

# Welcome back!

**Nameplates please. And technology encouraged today!**

**All TF materials are available at github.com/nolankav/api-202.**

**If you want to follow along, download the dataset here:**

In R: `df <- read.csv ("http://tinyurl.com/api-202-tf-3")`

In Excel: http://tinyurl.com/api-202-tf-4

# Dummy variables and interactions

API 202: TF Session 3

R

Nolan M. Kavanagh  
February 13, 2026



# Goals for today

- 1. Review core concepts in regression analysis.**
- 2. Review the principles of interactions in regression.**
- 3. Learn how to run interacted regressions.**
- 4. Practice interpreting interaction terms.**

We'll treat this session like a workshop with an interactive example.

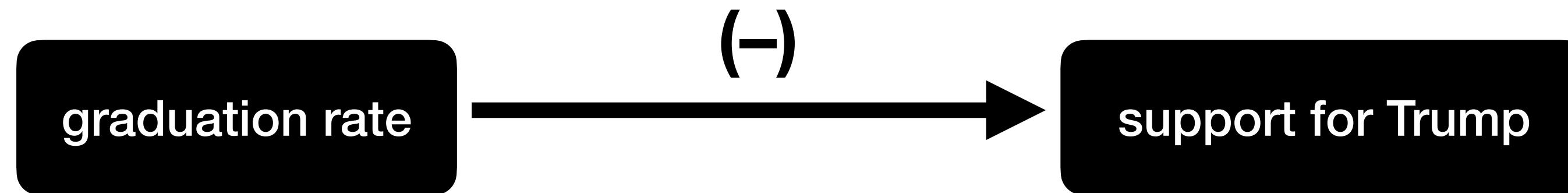
# Overview of our sample data

## Dataset of U.S. county-level characteristics in 2020

state	<b>State of county</b>	<i>Administrative</i>
county_fips	<b>County FIPS identifier</b>	<i>Administrative</i>
pc_under_18	<b>Percent of county under age 18</b>	<i>American Community Survey (2016–2020)</i>
pc_over_65	<b>Percent of county over age 65</b>	<i>American Community Survey (2016–2020)</i>
pc_male	<b>Percent of county that is male</b>	<i>American Community Survey (2016–2020)</i>
pc_black	<b>Percent of county that is Black</b>	<i>American Community Survey (2016–2020)</i>
pc_latin	<b>Percent of county that is Hispanic/Latino</b>	<i>American Community Survey (2016–2020)</i>
pc_hs_grad	<b>Percent of county that graduated high school</b>	<i>American Community Survey (2016–2020)</i>
unemploy_rate	<b>County unemployment rate (%)</b>	<i>American Community Survey (2016–2020)</i>
med_income_000s	<b>County median income (\$1,000s)</b>	<i>American Community Survey (2016–2020)</i>
pc_uninsured	<b>Percent of county without health insurance</b>	<i>American Community Survey (2016–2020)</i>
pc_trump	<b>Percent of county votes for Trump in 2020</b>	<i>MIT Election Lab</i>

# Let's revisit the Trump story.

We've learned that high school graduation rates were an important predictor of Trump's support in 2020.



