

# STA 235H - Multiple Regression: Interactions & Nonlinearity

Fall 2023

McCombs School of Business, UT Austin

# Before we start...

- Use the **knowledge check** portion of the JITT to assess your own understanding:
  - Be sure to answer the question correctly (look at the feedback provided)
  - Feedback are **guidelines**; Try to use your *own words*.
- If you are struggling with material covered in STA 301H: **Check the course website for resources and come to Office Hours.**
- **Office Hours Prof. Bennett:** Wed 10.30-11.30am and Thu 4.00-5.30pm

**No in-person class next week -- Recorded class**

# Today

- Quick **multiple regression** review:
  - Interpreting coefficients
  - Interaction models
- **Looking at your data:**
  - Distributions
- **Nonlinear models:**
  - Logarithmic outcomes
  - Polynomial terms



# Remember last week's example? The Bechdel Test

- **Three criteria:**
  1. At least two named women
  2. Who talk to each other
  3. About something besides a man



# Is it convenient for my movie to pass the Bechdel test?

```
lm(Adj_Revenue ~ bechdel_test + Adj_Budget + Metascore + imdbRating, data=bechdel)
```

##		Estimate	Std. Error	t value	Pr(> t )
##	(Intercept)	-127.0710	17.0563	-7.4501	0.0000
##	bechdel_test	11.0009	4.3786	2.5124	0.0121
##	Adj_Budget	1.1192	0.0367	30.4866	0.0000
##	Metascore	7.0254	1.9058	3.6864	0.0002
##	imdbRating	15.4631	3.3914	4.5595	0.0000

What does each column represent?

# Is it convenient for my movie to pass the Bechdel test?

```
lm(Adj_Revenue ~ bechdel_test + Adj_Budget + Metascore + imdbRating, data=bechdel)
```

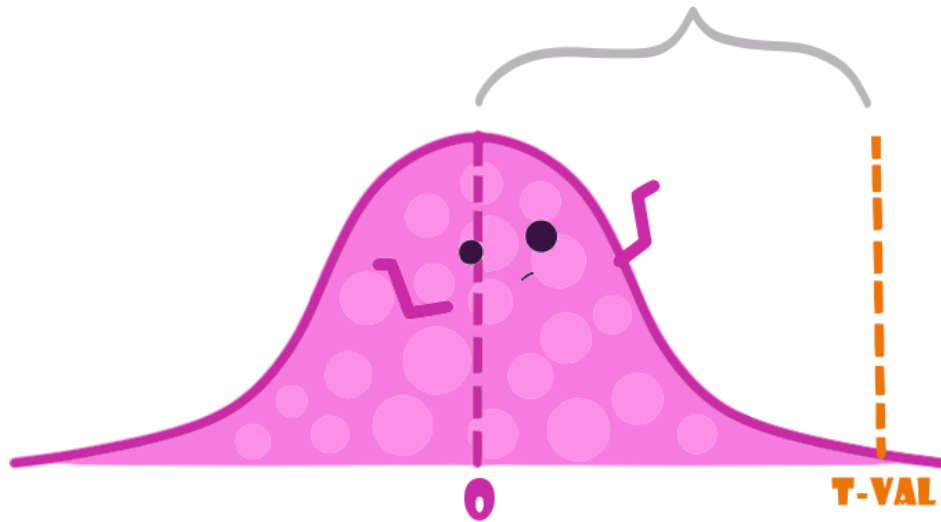
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- **"Estimate"**: Point estimates of our parameters  $\beta$ . We call them  $\hat{\beta}$ .
- **"Standard Error"** (SE): You can think about it as the variability of  $\hat{\beta}$ . The smaller, the more precise  $\hat{\beta}$  is!
- **"t-value"**: A value of the Student distribution that measures how many SE away  $\hat{\beta}$  is from 0. You can calculate it as  $tval = \frac{\hat{\beta}}{SE}$ . It relates to our null-hypothesis  $H_0 : \beta = 0$ .
- **"p-value"**: Probability of rejecting the null hypothesis and being *wrong* (Type I error). You want this to be as small as possible (statistically significant).

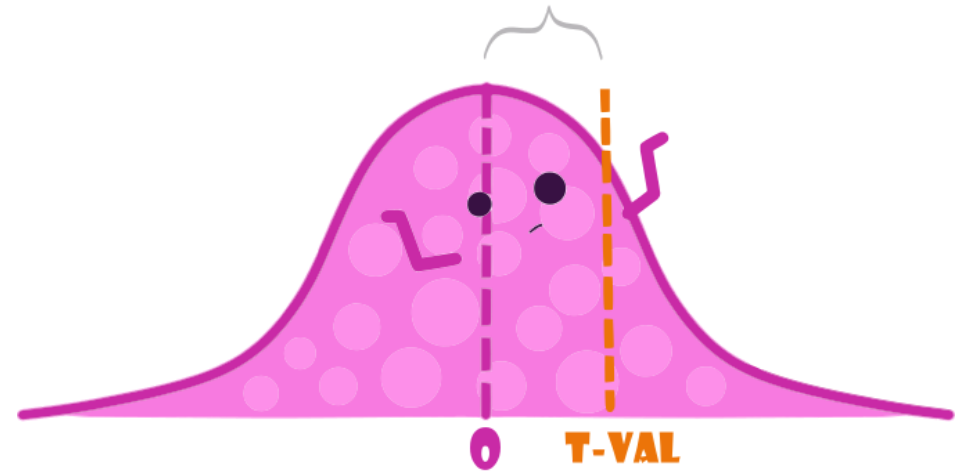
# Reminder: Null-Hypothesis

We are testing  $H_0 : \beta = 0$  vs  $H_1 : \beta \neq 0$

- "Reject the null hypothesis"



- "Not reject the null hypothesis"



Note: Figures adapted from @AllisonHorst's art

# Reminder: Null-Hypothesis

Reject the null if the t-value falls **outside** the dashed lines.





# One extra dollar in our budget

- Imagine now that you have an hypothesis that Bechdel movies also get more bang for their buck, e.g. they get more revenue for an additional dollar in their budget.

**How would you test that in an equation?**

**Interactions!**

# One extra dollar in our budget

Interaction model:

$$Revenue = \beta_0 + \beta_1 Bechdel + \beta_3 Budget + \beta_6 (Budget \times Bechdel) + \beta_4 IMDB + \beta_5 MetaScore + \varepsilon$$

How should we think about this?

- Write the equation for a movie that **does not pass the Bechdel test**. How does it look like?
- Now do the same for a movie that **passes the Bechdel test**. How does it look like?

