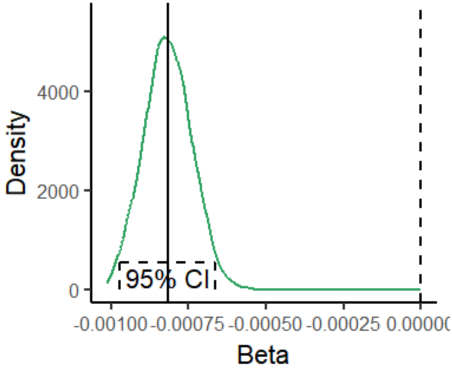

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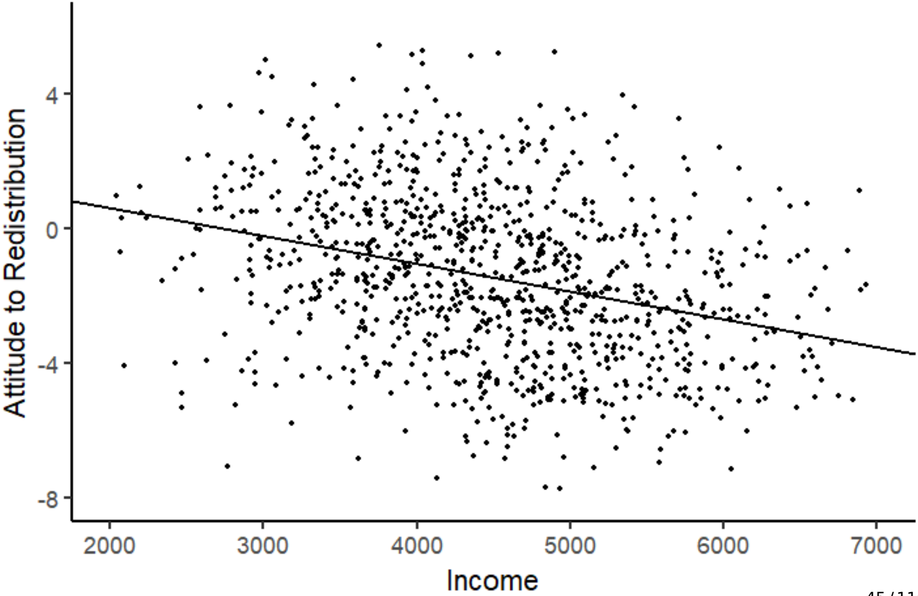

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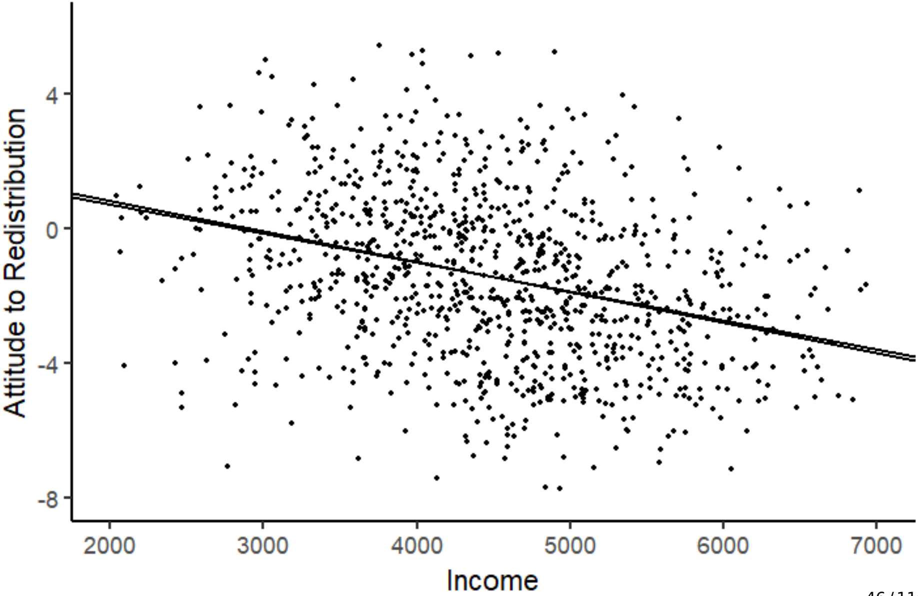

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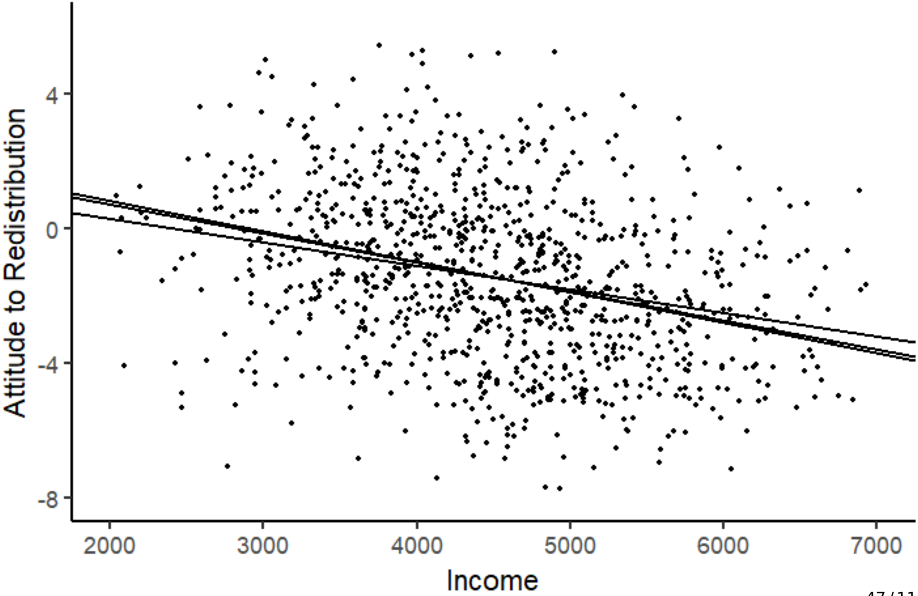

