

FLS 6441 - Methods III: Explanation and Causation

Week 1 - Review

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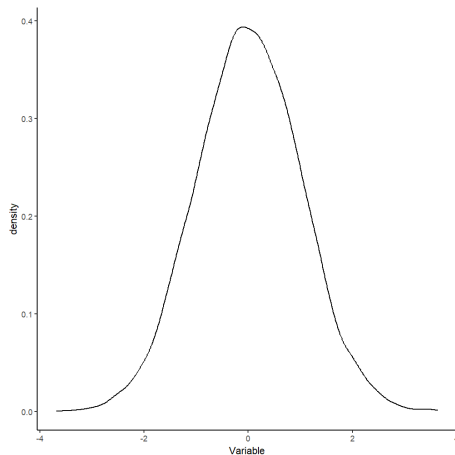
Course Objectives

1. temp

Data

1. We work with variables, which VARY!

	Variable
1	1.68
2	0.25
3	1.30
4	-1.12
5	-0.80
6	-0.54
7	-0.92
8	0.53
9	1.11
10	-0.63



Regression

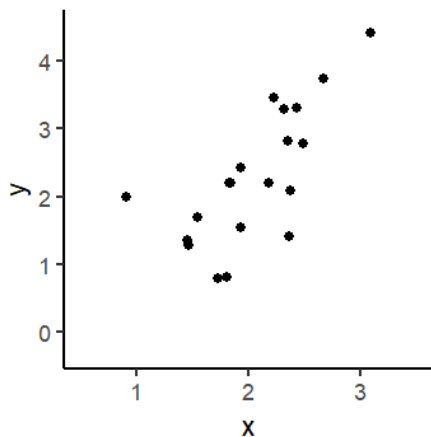
- ▶ Regression identifies the line through the data that minimizes the sum of squared vertical distances

Regression

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- ▶ $y_i = \alpha + \beta X_i + \epsilon_i$

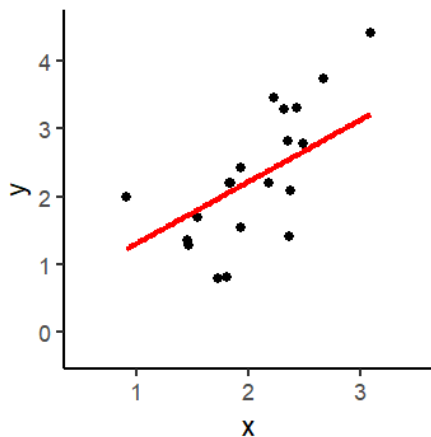
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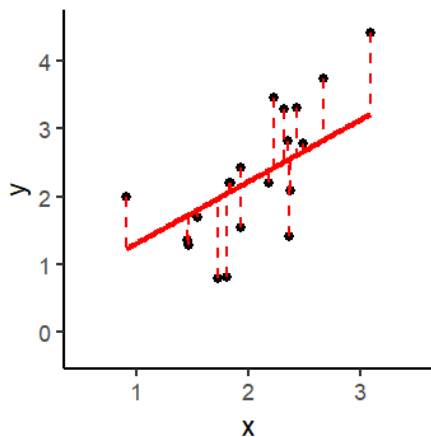
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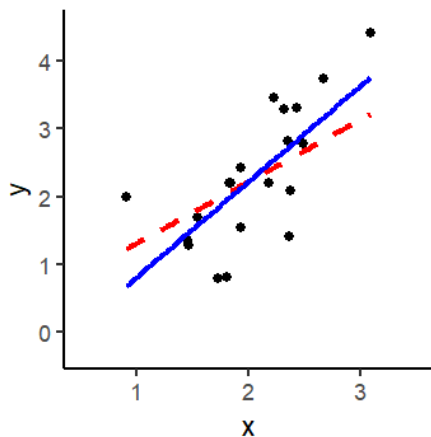
- ▶ Regression identifies the line through the data that minimizes the sum of squared vertical distances
- ▶ $y_i = \alpha + \beta X_i + \epsilon_i$



