Welcome!

Nameplates please. And technology encouraged today!

All TF materials are available at github.com/nolankav/api-203.

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

In R: `df <- read.csv("http://tinyurl.com/api-203-tf-1")`

Fixed Effects and the Holy IV

API 203: TF Session 1

R

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Goals for today

1. **Review the principles of fixed effects.**
2. **Learn how to run fixed effects regressions in R.**
3. **Practice interpreting fixed effects regressions.**
4. **Review the principles of instrumental variables.**

   (We'll learn how to run IVs in R next week.)

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

Overview of our sample data

Dataset of U.S. county characteristics in 2012, 2016, & 2020

`county_fips`	**County FIPS identifier**	*Administrative*
`state`	**State**	*Administrative*
`year`	**Year**	*Administrative*
`pop_over_18`	**County voting age population (i.e. over 18 years)**	*American Community Survey (5-year estimates)*
`med_inc_000s`	**County median income (in $1,000s)**	*American Community Survey (5-year estimates)*
`unemploy_rate`	**County unemployment rate (0–100)**	*American Community Survey (5-year estimates)*
`pc_uninsured`	**Percent of county without health insurance (0–100)**	*American Community Survey (5-year estimates)*
`all_votes`	**Total number of votes cast in election**	*MIT Election Lab*
`rep_votes`	**Total number of votes for Republican candidate**	*MIT Election Lab*
`turnout`	**Percent of county VAP that voted in election (0–100)**	*MIT Election Lab/Constructed*
`pc_rep`	**Percent of county votes for Republican (0–100)**	*MIT Election Lab/Constructed*

How do you win an election?

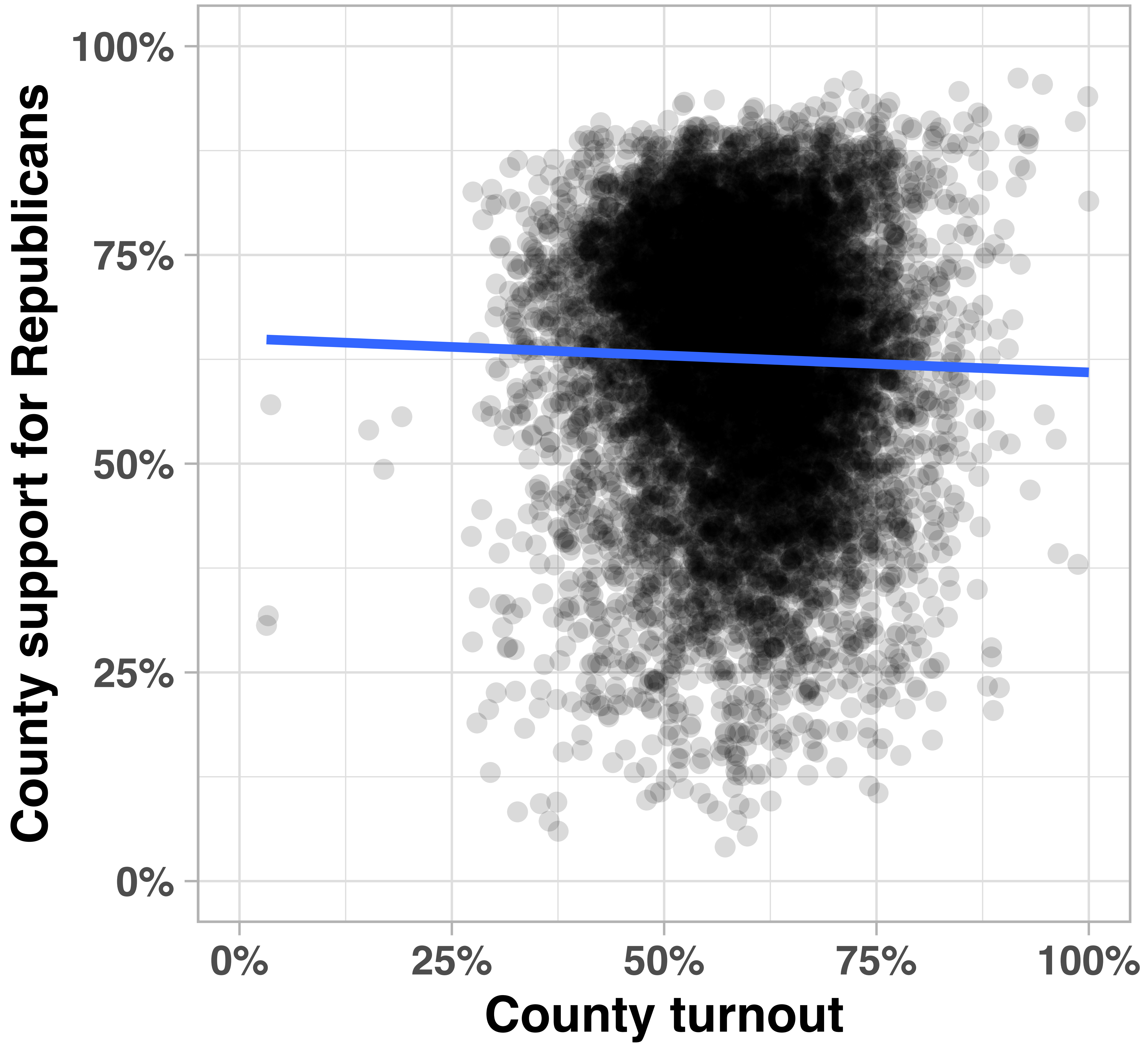
Some elections have higher turnout than others.