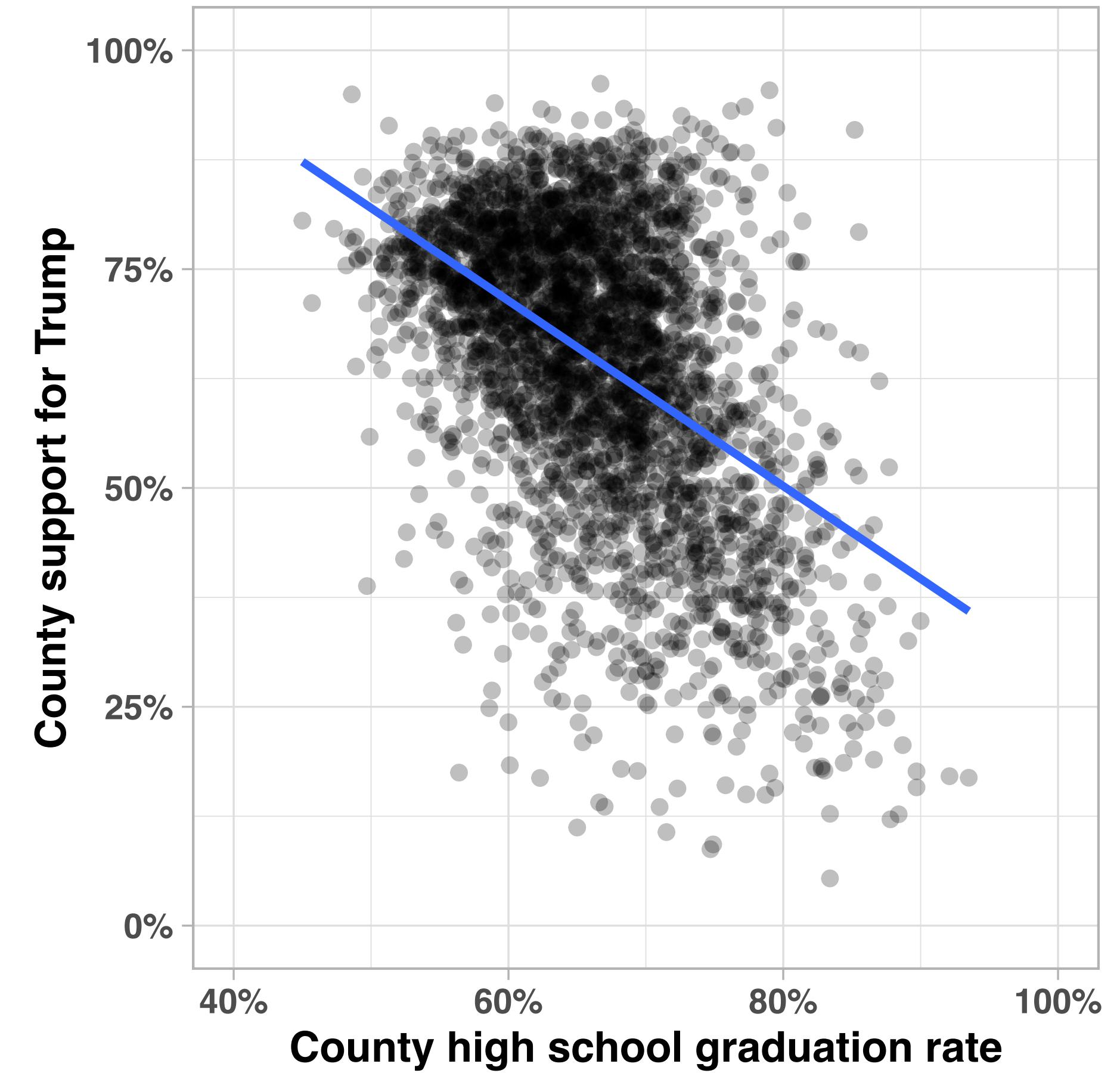
In Season 4 Episode 19, we learn that Homer never technically graduated high school (even though he does later in the episode).

This screenshot is from later in the series, but would he be more or less likely to support Trump than someone who graduated high school?



# We've seen this graph before.

```
# Graph graduation rate and Trump support
plot_1 <- ggplot(df, aes(x=pc_hs_grad, y=pc_trump)) +
  # Add scatterplot points
  geom_point(alpha=0.25) +
  # Labels of axes
  xlab("County high school graduation rate") +
  ylab("County support for Trump") +
  # Add best fit line
  geom_smooth(method="lm", se=F, formula = y~x) +
  # Cosmetic changes
  theme_light() + theme(text = element_text(face="bold")) +
  scale_y_continuous(limits=c(0,100),
                     labels = function(x) paste0(x,"%")) +
  scale_x_continuous(limits=c(40,100),
                     labels = function(x) paste0(x,"%"))
```



Note: `pc_hs_grad` and `pc_trump` are scaled 0–100, not 0–1.

# We've seen this regression before.

```
# Estimate regression
reg_1 <- lm(pc_trump ~ pc_hs_grad, data=df)
summary(reg_1)
```

Call:  
lm(formula = pc\_trump ~ pc\_hs\_grad, data = df)

Residuals:

Min	1Q	Median	3Q	Max
-57.719	-8.173	0.833	9.423	46.200

Coefficients:

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	134.92112	2.28637	59.01	<2e-16 ***
pc_hs_grad	-1.05882	0.03439	-30.79	<2e-16 ***
---				
Signif. codes:	0	'***'	0.001	'**'
	0.01	'*'	0.05	'. '
	0.1	' '	1	

Residual standard error: 14.13 on 3112 degrees of freedom  
Multiple R-squared: 0.2335, Adjusted R-squared: 0.2332  
F-statistic: 947.9 on 1 and 3112 DF, p-value: < 2.2e-16

Note: pc\_hs\_grad and pc\_trump are scaled 0–100, not 0–1.

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For each 1 percentage point (pp) increase in a county's high school graduation rate, there is an associated 1.1 pp decrease in support for Trump.