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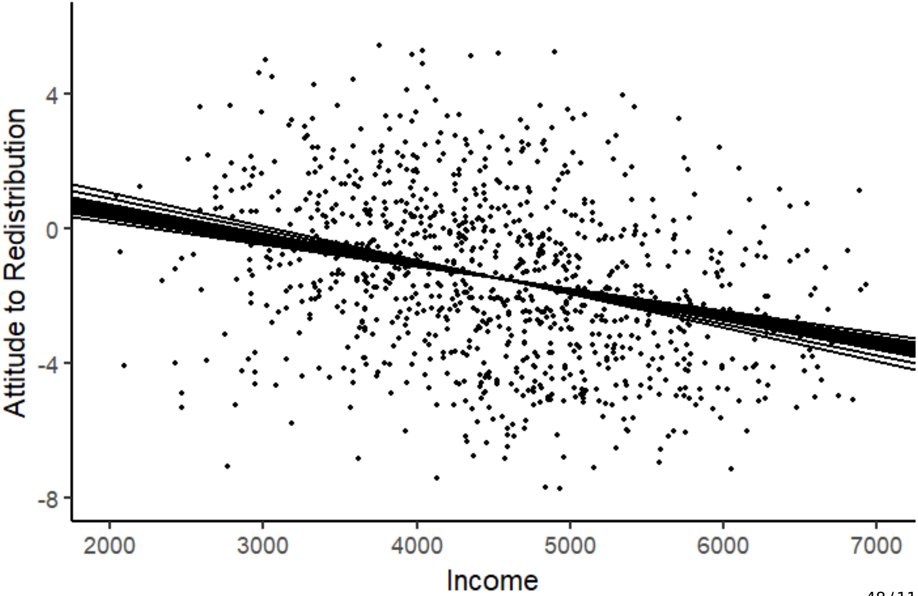

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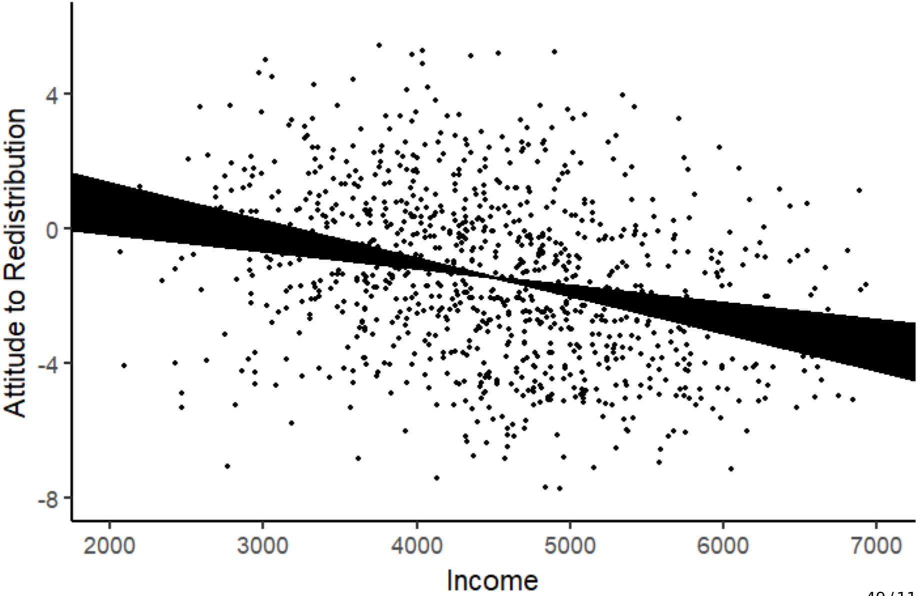

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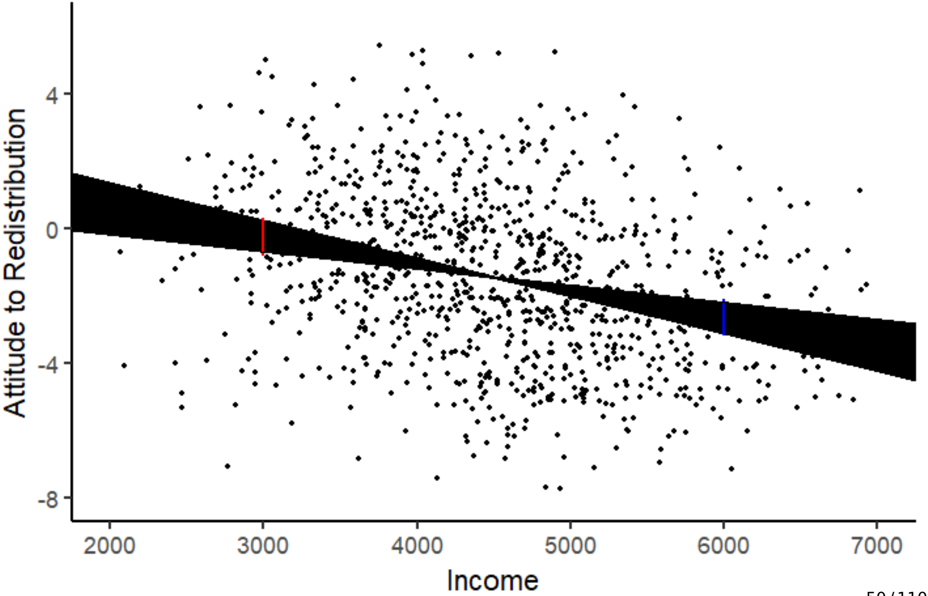

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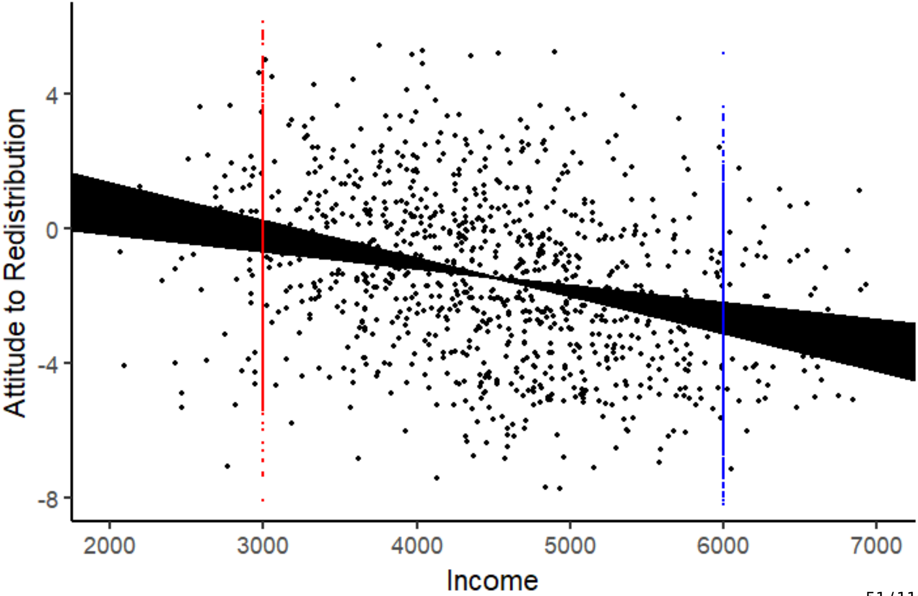