# One extra dollar in our budget

Now, let's interpret some coefficients:

- If  $Bechdel = 0$ , then:

$$Revenue = \beta_0 + \beta_3 Budget + \beta_4 IMDB + \beta_5 MetaScore + \varepsilon$$

- If  $Bechdel = 1$ , then:

$$Revenue = (\beta_0 + \beta_1) + (\beta_3 + \beta_6) Budget + \beta_4 IMDB + \beta_5 MetaScore + \varepsilon$$

- What is the **difference** in the association between budget and revenue for movies that pass the Bechdel test vs. those that don't?

# Let's put some data into it

```
lm(Adj_Revenue ~ bechdel_test*Adj_Budget + Metascore + imdbRating, data=bechdel)
```

##	Estimate	Std. Error	t value	Pr(> t )
## (Intercept)	-124.1997	17.4932	-7.0999	0.0000
## bechdel_test	7.5138	6.4257	1.1693	0.2425
## Adj_Budget	1.0926	0.0513	21.2865	0.0000
## Metascore	7.1424	1.9126	3.7344	0.0002
## imdbRating	15.2268	3.4069	4.4694	0.0000
## bechdel_test:Adj_Budget	0.0546	0.0737	0.7416	0.4585

- What is the association between budget and revenue for movies that **pass the Bechdel test**?
- What is the difference in the association between budget and revenue for **movies that pass vs movies that don't pass the Bechdel test**?
- Is that difference **statistically significant** (at conventional levels)?

**Let's look at another example**

# Cars, cars, cars

- Used cars in South California (from this week's JITT)

```
cars <- read.csv("https://raw.githubusercontent.com/maibennett/sta235/main/exampleSite/content/Classes/Week2/1_OLS/data/Sc  
names(cars)
```

```
## [1] "type"      "certified" "body"      "make"      "model"     "trim"  
## [7] "mileage"   "price"     "year"     "dealer"    "city"      "rating"  
## [13] "reviews"   "badge"
```

Data source: "Modern Business Analytics" (Taddy, Hendrix, & Harding, 2018)

# Luxury vs. non-luxury cars?

Do you think there's a difference between how price changes over time for luxury vs non-luxury cars?

How would you test this?

**Let's go to R**



# Models with interactions

- You include the interaction between two (or more) covariates:

$$\widehat{Price} = \beta_0 + \hat{\beta}_1 Rating + \hat{\beta}_2 Miles + \hat{\beta}_3 Luxury + \hat{\beta}_4 Year + \hat{\beta}_5 Luxury \times Year$$

- $\hat{\beta}_3$  and  $\hat{\beta}_4$  are considered the **main effects** (no interaction)
- The coefficient you are interested in is  $\hat{\beta}_5$ :
  - Difference in the **price change** for one additional year between **luxury vs non-luxury cars**, holding other variables constant.

# Now it's your turn

- Looking at this equation:

$$\widehat{Price} = \beta_0 + \hat{\beta}_1 Rating + \hat{\beta}_2 Miles + \hat{\beta}_3 Luxury + \hat{\beta}_4 Year + \hat{\beta}_5 Luxury \times Year$$

- 1) What is the association between price and year for non-luxury cars?
- 2) What is the association between price and year for luxury cars?

# Looking at our data

- We have dived into running models head on. **Is that a good idea?**



**What should we do before we ran any model?**

**Inspect your data!**

# Some ideas:

- Use `vtable`:

```
library(vtable)

vtable(cars)
```

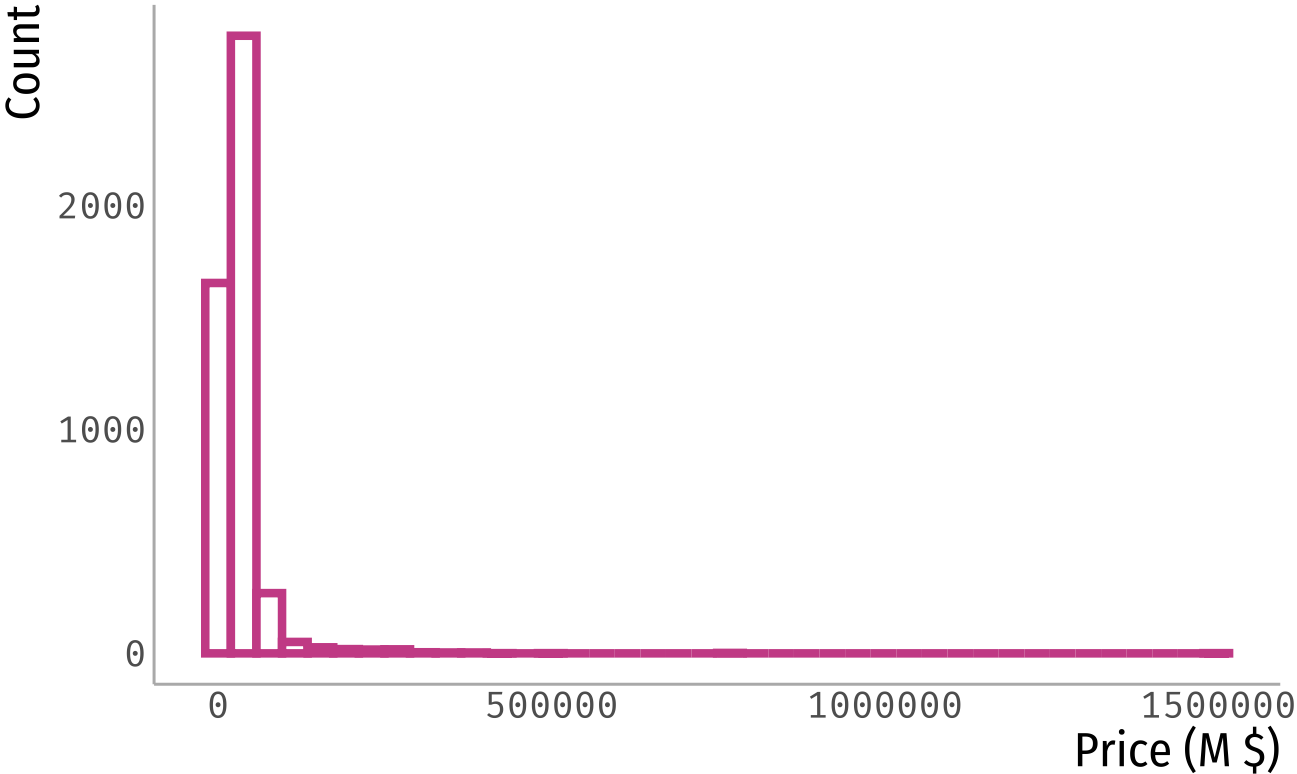
- Use `summary` to see the min, max, mean, and quartile:

```
cars %>% select(price, mileage, year) %>% summary(.)
```

```
##      price      mileage      year
## Min.   : 1790  Min.    :    0  Min.   :1966
## 1st Qu.: 16234 1st Qu.:    5  1st Qu.:2017
## Median : 23981 Median :   56  Median :2019
## Mean   : 32959 Mean    : 21873  Mean   :2018
## 3rd Qu.: 36745 3rd Qu.: 36445  3rd Qu.:2020
## Max.   :1499000 Max.    :292952  Max.   :2021
```