When more people turn out to vote, which party benefits: Democrats or Republicans?

turnout $\xrightarrow{?}$ support for each party

We could start with a pooled regression.

```
# Graph pooled turnout and percent Republican
plot_1 <- ggplot() +

  # Add scatterplot points
  geom_point(data=df, aes(x=turnout, y=pc_rep), alpha=0.15) +

  # Labels of axes
  xlab("County turnout") +
  ylab("County support for Republicans") +

  # 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(0,100),
                     labels = function(x) paste0(x,"%")) +

  # Add line of best fit
  geom_smooth(data=df, aes(x=turnout, y=pc_rep),
              method="lm", se=F, formula = y~x)

# Print graph
print(plot_1)
```

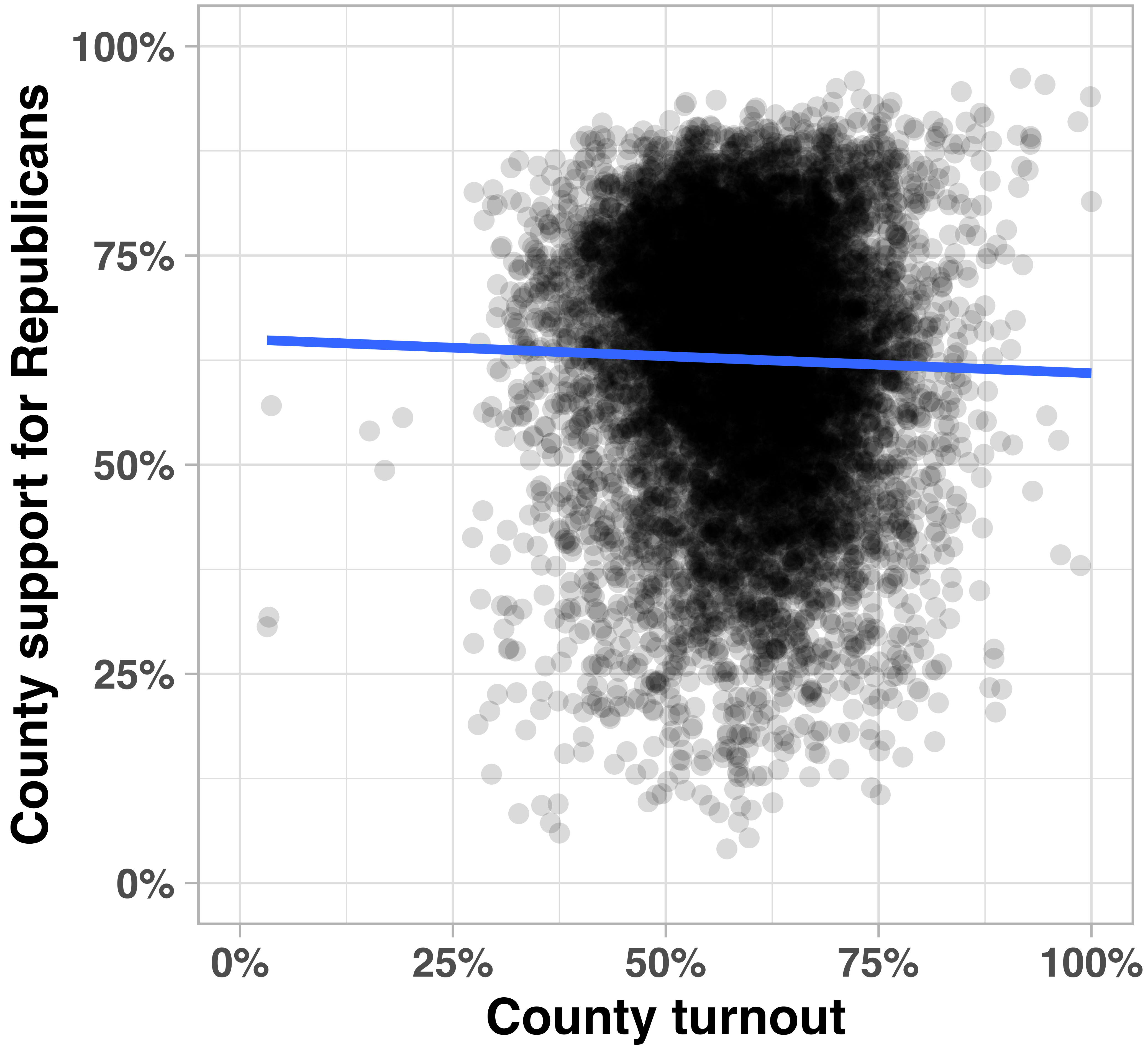


We could start with a pooled regression.

Here, we have pooled all county-years from 2012, 2016, and 2020 together.

Each point is one county in one year, e.g. Philadelphia County in 2016.

It looks like higher turnout modestly hurts support for Republican presidential candidates.



We could start with a pooled regression.

```
# Load package
library(fixest) # Modeling tools

# Estimate between-county regression
model_1 <- feols(pc_rep ~ turnout | 0, df)
summary(model_1)

OLS estimation, Dep. Var.: pc_rep
Observations: 9,345
Standard-errors: IID
             Estimate Std. Error  t value  Pr(>|t|)
(Intercept) 65.084073   0.888754 73.23068 < 2.2e-16 ***
turnout     -0.042113   0.014729 -2.85919 0.0042566 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
RMSE: 15.7   Adj. R2: 7.673e-4
```

We will use “feols()” from the “fixest” package.

We set it up much like “lm()” except that fixed effects come after the bar. Here, “0” indicates that we don’t yet have any fixed effects.

Note: `turnout` and `pc_rep` are coded 0–100.

We could start with a pooled regression.

```r
# Load package
library(fixest) # Modeling tools

# Estimate between-county regression
model_1 <- feols(pc_rep ~ turnout | 0, df)
summary(model_1)
```

<u>Across</u> all county-years from 2012 to 2020, a 1 pp increase in county turnout was associated with 0.04 pp less support for the Republican presidential candidate. It was statistically significant.