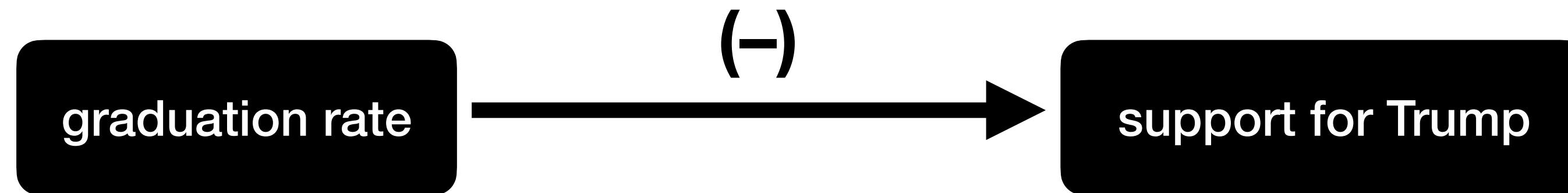
The association is statistically significant.



Note: `pc_hs_grad` and `pc_trump` are scaled 0–100, not 0–1.

# Let's revisit the Trump story.

We've learned that high school graduation rates were an important predictor of Trump's support in 2020.



But is this true for every community?

In Season 4 Episode 19, we learn that Homer never technically graduated high school (even though he does later in the episode).

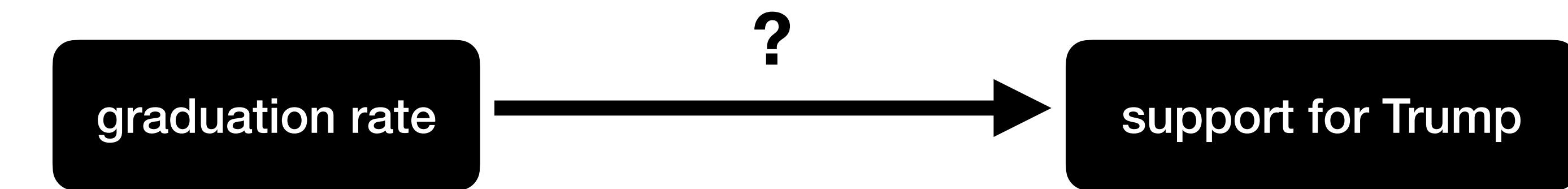
This screenshot is from later in the series, but would he be more or less likely to support Trump than someone who graduated high school?



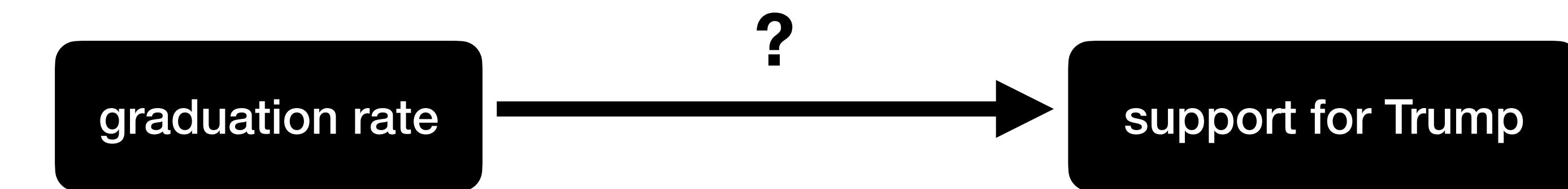
# Let's consider minoritized communities.

Is the association different for majority-Black or Latin counties, compared to majority-white counties?

**Majority-Black or Latin counties**



**Other counties**



# OK, let's make a dummy variable.

It should equal 1 for counties that are majority-Black or Latin.

Meanwhile, it should equal 0 for all other counties.

```
# Generate dummy variable  
# Majority-Black or Latin counties  
df <- df %>% mutate(  
  majority = case_when(  
    pc_black >= 50 | pc_latin >= 50 ~ 1,  
    TRUE ~ 0  
)
```

If a county meets either criterion, assign it a value of 1.



For all other counties, put 0.