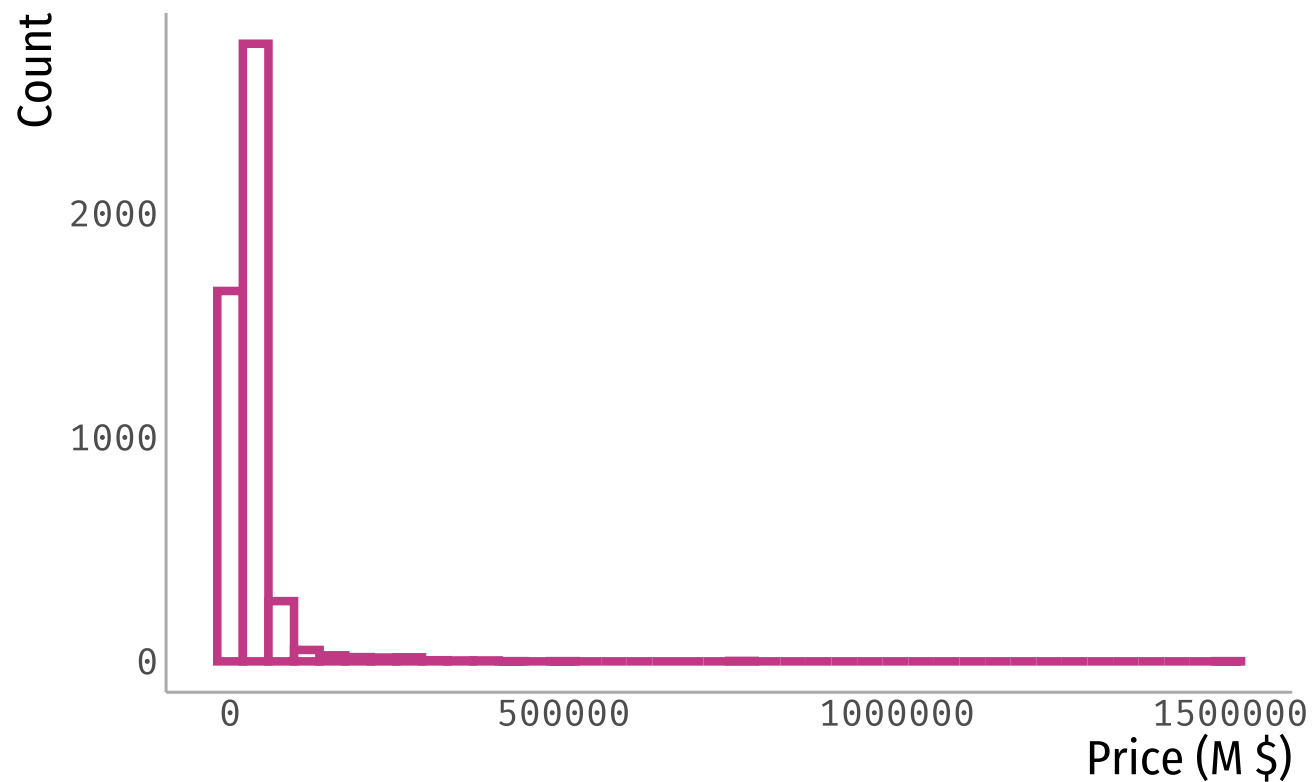
- Plot your data!

# Look at the data



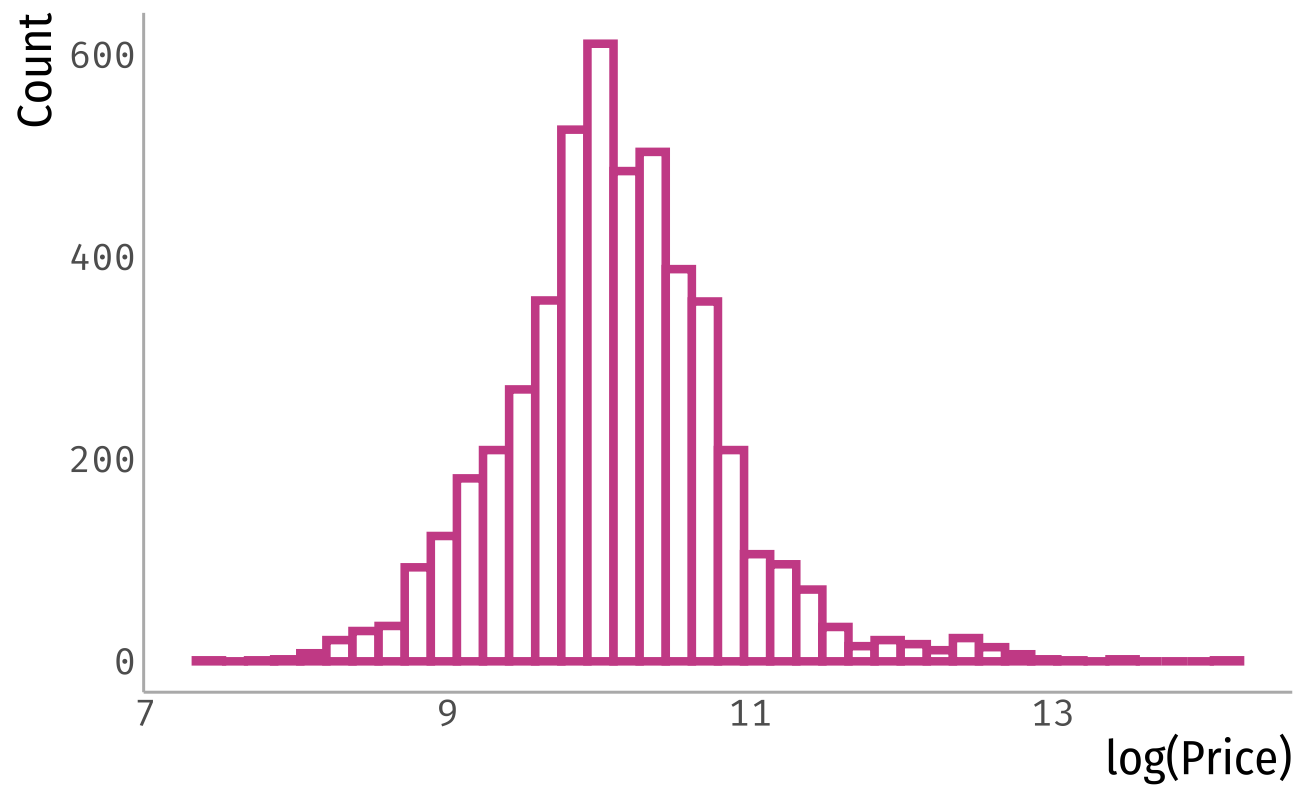
# Look at the data

What can you say about this variable?