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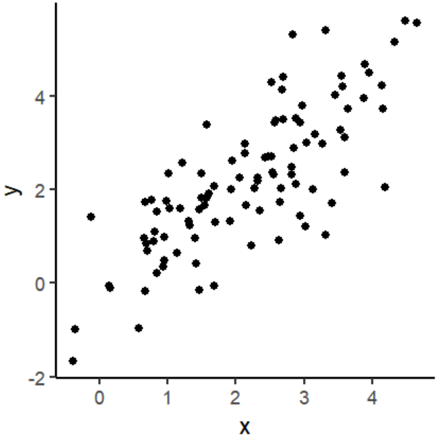

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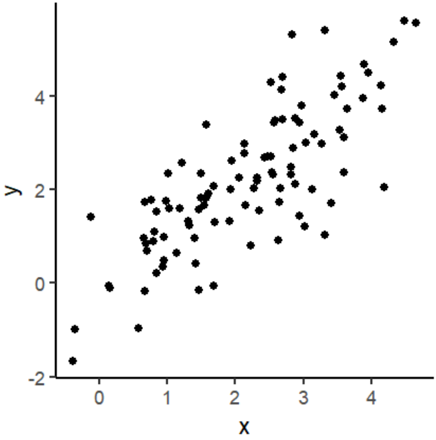

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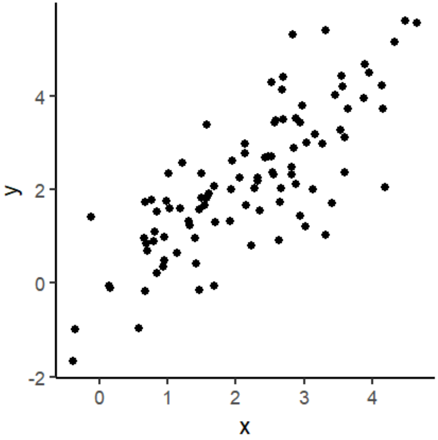

- Correlation is 0.781
- Regression Results:

	term	estimate
1	(Intercept)	0.006
2	x	1.008

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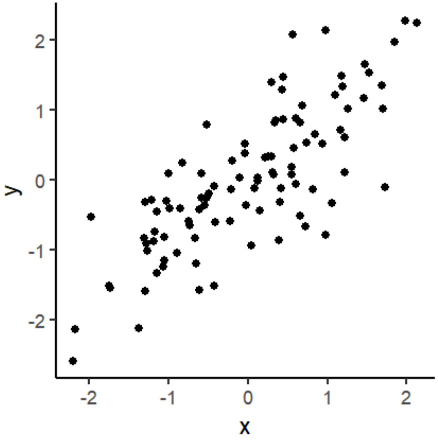
- $\hat{\beta} = cor(x, y) * \frac{\sigma_Y}{\sigma_X}$



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

	term	estimate
1	(Intercept)	0.000
2	x	0.781

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

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

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

Section 2

Guide to 'Smart' Regression

Regression Guide

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

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

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

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  - "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?"

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- Only include controls where there is theory or evidence that this variable could be an **omitted variable**
- Controlling for post-treatment variables can make your estimate *worse*

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- 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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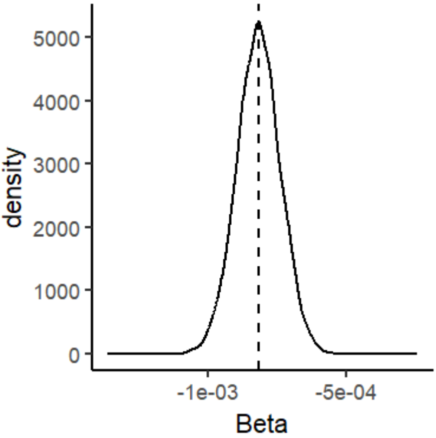

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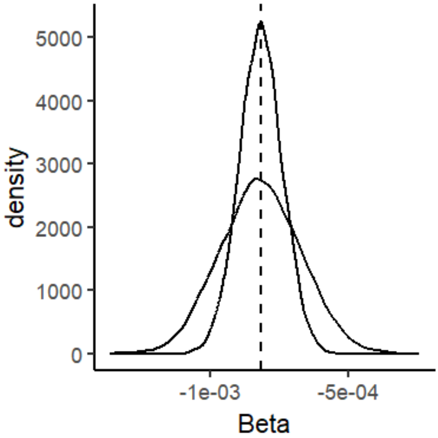

- With clustered SEs, the wider distribution of our betas suggests we're *less* confident β is close to -0.0008175

7. Interpreting Regression Results

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- 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:** $log(\frac{Pr(y_i=1)}{Pr(y_i=0)}) = \alpha + \beta D_i + \epsilon$
  - 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:** $log(\frac{Pr(y_i=C)}{Pr(y_i=B)}) = \alpha + \beta D_i + \epsilon$
  - 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 B to the outcome category C, holding other variables constant

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

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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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gender1	−2.942614*** (0.700510)
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Constant	0.112903 (0.454926)
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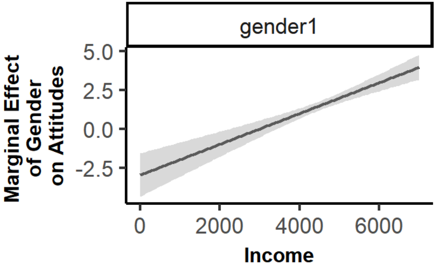

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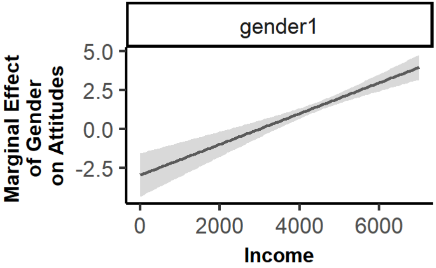