# Let's consider our regression function.



# Let's consider our regression function.

$$(Trump)_i = \beta_0 + \beta_1(HS\_grad)_i + \beta_2(majority)_i + \beta_3(HS\_grad * majority)_i + u_i$$

**high school graduation rate**  
measured in percent (0–100)

**dummy for majority-Black/Latin**  
1 = majority-Black/Latin county  
0 = all other counties

interaction between  
our two predictors

# Let's consider our regression function.

**Other counties**  $(Trump)_i = \beta_0 + \beta_1(HS\_grad)_i + \beta_2(majority)_i + \beta_3(HS\_grad * majority)_i + u_i$   
**here, majority = 0**

**Majority-Black or  
Latin counties**

**here, majority = 1**

$$(Trump)_i = \beta_0 + \beta_1(HS\_grad)_i + \beta_2(majority)_i + \beta_3(HS\_grad * majority)_i + u_i$$

# Let's consider our regression function.

**Other counties**  
here, majority = 0

$$(Trump)_i = \beta_0 + \beta_1(HS\_grad)_i + \beta_2(majority)_i + \beta_3(HS\_grad * majority)_i + u_i$$

these terms go to 0

$$(Trump)_i = \beta_0 + \beta_1(HS\_grad)_i + u_i$$

**Majority-Black or Latin counties**

here, majority = 1

$$(Trump)_i = \beta_0 + \beta_1(HS\_grad)_i + \beta_2(majority) + \beta_3(HS\_grad * majority)_i + u_i$$

these terms are just 1

$$(Trump)_i = \beta_0 + \beta_1(HS\_grad)_i + \beta_2 + \beta_3(HS\_grad)_i + u_i$$