# Logarithms to the rescue?



# How would we interpret coefficients now?

- Let's interpret the coefficient for *Miles* in the following equation:

$$\log(\textit{Price}) = \beta_0 + \beta_1 \textit{Rating} + \beta_2 \textit{Miles} + \beta_3 \textit{Luxury} + \beta_4 \textit{Year} + \varepsilon$$

- Remember:  $\beta_2$  represents the average change in the outcome variable,  $\log(\textit{Price})$ , for a one-unit increase in the independent variable *Miles*.
  - *Think about the units of the dependent and independent variables!*

# A side note on log-transformed variables...

$$\log(Y) = \hat{\beta}_0 + \hat{\beta}_1 X$$

We want to compare the outcome for a regression with  $X = x$  and  $X = x + 1$

$$\log(y_0) = \hat{\beta}_0 + \hat{\beta}_1 x \quad (1)$$

and

$$\log(y_1) = \hat{\beta}_0 + \hat{\beta}_1 (x + 1) \quad (2)$$

- Let's subtract (2) - (1)!

## A side note on log-transformed variables...

$$\log(y_1) - \log(y_0) = \hat{\beta}_0 + \hat{\beta}_1(x + 1) - (\hat{\beta}_0 + \hat{\beta}_1 x)$$

$$\log\left(\frac{y_1}{y_0}\right) = \hat{\beta}_1$$

$$\log\left(1 + \frac{y_1 - y_0}{y_0}\right) = \hat{\beta}_1$$

## A side note on log-transformed variables...

$$\log(y_1) - \log(y_0) = \hat{\beta}_0 + \hat{\beta}_1(x + 1) - (\hat{\beta}_0 + \hat{\beta}_1 x)$$

$$\log\left(\frac{y_1}{y_0}\right) = \hat{\beta}_1$$

$$\log\left(1 + \frac{y_1 - y_0}{y_0}\right) = \hat{\beta}_1$$

$$\rightarrow \frac{\Delta y}{y} = \exp(\hat{\beta}_1) - 1$$

# An important approximation

$$\log(y_1) - \log(y_0) = \hat{\beta}_0 + \hat{\beta}_1(x + 1) - (\hat{\beta}_0 + \hat{\beta}_1 x)$$

$$\log\left(\frac{y_1}{y_0}\right) = \hat{\beta}_1$$

$$\log\left(1 + \frac{y_1 - y_0}{y_0}\right) = \hat{\beta}_1$$

$$\approx \frac{y_1 - y_0}{y_0} = \hat{\beta}_1$$

$$\rightarrow \% \Delta y = 100 \times \hat{\beta}_1$$

# How would we interpret coefficients now?

- Let's interpret the coefficient for *Miles* in the following equation:

$$\log(\text{Price}) = \beta_0 + \beta_1 \text{Rating} + \beta_2 \text{Miles} + \beta_3 \text{Luxury} + \beta_4 \text{Year} + \varepsilon$$

- For an additional 1,000 miles (*Note: Remember Miles is measured in thousands of miles*), the logarithm of the price increases/decreases, on average, by  $\hat{\beta}_2$ , holding other variables constant.
- For an additional 1,000 miles, the price increases/decreases, on average, by  $100 \times \hat{\beta}_2\%$ , holding other variables constant.

# How would we interpret coefficients now?

```
summary(lm(log(price) ~ rating + mileage + luxury + year, data = cars))
```

```
##
## Call:
## lm(formula = log(price) ~ rating + mileage + luxury + year, data = cars)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -1.14398 -0.29213 -0.02541  0.26465  2.28644
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  2.5110336   0.1518738   16.534 < 2e-16 ***
## rating       0.0302667   0.0057670    5.248 1.69e-07 ***
## mileage     -0.0098415   0.0004327  -22.745 < 2e-16 ***
## luxury       0.5527371   0.0228132   24.229 < 2e-16 ***
## year        0.0118467   0.0030083    3.938 8.48e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.4361 on 2085 degrees of freedom
## Multiple R-squared:  0.4692,    Adjusted R-squared:  0.4682
## F-statistic: 460.7 on 4 and 2085 DF,  p-value: < 2.2e-16
```



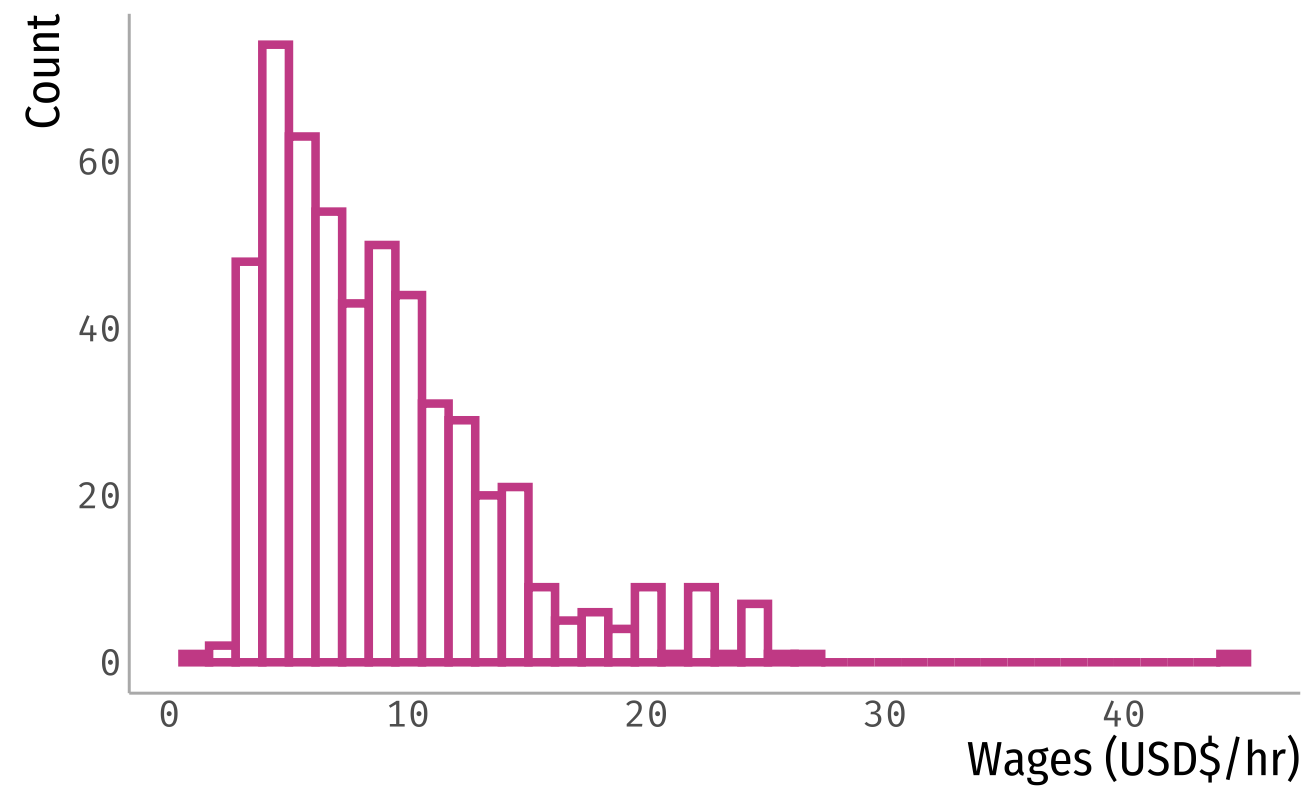
# Adding polynomial terms

- Another way to capture **nonlinear associations** between the outcome (Y) and covariates (X) is to include **polynomial terms**:

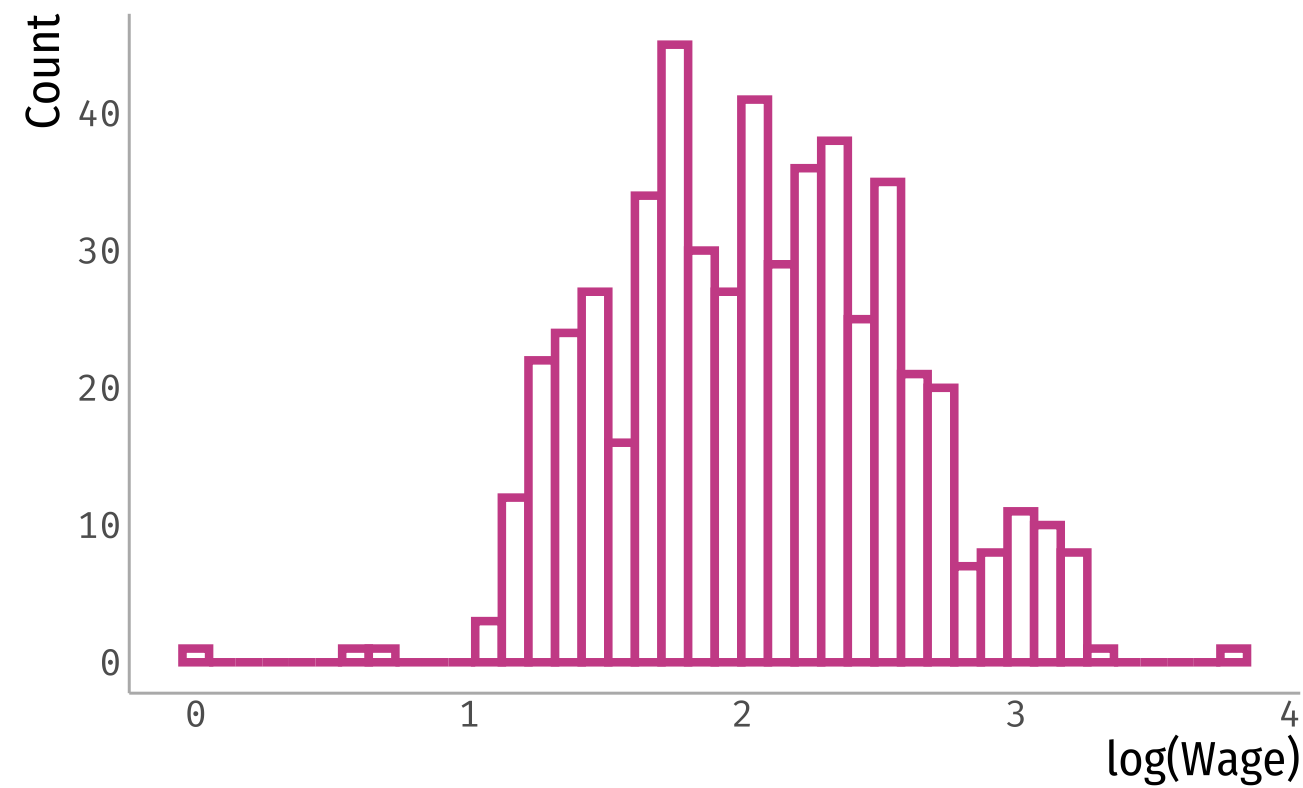
- e.g.  $Y = \beta_0 + \beta_1 X + \beta_2 X^2 + \varepsilon$

- Let's look at an example!