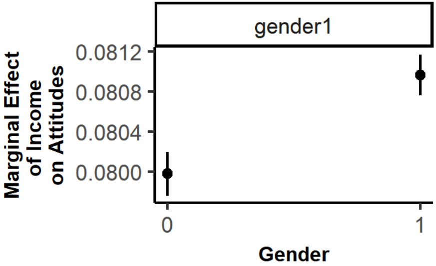

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  - And p-values are arbitrary (0.049 vs. 0.051)
- Better to make specific *predictions* of how changes in D produce changes in Y

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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:

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

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

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

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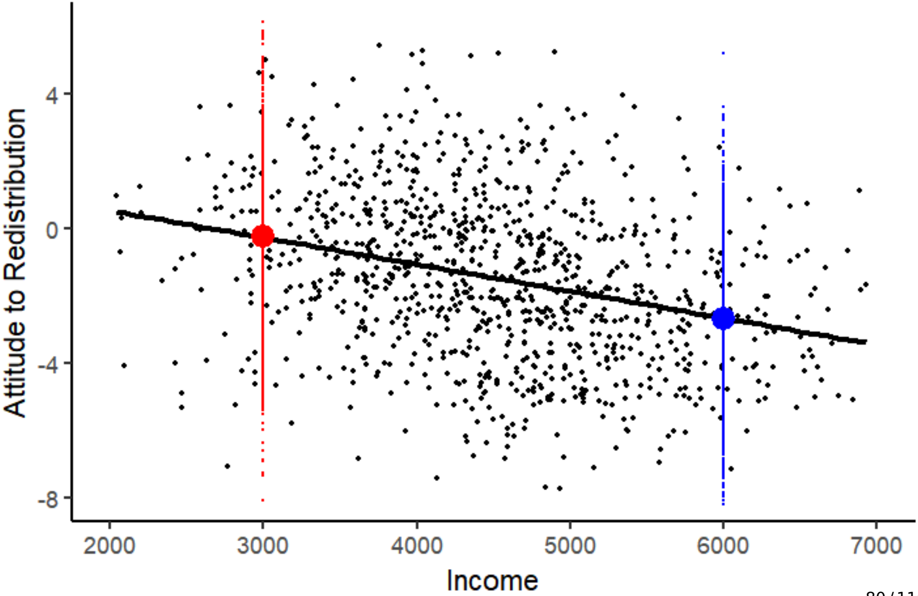
Increasing Income from 3000 to 6000:

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

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

$$\Delta Attitude_i = -2.454$$

8. Predictions from Regressions



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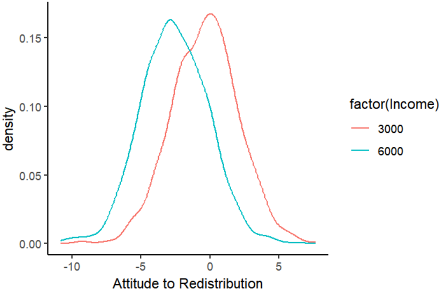

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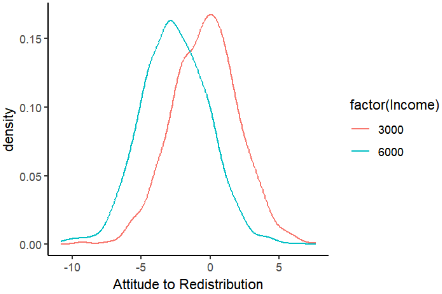
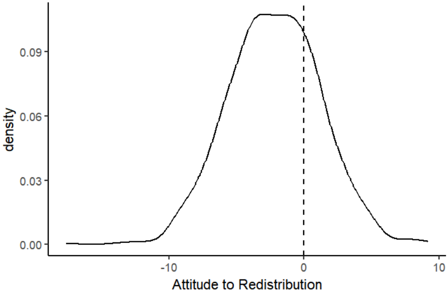


First Differences:



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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

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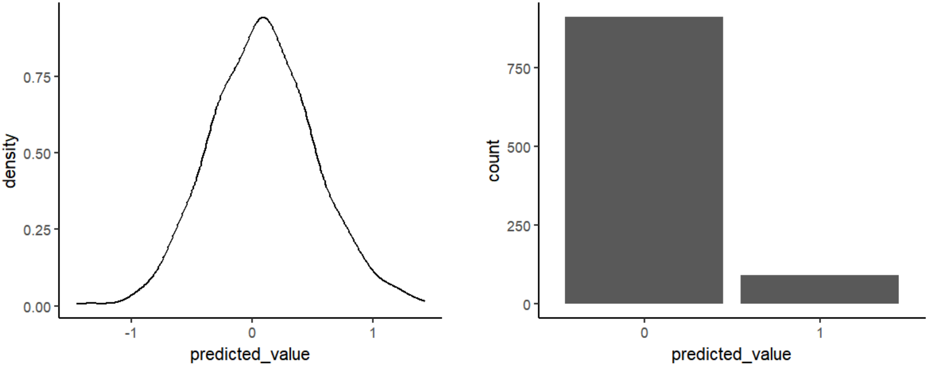
- The regression model matters because the wrong model makes non-sensical predictions
- Consider a binary outcome: $Gender_i = \alpha + \beta Income_i + \epsilon_i$
- Compare the OLS and Logit **predictions** of gender for an income of R$3000:



Section 3

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- These all require **research design**, **theory** and **assumptions**