- ▶ Sum of Squared distances = 10.39

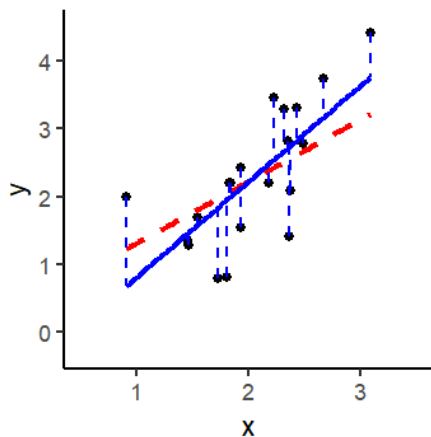
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- ▶ Sum of Squared distances
= 9.19

Regression

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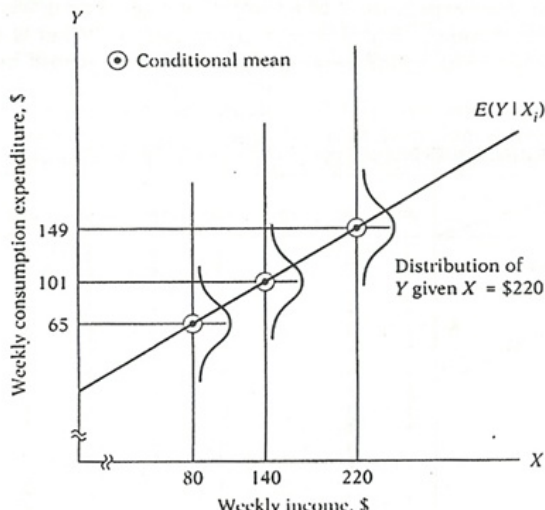
- ▶ Regression is a **Conditional Expectation Function**
- ▶ Conditional on x , what is our expectation (mean value) of y ?
- ▶ $E(y|x)$
- ▶ When age is 20 ($x = 40$), the average salary is R1.000 ($y = 1.000$)
- ▶ When age is 40 ($x = 40$), the average salary is R2.000 ($y = 2.000$)

Regression

- ▶ Regression is a **Conditional Expectation Function**: $E(y|x)$

Regression

- ▶ Regression is a **Conditional Expectation Function**: $E(y|x)$
- ▶ It predicts the **mean**, not the median, not the minimum, not the maximum



Regression

$$\hat{\beta}_1 = \frac{\sum_i (x_i - \bar{x})(y_i - \bar{y})}{\sum_i (x_i - \bar{x})^2}$$
$$\hat{\beta}_0 = \bar{y} - \hat{\beta}_1 \bar{x}$$

Regression

- ▶ Regression with two variables is very similar to calculating correlation

Regression

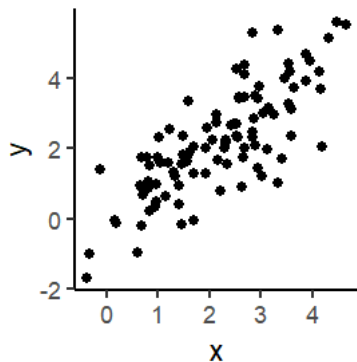
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Regression

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- ▶ $\hat{\beta} = \text{cor}(x, y) * \frac{\sigma_Y}{\sigma_X}$
- ▶ It's *identical* if we standardize both variables first ($\frac{(x-\bar{x})}{\sigma_x}$)

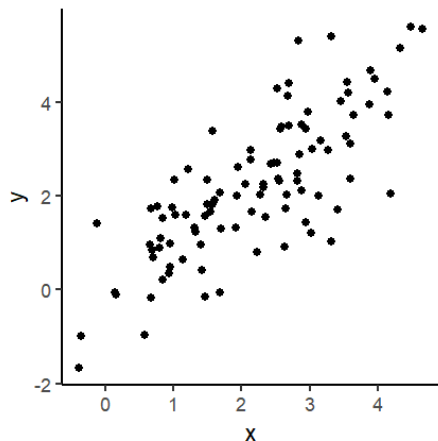
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Regression

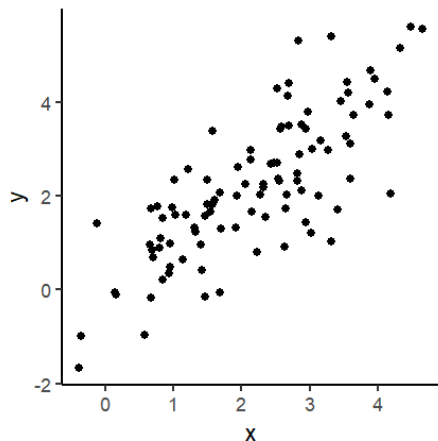
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- ▶ Correlation is 0.781