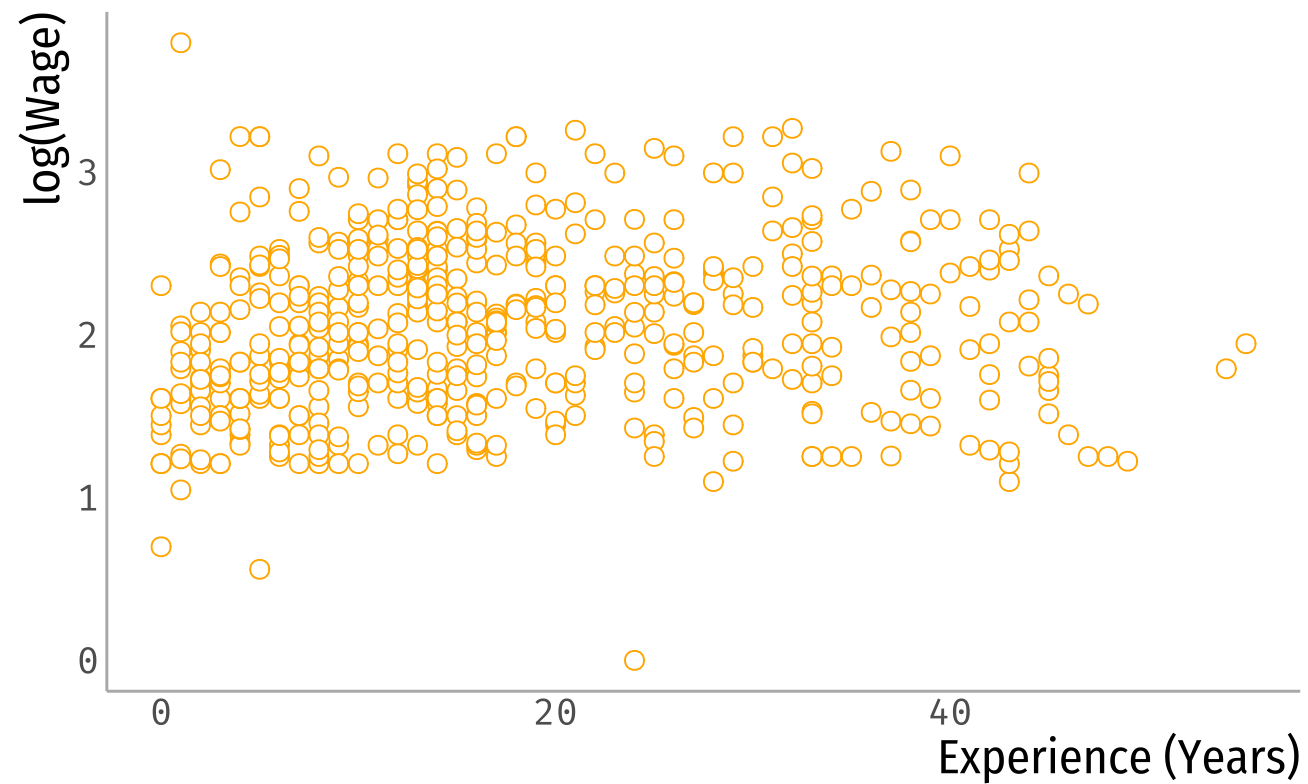
# Determinants of wages: CPS 1985



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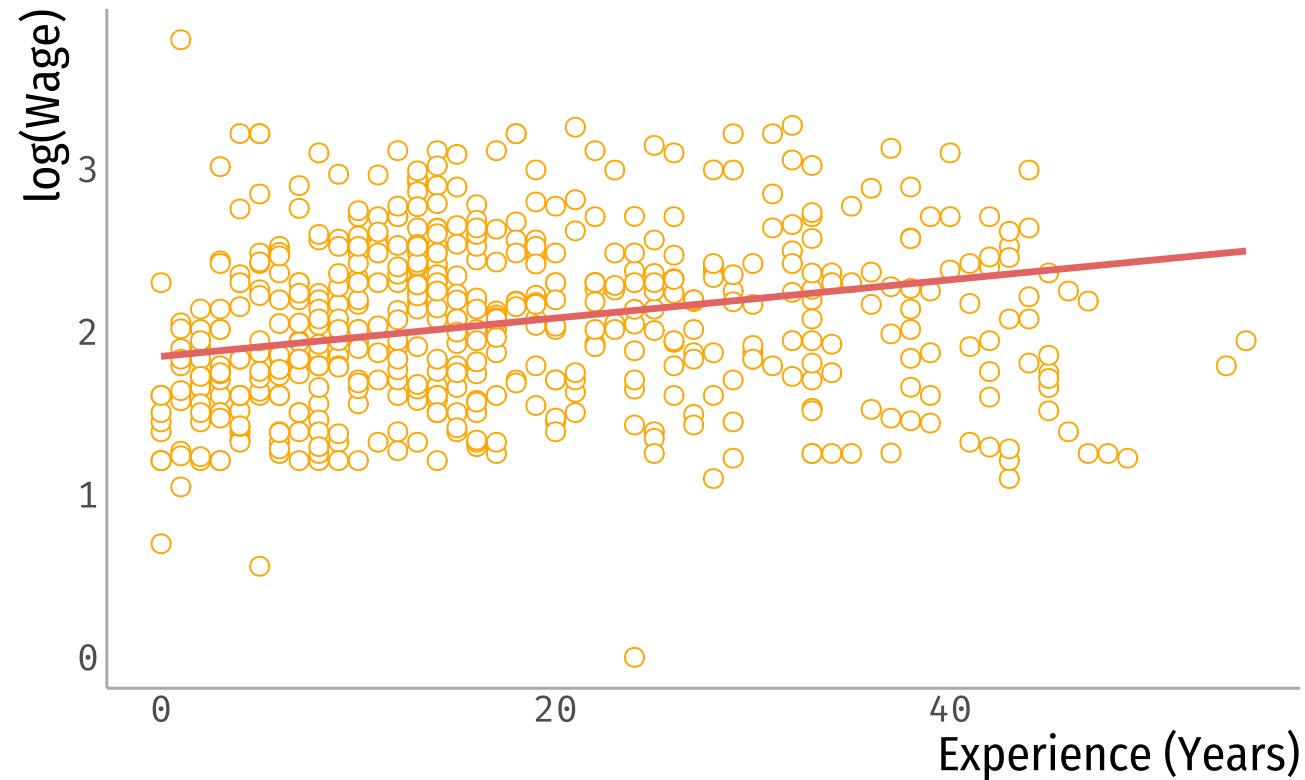