$$(Trump)_i = (\beta_0 + \beta_2) + (\beta_1 + \beta_3)(HS\_grad)_i + u_i$$

rearrange our terms

# Let's consider our regression function.

**Other counties**  
here, majority = 0

$$(Trump)_i = \beta_0 + \beta_1(HS\_grad)_i + u_i$$

**Majority-Black or  
Latin counties**  
here, majority = 1

$$(Trump)_i = (\beta_0 + \beta_2) + (\beta_1 + \beta_3)(HS\_grad)_i + u_i$$

# Let's consider our regression function.

**Other counties**  
here, majority = 0

$$(Trump)_i = \beta_0 + \beta_1(HS\_grad)_i + u_i$$

$\beta_2$  gives us the difference in intercepts  
i.e. the difference in predicted Trump support for majority-Black/Latin vs. other counties with graduation rates of 0%.

**Majority-Black or Latin counties**  
here, majority = 1

$$(Trump)_i = (\beta_0 + \beta_2) + (\beta_1 + \beta_3)(HS\_grad)_i + u_i$$

# Let's consider our regression function.

**Other counties**  
here, majority = 0

$$(Trump)_i = \beta_0 + \beta_1(HS\_grad)_i + u_i$$

**$\beta_2$  gives us the difference in intercepts**

i.e. the difference in predicted Trump support for majority-Black/Latin vs. other counties with graduation rates of 0%.

**Majority-Black or Latin counties**  
here, majority = 1

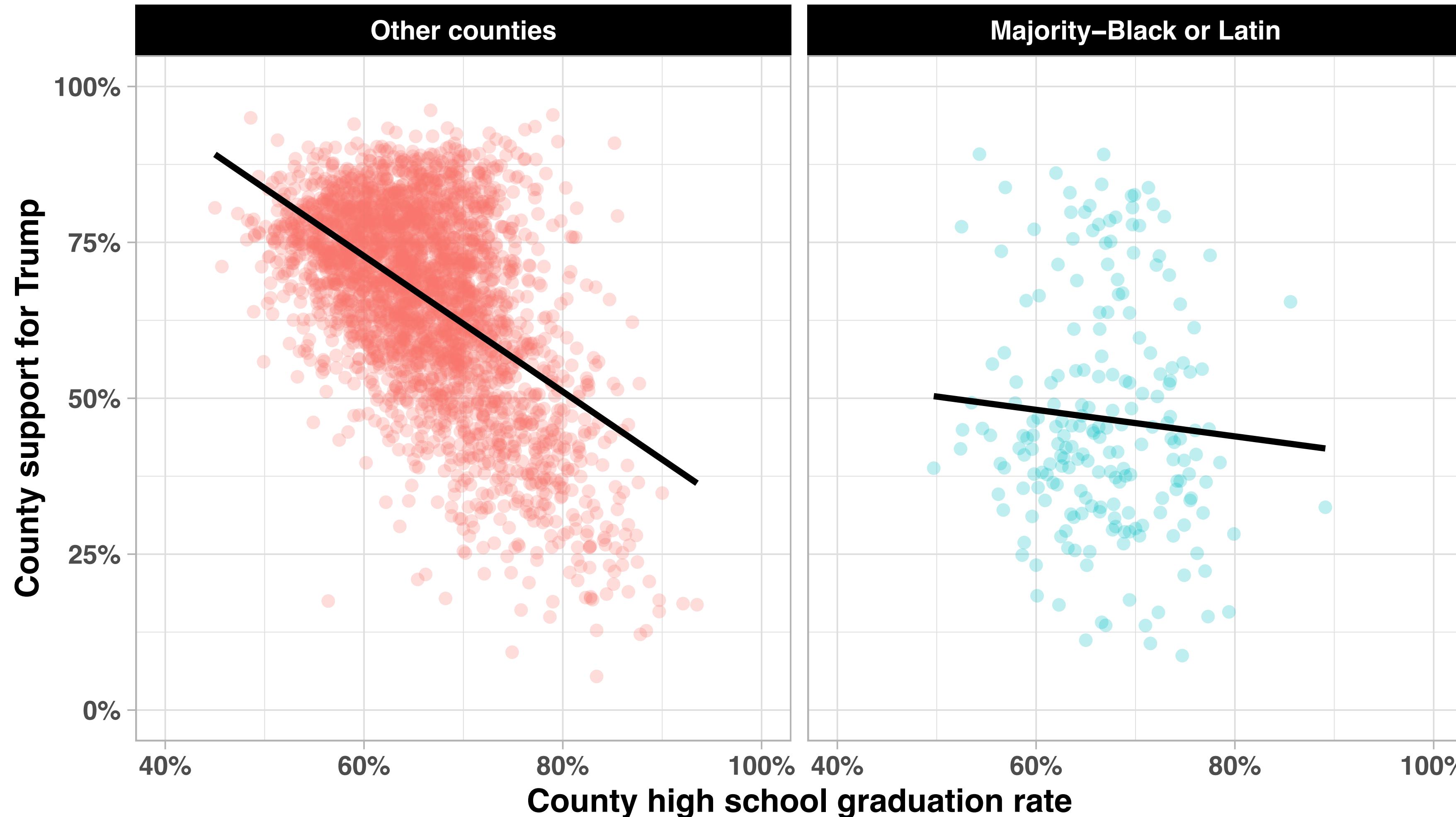
$$(Trump)_i = (\beta_0 + \beta_2) + (\beta_1 + \beta_3)(HS\_grad)_i + u_i$$