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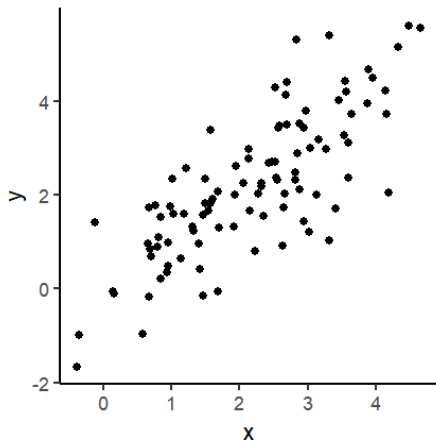


- ▶ Correlation is 0.781
- ▶ Regression Results:

	term	estimate
1	(Intercept)	0.006
2	x	1.008

Regression

- ▶ Regression with two variables is very similar to calculating correlation:
- ▶ $\hat{\beta} = \text{cor}(x, y) * \frac{\sigma_Y}{\sigma_X}$
- ▶ It's *identical* if we standardize both variables first ($\frac{(x-\bar{x})}{\sigma_x}$)



- ▶ Correlation is 0.781
- ▶ Standardized Regression Results:

	term	estimate
1	(Intercept)	0.000
2	x	0.781

Regression

- ▶ Regression with **multiple** variables is very similar to calculating **partial** correlation:

Regression

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- ▶ Just a small difference in the denominator (how we standardize the measure)

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

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

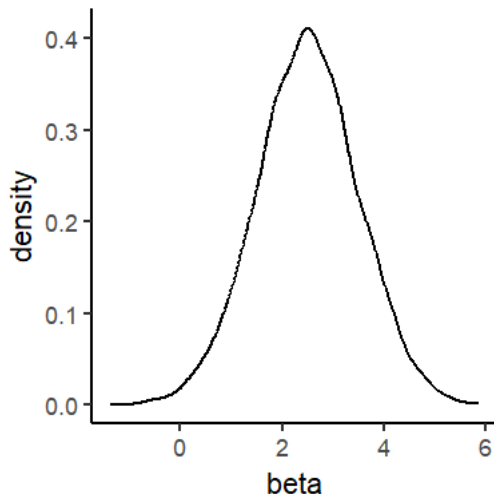
- ▶ **There is no magic in regression, it's just correlation**

Regression

- ▶ We **NEVER** know the true value of β

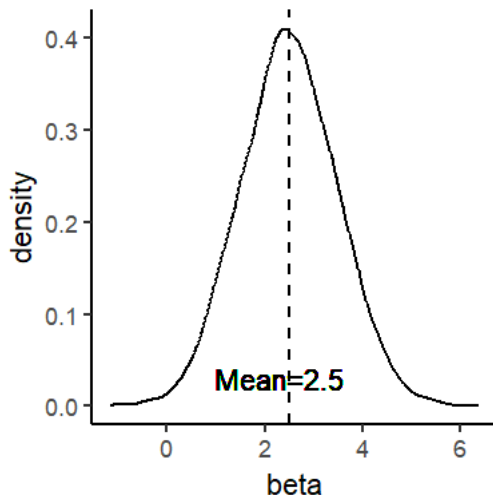
Regression

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- ▶ We **estimate a distribution** for β