# Experience vs wages: CPS 1985



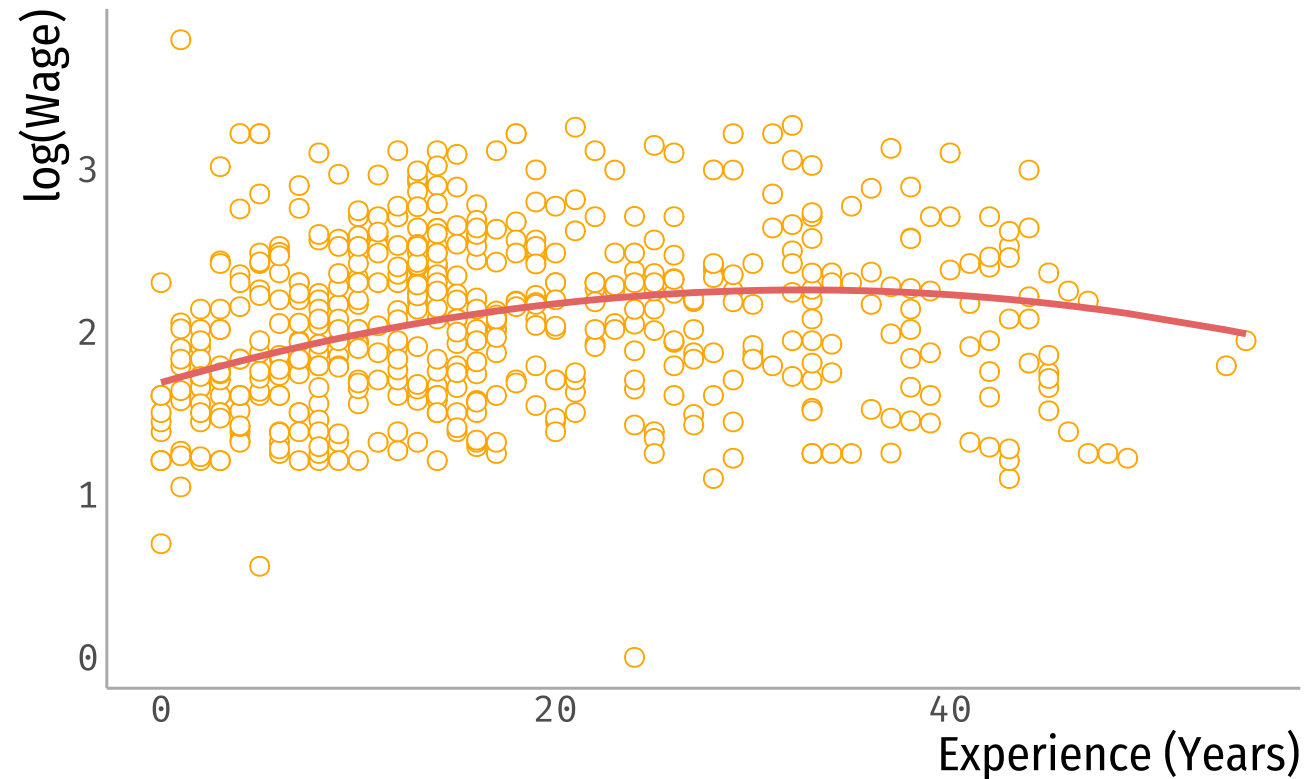
# Experience vs wages: CPS 1985

$$\log(Wage) = \beta_0 + \beta_1 Educ + \beta_2 Exp + \varepsilon$$



# Experience vs wages: CPS 1985

$$\log(Wage) = \beta_0 + \beta_1 Educ + \beta_2 Exp + \beta_3 Exp^2 + \varepsilon$$



# Mincer equation

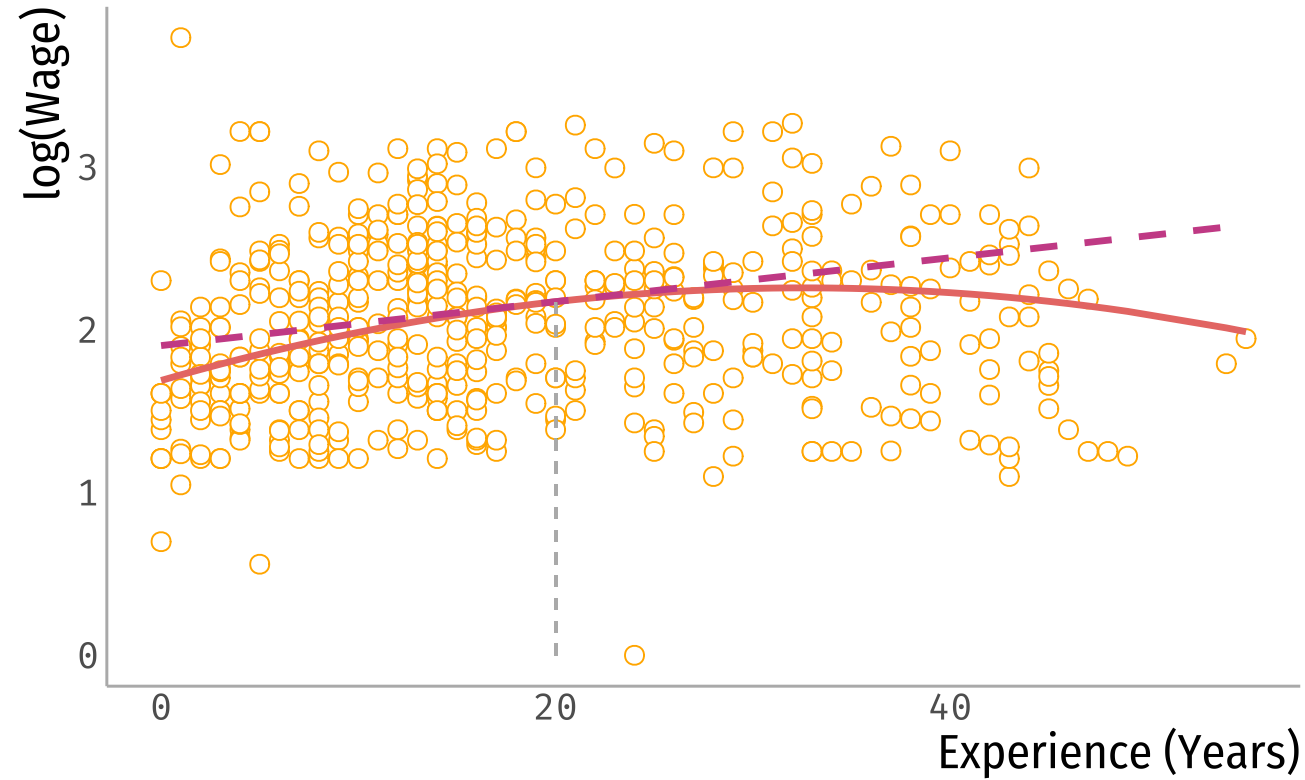
$$\log(Wage) = \beta_0 + \beta_1 Educ + \beta_2 Exp + \beta_3 Exp^2 + \varepsilon$$

- Interpret the coefficient for **education**

*One additional year of education is associated, on average, to  $\hat{\beta}_1 \times 100\%$  increase in hourly wages, holding experience constant*

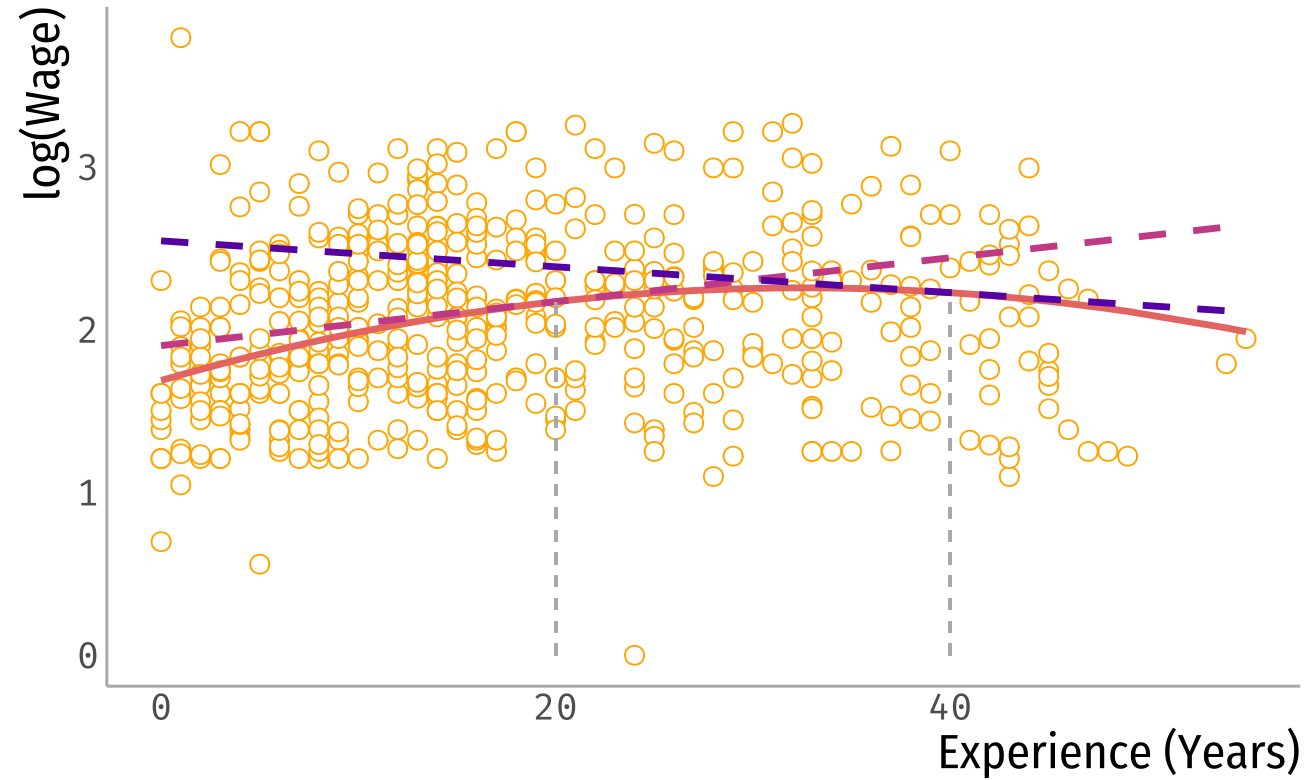
- What is the association between experience and wages?