**$\beta_3$  gives us the difference in slopes**

i.e. the difference in the association between graduation rates and Trump support for majority-Black/Latin vs. other counties.

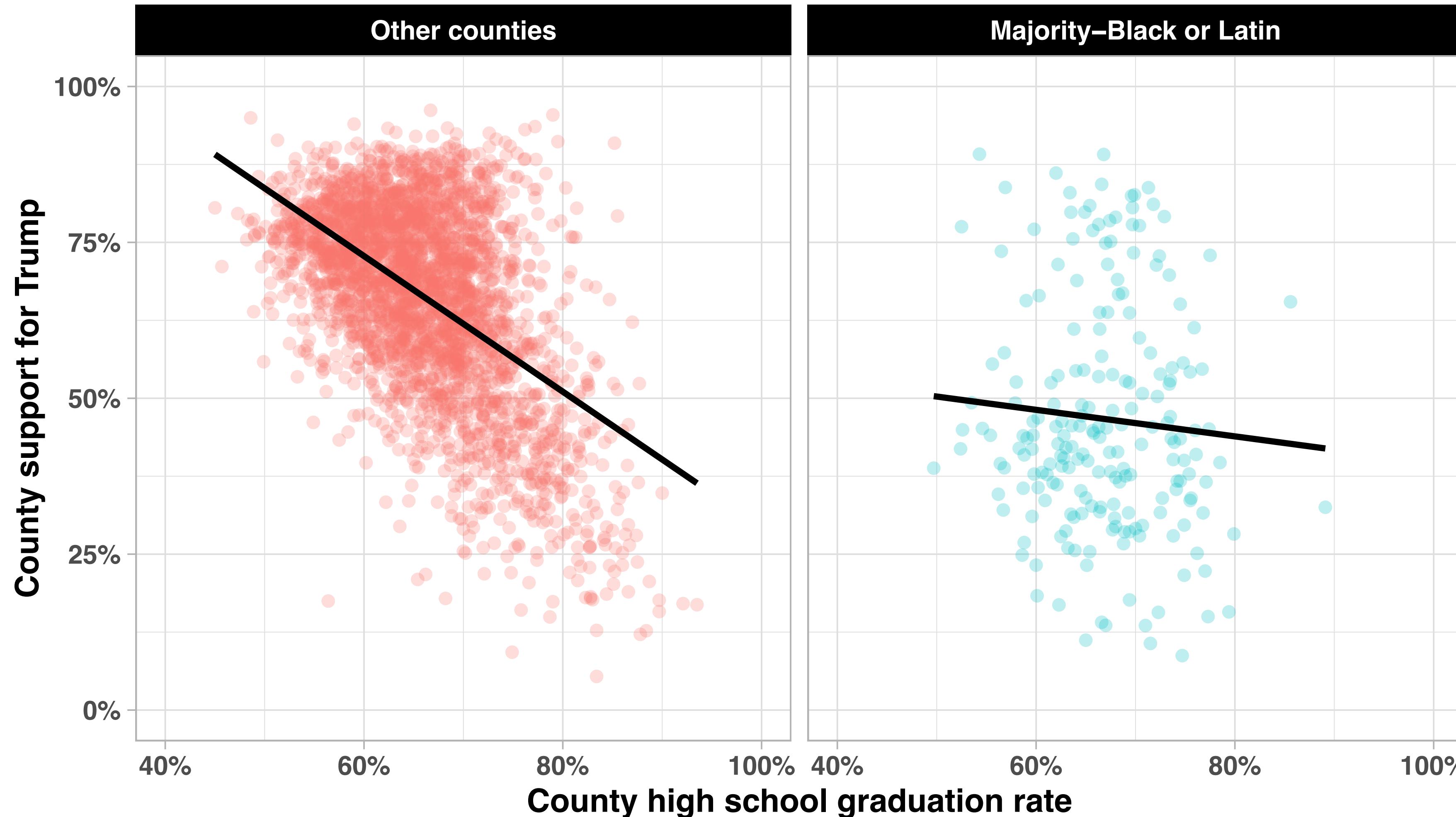


# Show me the graph already!



See the online script file for the code to make these graphs.

# Show me the graph already!



**Clearly, these  
are different  
relationships!**

See the online script file for the code to make these graphs.

# Show me the regression already!

```
# Estimate interacted regression  
reg_2 <- lm(pc_trump ~ pc_hs_grad + majority + pc_hs_grad*majority, data=df)  
summary(reg_2)
```



To interact two variables, just add a “\*” between them.

**Note:** Using “\*” will automatically include the main effects (so we don’t need to separately add `pc_hs_grad` and `majority`).

If we only wanted the interacted term and no main effects, we could use “:” instead, i.e. `pc_trump ~ pc_hs_grad:majority`.

But it’s rare not to want the main effects.

# Show me the regression already!

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# Estimate interacted regression
reg_2 <- lm(pc_trump ~ pc_hs_grad + majority + pc_hs_grad*majority, data=df)
summary(reg_2)
```

Call:

```
lm(formula = pc_trump ~ pc_hs_grad + majority + pc_hs_grad *
    majority, data = df)
```

Residuals:

Min	1Q	Median	3Q	Max
-59.233	-8.557	-0.072	8.636	45.507

Coefficients:

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	138.04241	2.20351	62.647	< 2e-16 ***
pc_hs_grad	-1.08732	0.03317	-32.785	< 2e-16 ***
majority	-77.12618	9.81818	-7.855	5.44e-15 ***
pc_hs_grad:majority	0.87450	0.14638	5.974	2.58e-09 ***

---

Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 13.27 on 3110 degrees of freedom

Multiple R-squared: 0.3246, Adjusted R-squared: 0.3239

F-statistic: 498.2 on 3 and 3110 DF, p-value: < 2.2e-16

Note: pc\_hs\_grad and pc\_trump are scaled 0–100, not 0–1.

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The predicted support for Trump in an “other” county with a high school graduation rate of 0% is 138%.

It's significantly different from 0.

It's also not especially meaningful.

Note: pc\_hs\_grad and pc\_trump are scaled 0–100, not 0–1.

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For “other” counties, a 1 pp increase  
in the graduation rate is associated  
with 1.1 pp lower support for Trump.

It's significantly different from 0.



Note: pc\_hs\_grad and pc\_trump are scaled 0–100, not 0–1.

# Show me the regression already!

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# Estimate interacted regression
reg_2 <- lm(pc_trump ~ pc_hs_grad + majority + pc_hs_grad*majority, data=df)
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A majority-Black or Latin county with 0% graduation has, on average, 77 pp less support for Trump than an “other” county with 0% graduation.