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

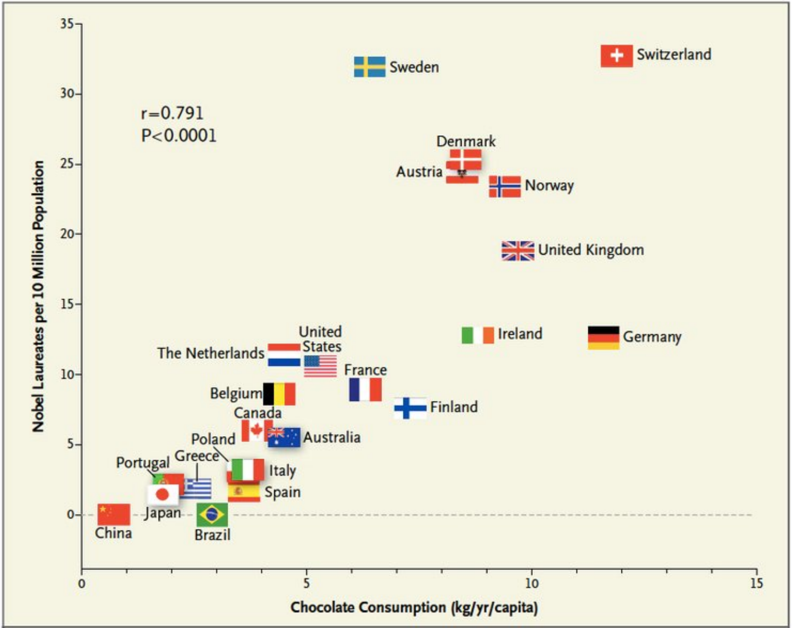
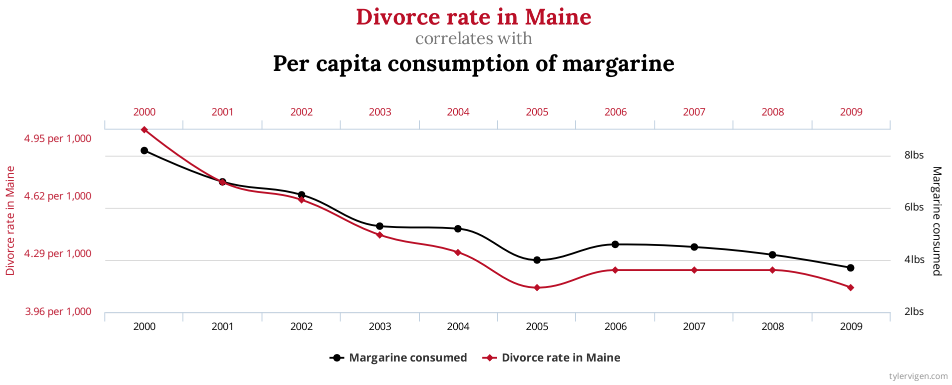


Figure 1. Correlation between Countries' Annual Per Capita Chocolate Consumption and the Number of Nobel Laureates per 10 Million Population.


Divorce rate in Maine
correlates with
Per capita consumption of margarine
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
4.95 per 1,000
4.62 per 1,000
4.29 per 1,000
3.96 per 1,000
Divorce rate in Maine
8lbs
6lbs
4lbs
2lbs
Margarine consumed
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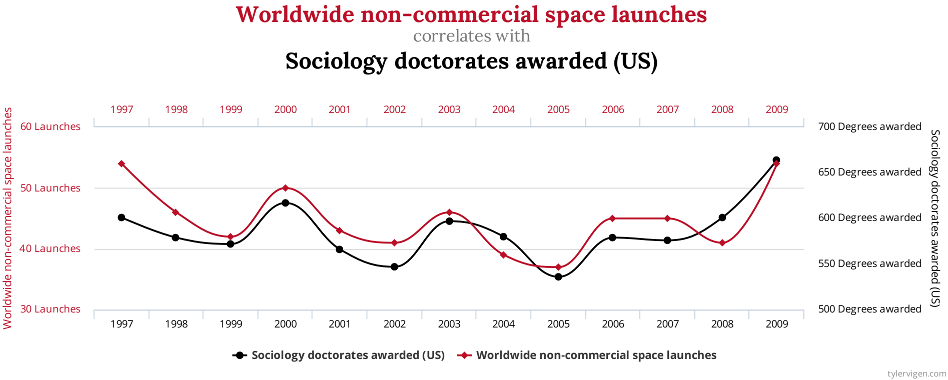
tylervigen.com



Worldwide non-commercial space launches
correlates with
Sociology doctorates awarded (US)
1997
1998
1999
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
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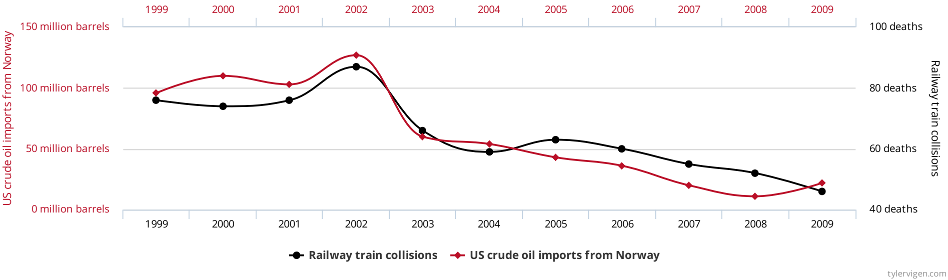
tylervigen.com

US crude oil imports from Norway

correlates with

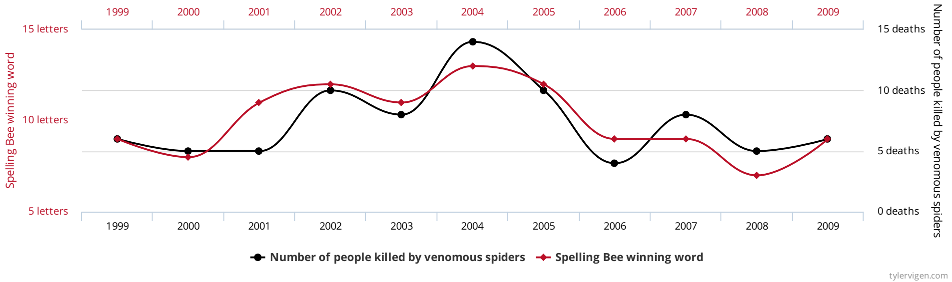
Drivers killed in collision with railway train



Letters in Winning Word of Scripps National Spelling Bee

correlates with

Number of people killed by venomous spiders



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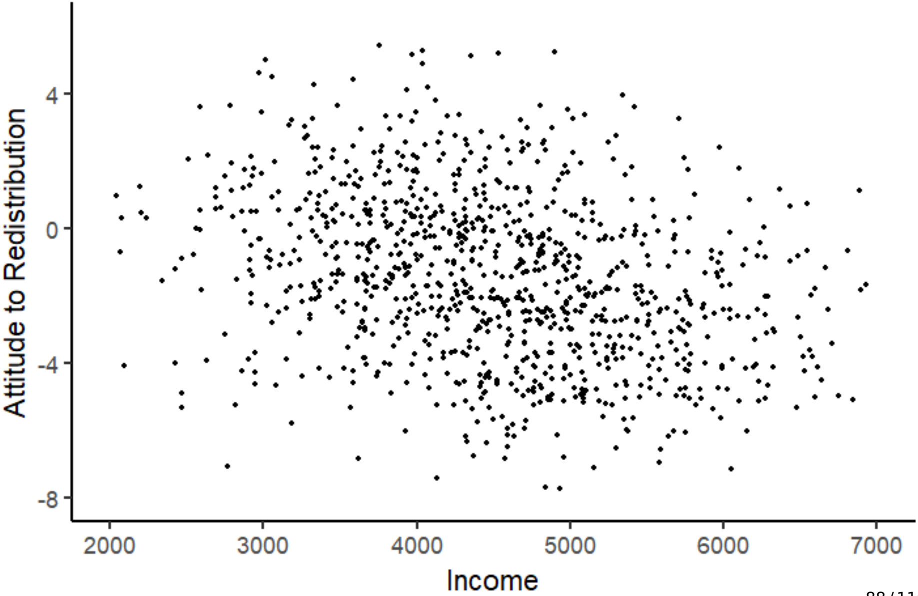