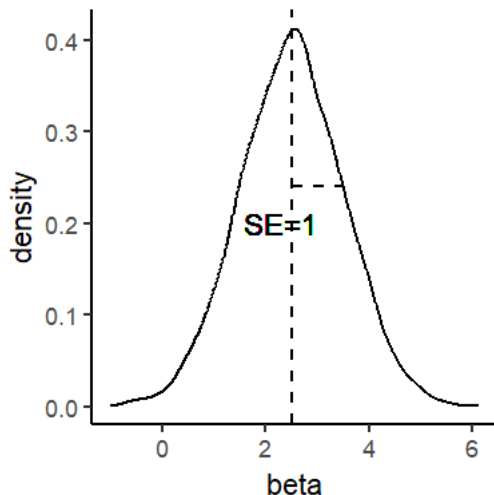
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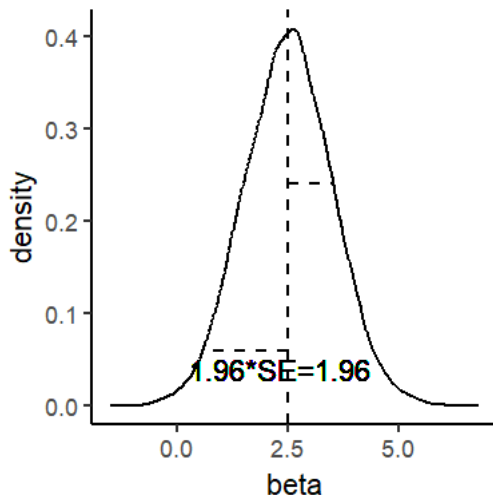
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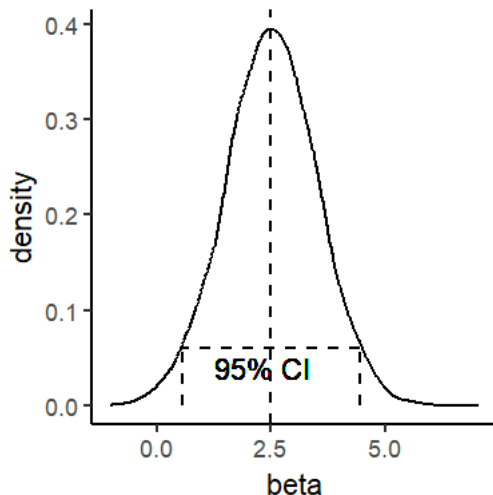
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Regression Guide

1. **Choose variables and measures:** To test a specific hypothesis
2. **Choose a Model/Link Function:** Should match the data type of your outcome variable
3. **Choose Covariates:** To match your strategy of inference
4. **Choose Fixed Effects:** To focus on a specific level of variation
5. **Choose Error Structure:** To match known dependencies/clustering in the data
6. **Interpret the coefficients:** Depending on the type/scale of the explanatory variable

2. Regression Models

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

- ▶ Continuous -> Ordinary Least Squares

```
zelig(Y ~ X, data=d, model="ls")
```

- ▶ Binary -> Logit

```
zelig(Y ~ X, data=d, model="logit")
```

- ▶ Unordered categories -> Multinomial logit

```
zelig(Y ~ X, data=d, model="mlogit")
```

- ▶ Ordered categories -> Ordered logit

```
zelig(Y ~ X, data=d, model="ologit")
```

- ▶ Count -> Poisson

```
zelig(Y ~ X, data=d, model="poisson")
```

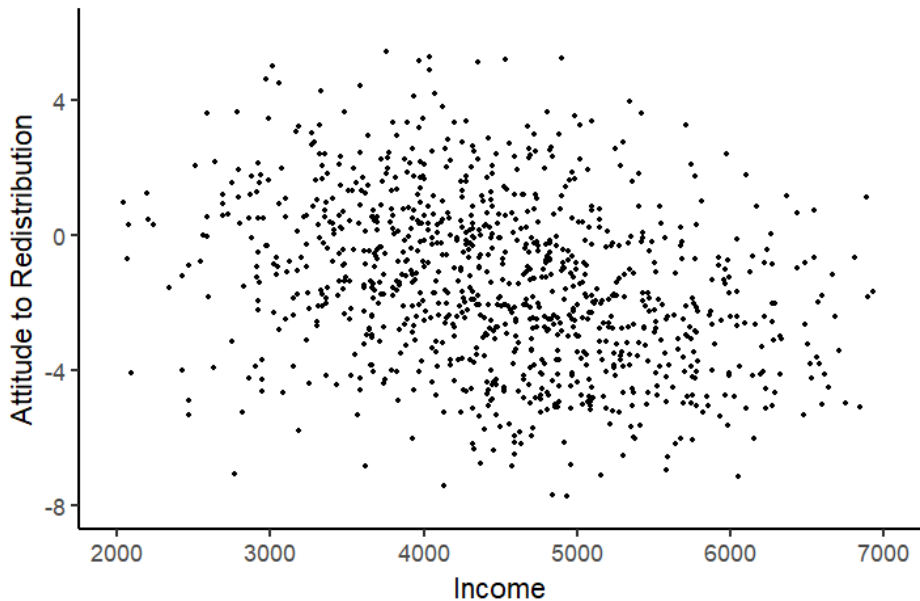
6. Interpreting Regression Results

- ▶ Difficult! It depends on the scale of the explanatory variable, scale of the outcome, the regression model we used, and the presence of any interaction
- ▶ Basic OLS:
 - ▶ 1 [unit of explanatory variable] change in the explanatory variable is associated with a β [unit of outcome variable] change in the outcome