# Interpreting coefficients in quadratic equation

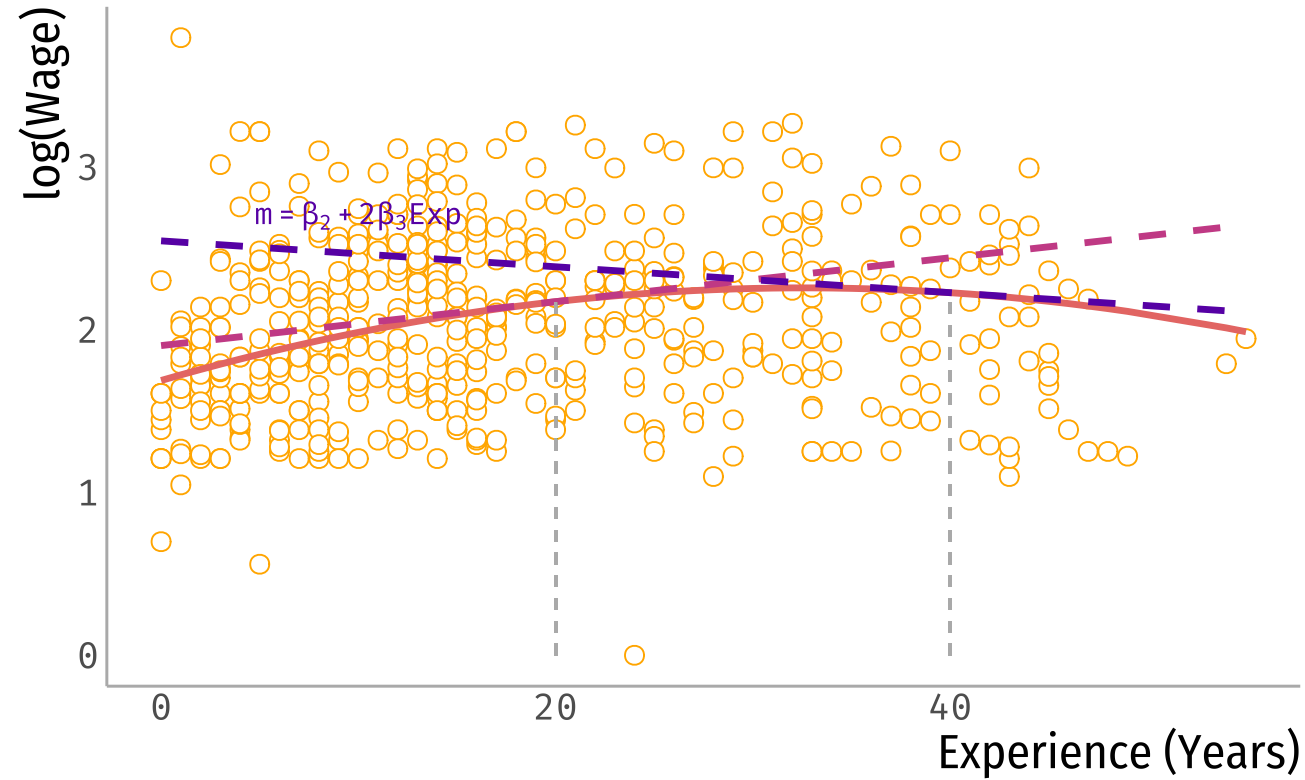




# Interpreting coefficients in quadratic equation



# Interpreting coefficients in quadratic equation



# Interpreting coefficients in quadratic equation

$$\log(Wage) = \beta_0 + \beta_1 Educ + \beta_2 Exp + \beta_3 Exp^2 + \varepsilon$$

What is the association between experience and wages?

- Pick a value for  $Exp_0$  (e.g. mean, median, one value of interest)

*Increasing work experience from  $Exp_0$  to  $Exp_0 + 1$  years is associated, on average, to a  $(\hat{\beta}_2 + 2\hat{\beta}_3 \times Exp_0)100\%$  increase on hourly wages, holding education constant*

*Increasing work experience from 20 to 21 years is associated, on average, to a  $(\hat{\beta}_2 + 2\hat{\beta}_3 \times 20)100\%$  increase on hourly wages, holding education constant*

# Let's put some numbers into it

```
summary(lm(log(wage) ~ education + experience + I(experience^2), data = CPS1985))
```

```
##
## Call:
## lm(formula = log(wage) ~ education + experience + I(experience^2),
##     data = CPS1985)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -2.12709 -0.31543  0.00671  0.31170  1.98418
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)    0.5203218   0.1236163     4.209 3.01e-05 ***
## education      0.0897561   0.0083205    10.787 < 2e-16 ***
## experience     0.0349403   0.0056492     6.185 1.24e-09 ***
## I(experience^2) -0.0005362  0.0001245    -4.307 1.97e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.4619 on 530 degrees of freedom
## Multiple R-squared:  0.2382,    Adjusted R-squared:  0.2339
## F-statistic: 55.23 on 3 and 530 DF,  p-value: < 2.2e-16
```

- Increasing experience from 20 to 21 years is associated with an average increase in wages of 1.35%, holding education constant.

# Main takeaway points

- The model you fit **depends on what you want to analyze**.
- **Plot your data!**
- Make sure you capture associations that **make sense**.



# Next week



- Issues with regressions and our data:
  - Outliers?
  - Heteroskedasticity
- Regression models with discrete outcomes:
  - Probability linear models

# References

- Ismay, C. & A. Kim. (2021). "Statistical Inference via Data Science". Chapter 6 & 10.
- Keegan, B. (2018). "The Need for Openness in Data Journalism". *Github Repository*