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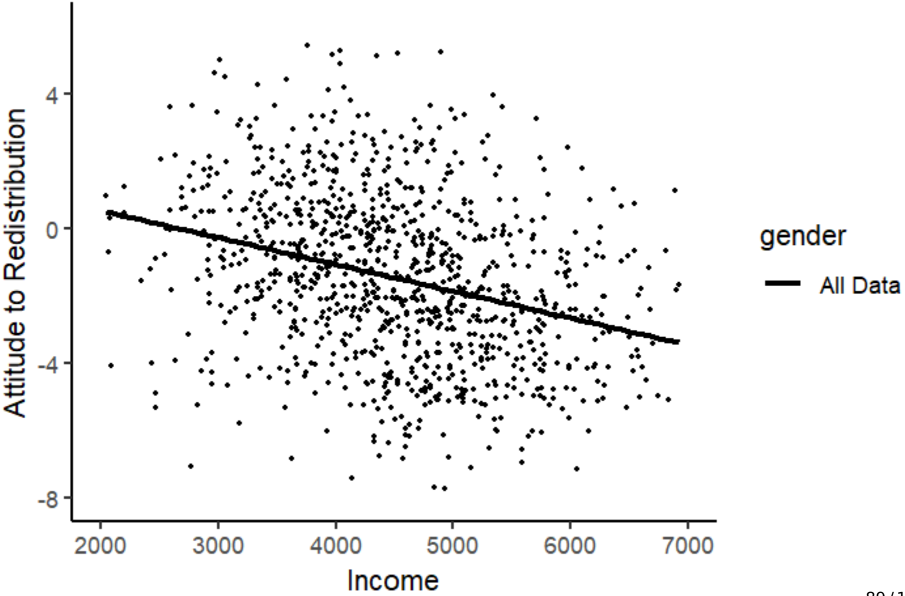

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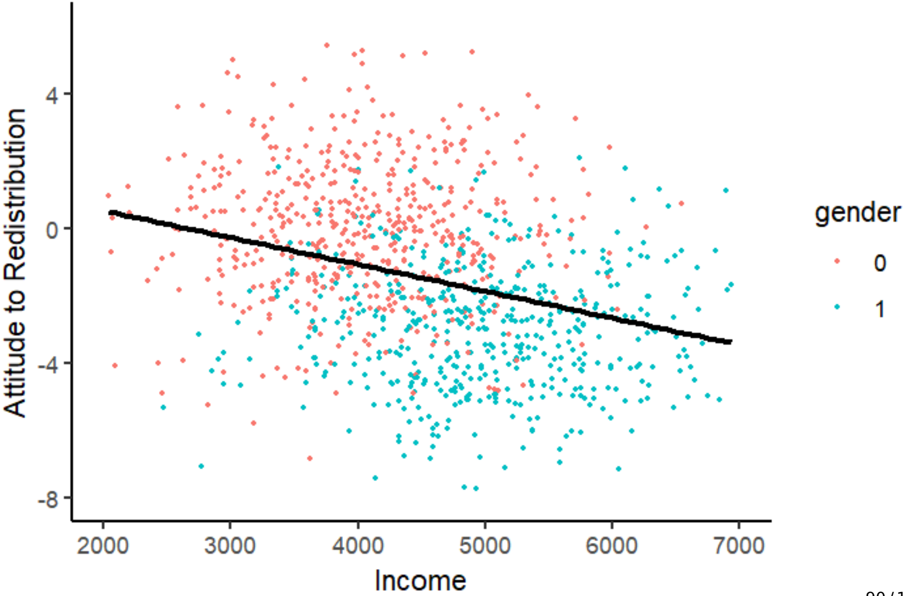

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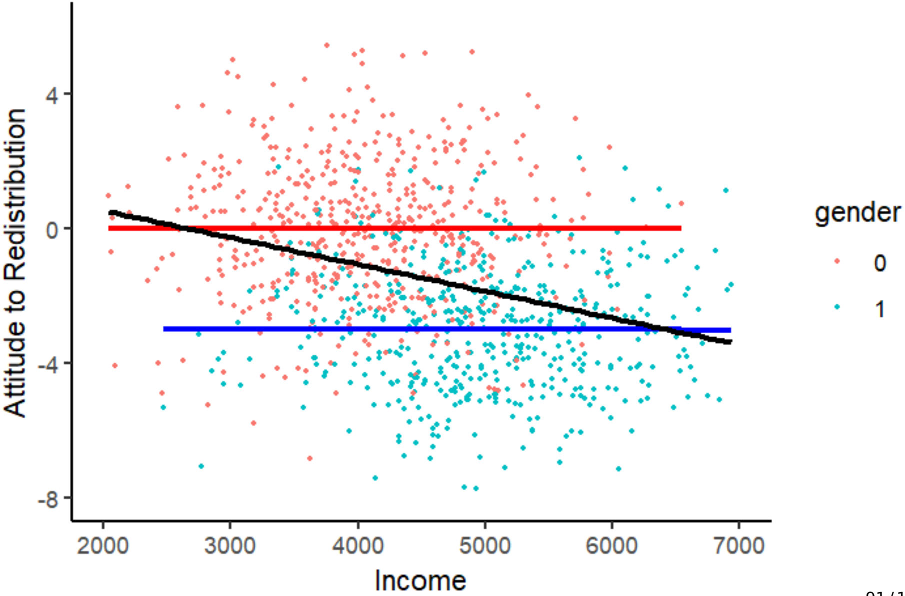

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	Dependent variable:
	redist
income	−0.011 (0.029)
gender1	−1.201*** (0.058)
Constant	0.589*** (0.038)
Observations	1,000
Note:	*p<0.1; **p<0.05; ***p<0.01

	Dependent variable:
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  - It minimizes the *prediction errors* for Y
- But that doesn't mean it identifies the direction of causation!