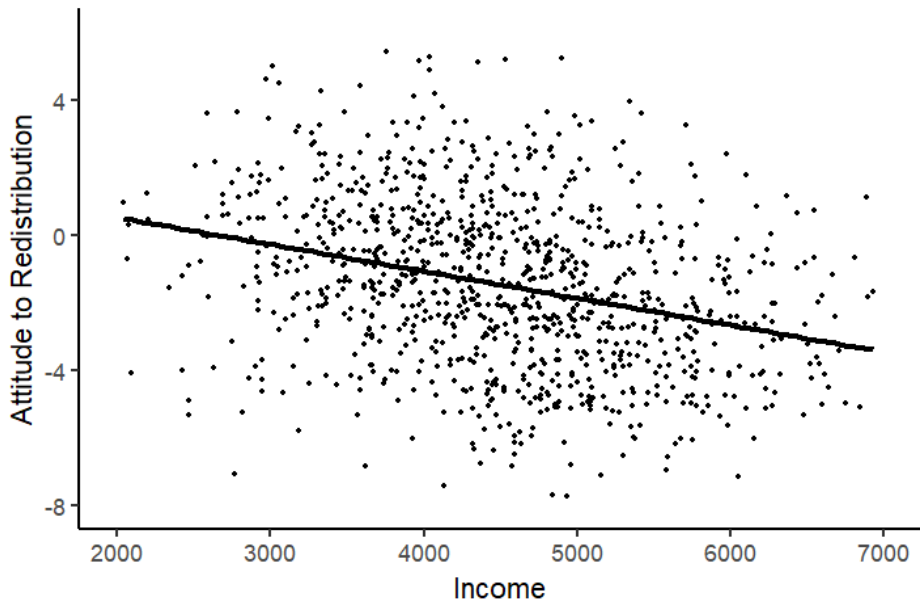
Predictions from Regressions

- temp

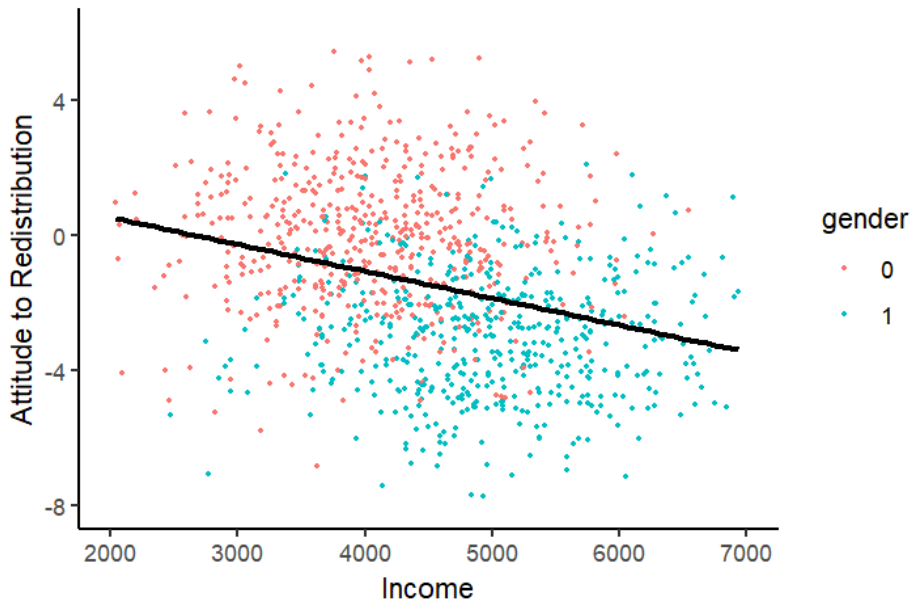
Omitted Variable Bias



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