It's significantly different from 0.

Doing the math:  $138 - 77 = 61\%$  support.

Note: pc\_hs\_grad and pc\_trump are scaled 0–100, not 0–1.

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The association between graduation rates and Trump support is 0.87 pp more positive for majority-Black or Latin counties, compared to “other counties.”

It's significantly different from 0.

Doing the math:  $-1.09 + 0.87 = -0.22$ , which is a much flatter slope.

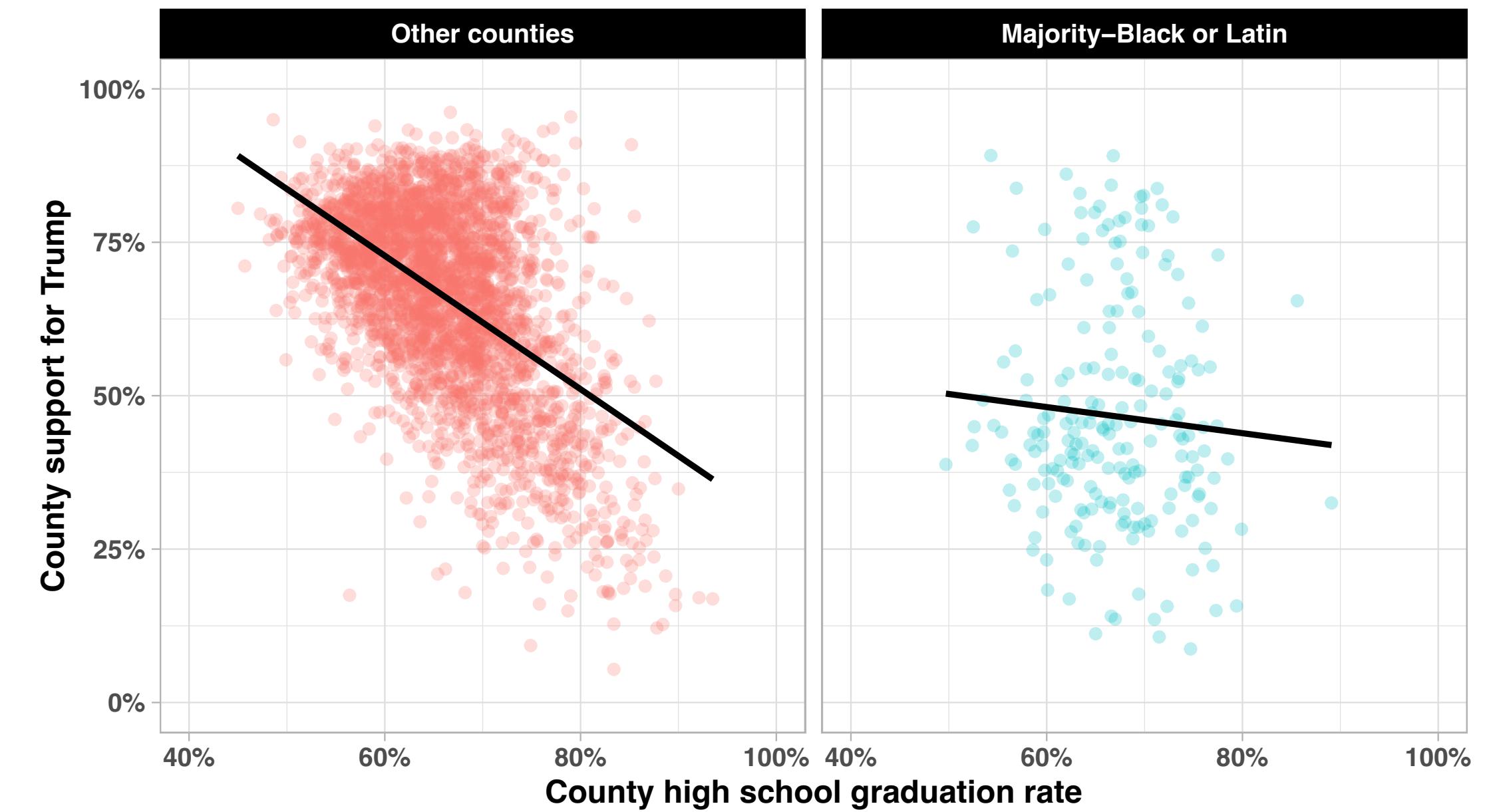
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# Putting it all together

	Model 1	Model 2
<b>Intercept</b>	<b>134.92***</b> (2.29)	<b>138.04***</b> (2.20)
<b>County graduation rate</b>	<b>-1.06***</b> (0.03)	<b>-1.09***</b> (0.03)
<b>Majority-Black or Latin county</b>		<b>-77.13***</b> (9.82)
<b>Grad. rate * Majority-Black or Latin</b>		<b>0.87***</b> (0.15)
Num.Obs.	3114	3114
R2	0.233	0.325
R2 Adj.	0.233	0.325

\*p<0.05, \*\*p<0.01, \*\*\*p<0.001

$$(Trump)_i = \hat{\beta}_0 + \hat{\beta}_1(HS\_grad)_i + \hat{u}_i$$



$$(Trump)_i = (\hat{\beta}_0 + \hat{\beta}_2) + (\hat{\beta}_1 + \hat{\beta}_3)(HS\_grad)_i + \hat{u}_i$$

$$\beta_0 + \beta_2 = 138 - 77 = 61$$

$$\beta_1 + \beta_3 = -1.09 + 0.87 = -0.22$$

Note: pc\_hs\_grad and pc\_trump are scaled 0–100, not 0–1.

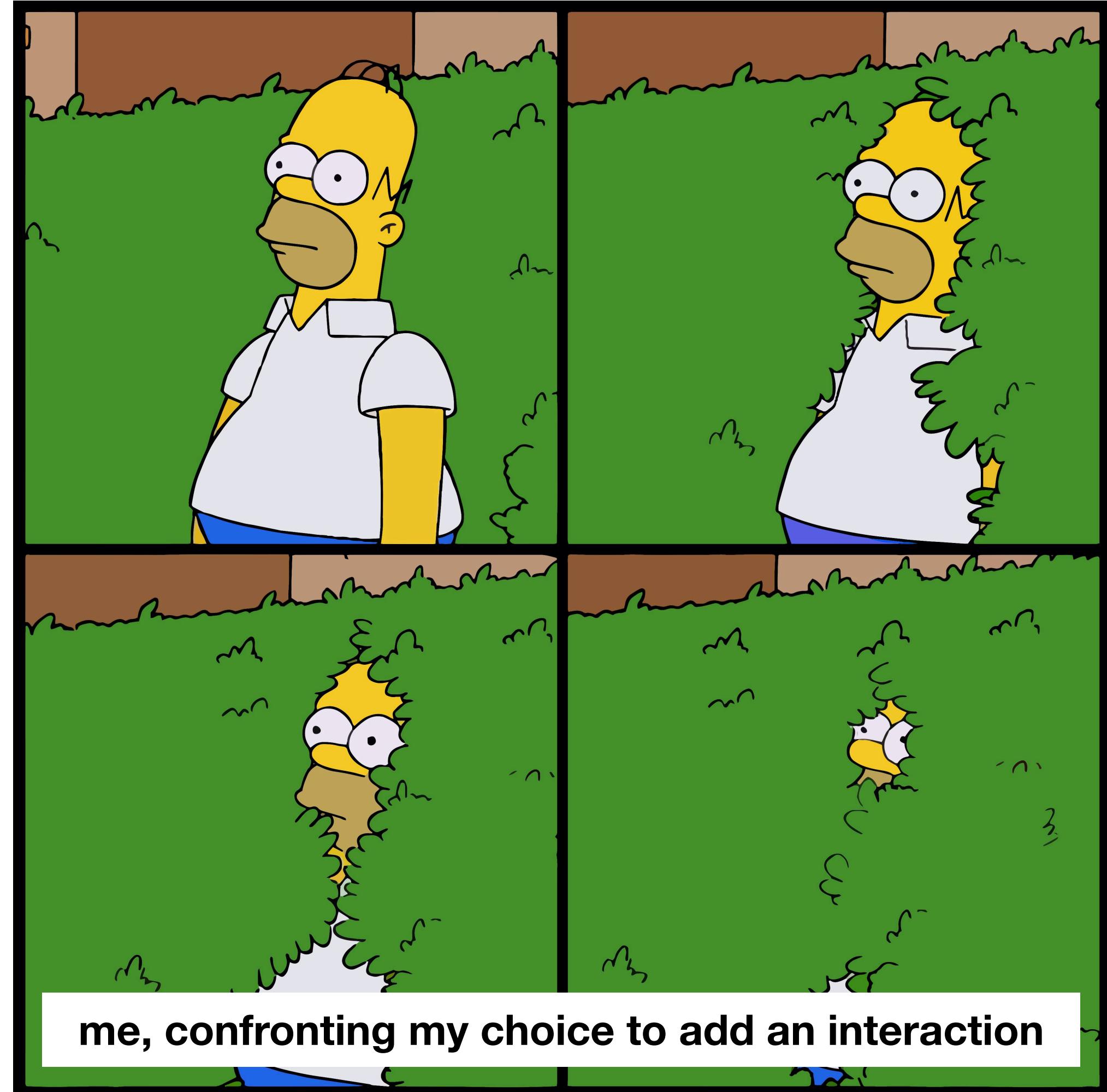
# What did we learn?

**Interactions are hard to interpret.**

**Start by writing out the regression functions.**

**We don't always need interactions.**

**But they can add richness to our models.**



**However, watch out for statistical power. We need much larger samples to estimate interactions than main effects.**