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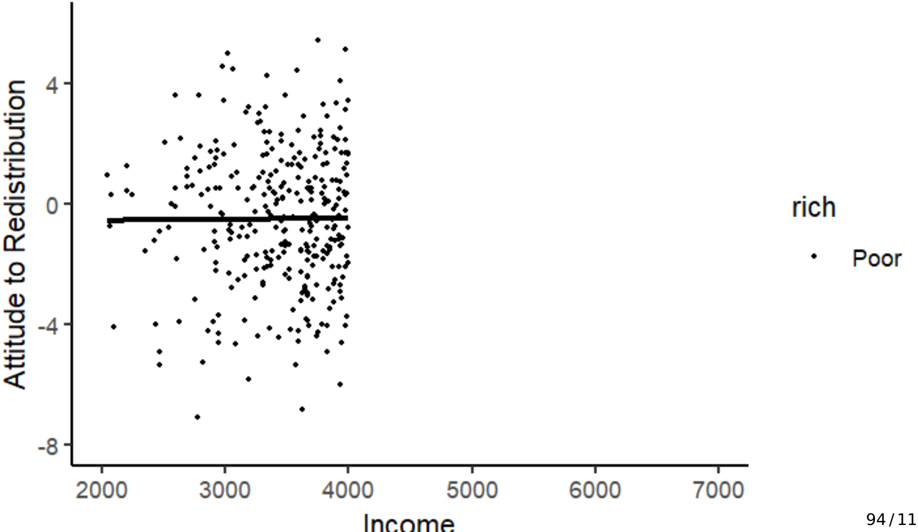
- But negative attitudes to redistribution might also make you more likely to work in the private sector and cause you to receive a higher salary
- Both would look the same in a regression
- We cannot *explain* the relationship with a regression

3. Selection Bias

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



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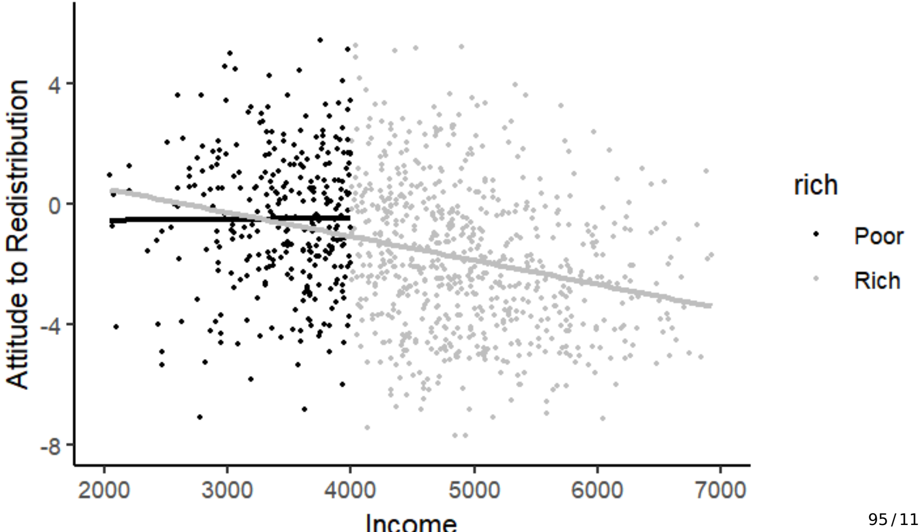

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  1. **Selection into existence**
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- In each case, we don't see the *full* relationship between D and Y
- So our regression estimates are biased

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     - 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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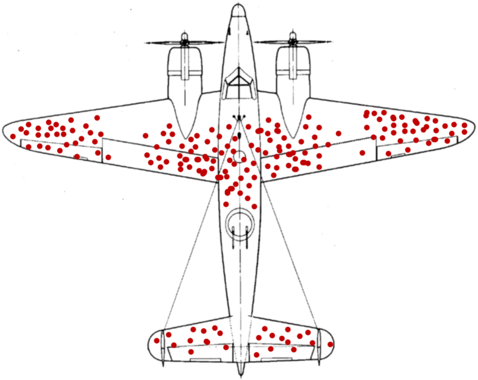

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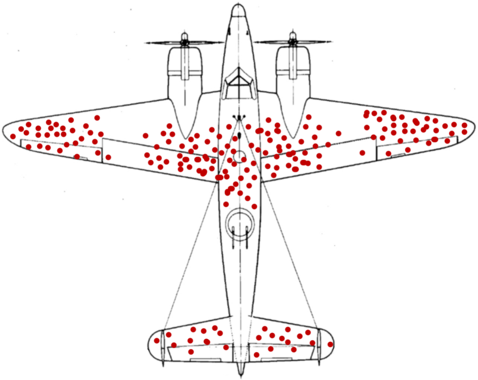

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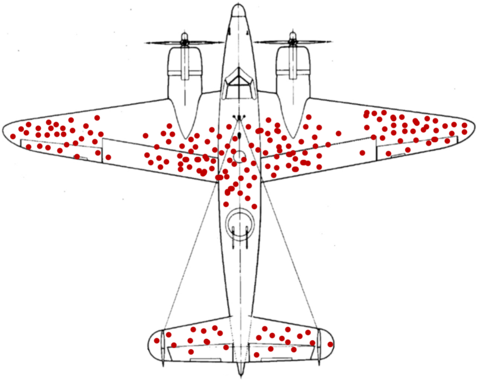

- Where would additional armour protect bombers?
- Returned bombers got hit
- But we do not know where *bombers that did not return* got hit

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The rich refuse to answer surveys for fear of paying taxes

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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?

Very likely!

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

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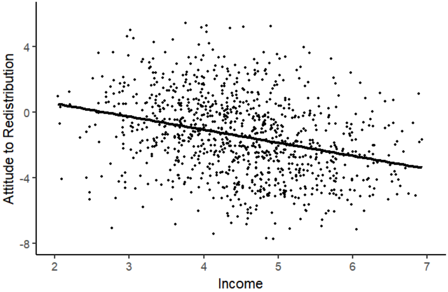
Accurate Data:



	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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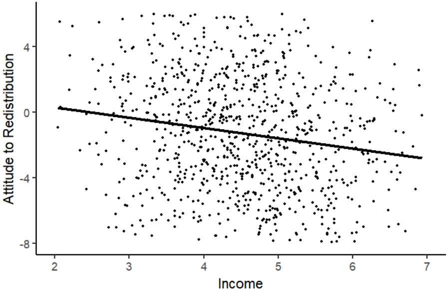
Noise in the **outcome variable**:



	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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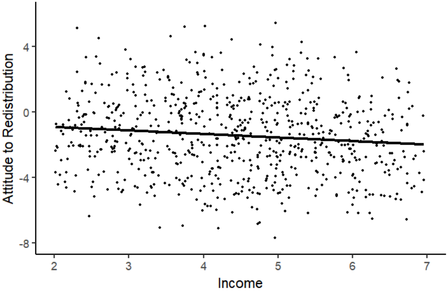
Noise in the **explanatory** variable:



	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

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Lack of overlap probably means we *cannot* explain outcomes with this data

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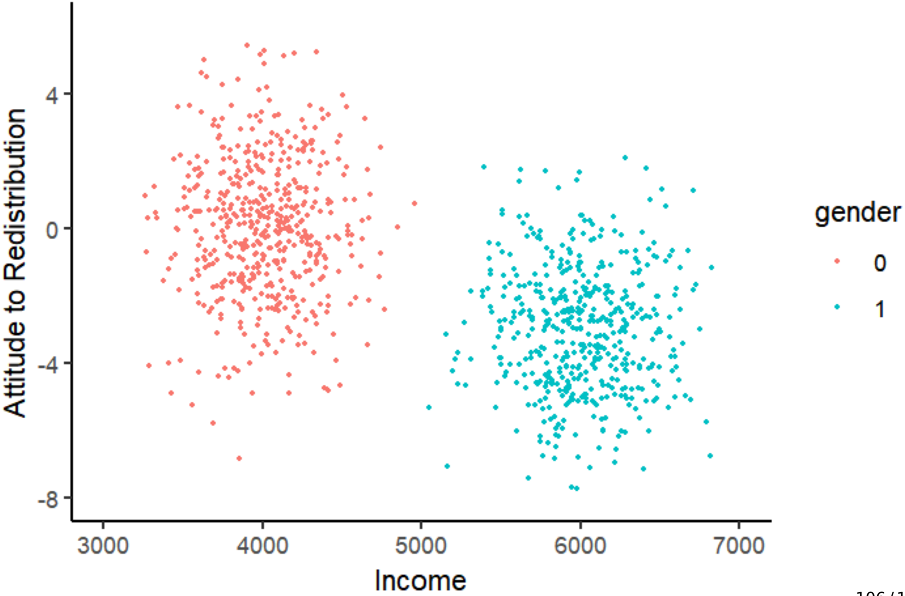

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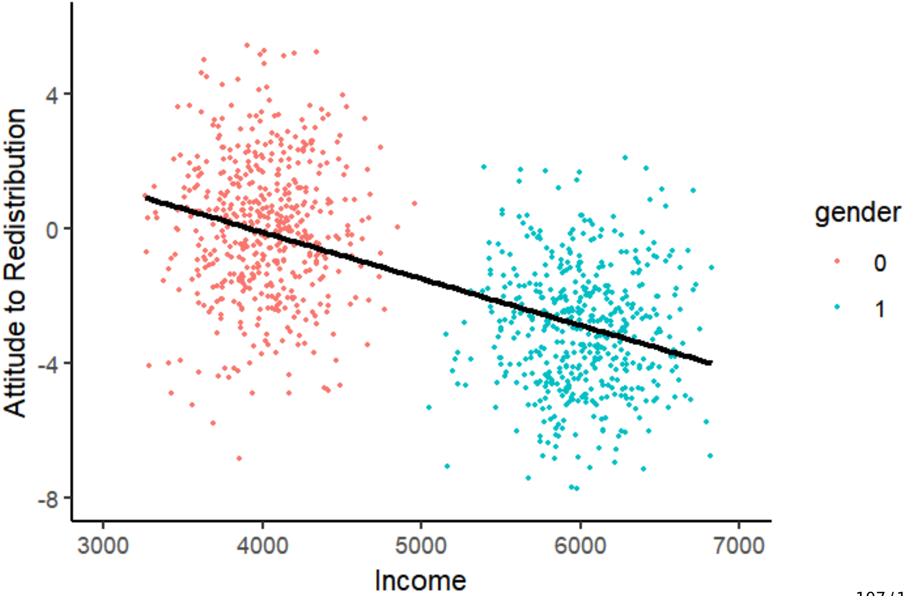

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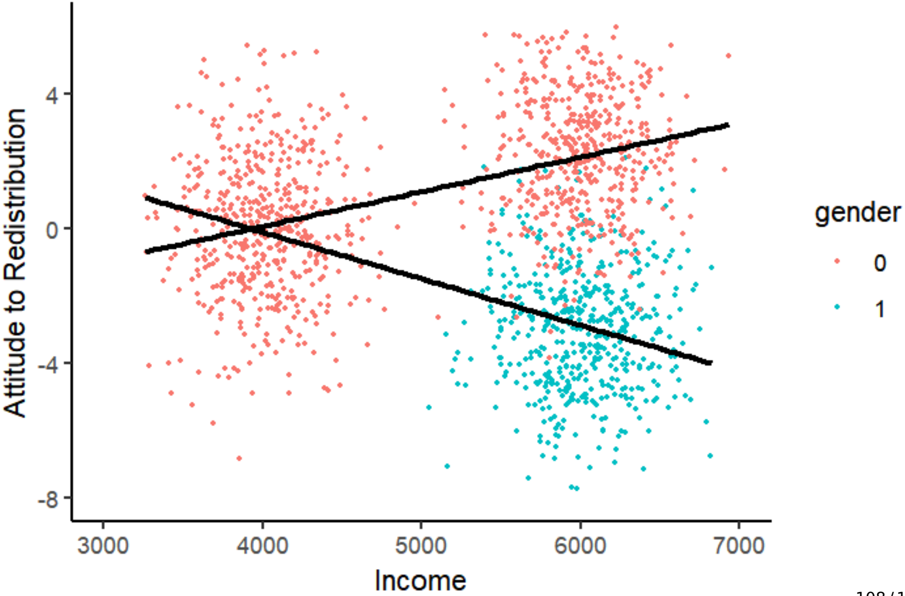

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And of **model dependence** - our results depend on the functional form (linear, quadratic etc.) in our regression model

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Explanation depends on research design, data selection, assumptions and qualitative evidence