(Yes, it's a mouthful.)

```
OLS estimation, Dep. Var.: pc_rep
Observations: 9,345
Standard-errors: IID
             Estimate Std. Error  t value  Pr(>|t|)
(Intercept) 65.084073   0.888754 73.23068 < 2.2e-16 ***
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RMSE: 15.7   Adj. R2: 7.673e-4
```
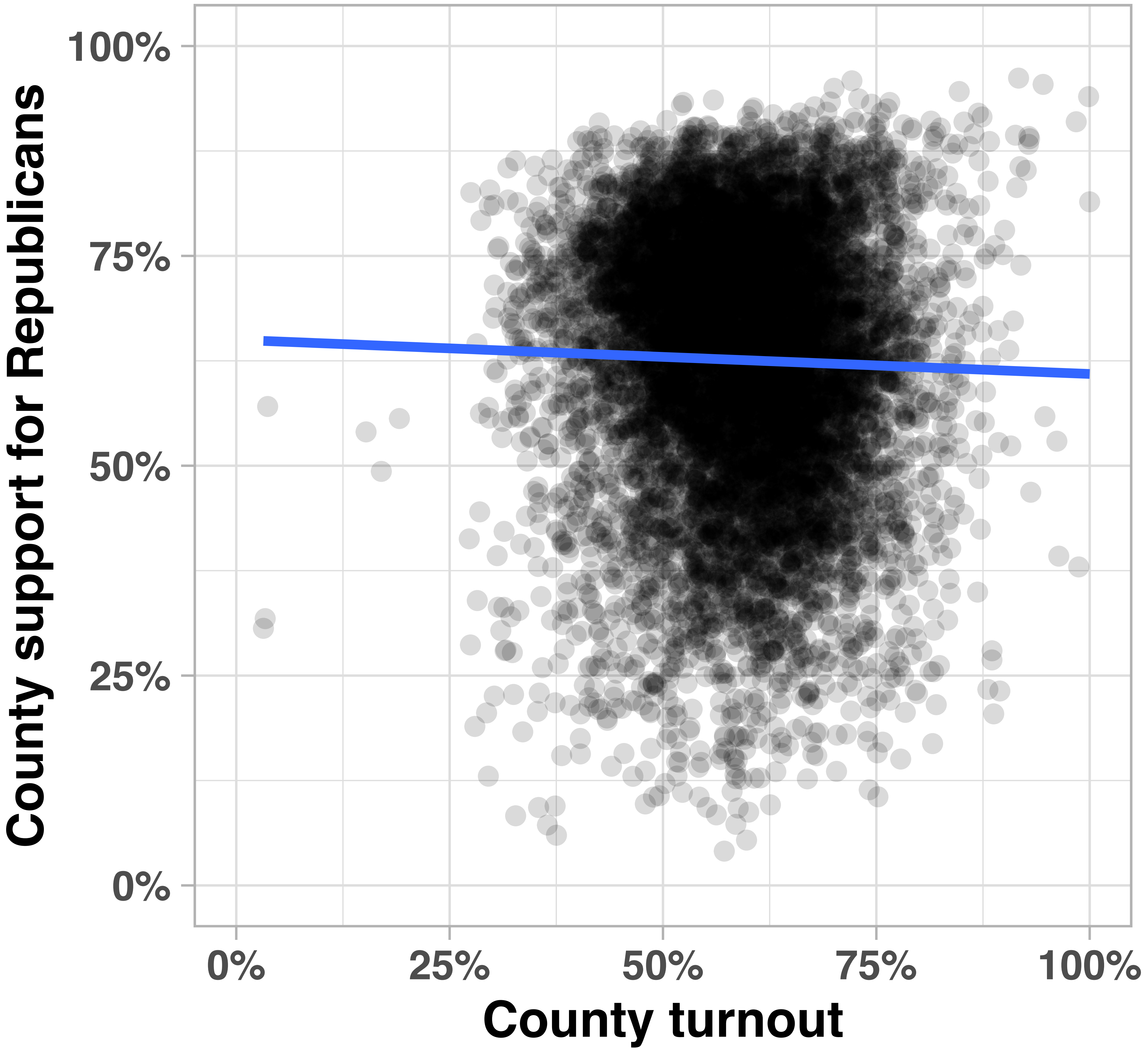

Note: `turnout` and `pc_rep` are coded 0–100.

We could add a few controls.

	Model 1	Model 2
County turnout (0–100)	**–0.04****	**–0.09*****
	(0.01)	(0.01)
County median income ($1,000s)		**–0.40*****
		(0.01)
County unemployment rate (0–100)		**–2.17*****
		(0.05)
Num.Obs.	9345	9345
County fixed effects	No	No
R2	0.001	0.202
R2 Adj.	0.001	0.201

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



Note: `pc_rep` is coded 0–100.

But what are we missing?

But what are we missing?

The potential omitted variables are endless!

- State election laws
- County election procedures
- County gender balance
- County age distribution
- County racial composition
- County major industries
- County insurance rate
- County partisan inclinations
- County geography
- And on and on

All of these are potential threats to inference!

What can we do?

One option is controlling for all of them, but we'd still end up missing omitted variables.

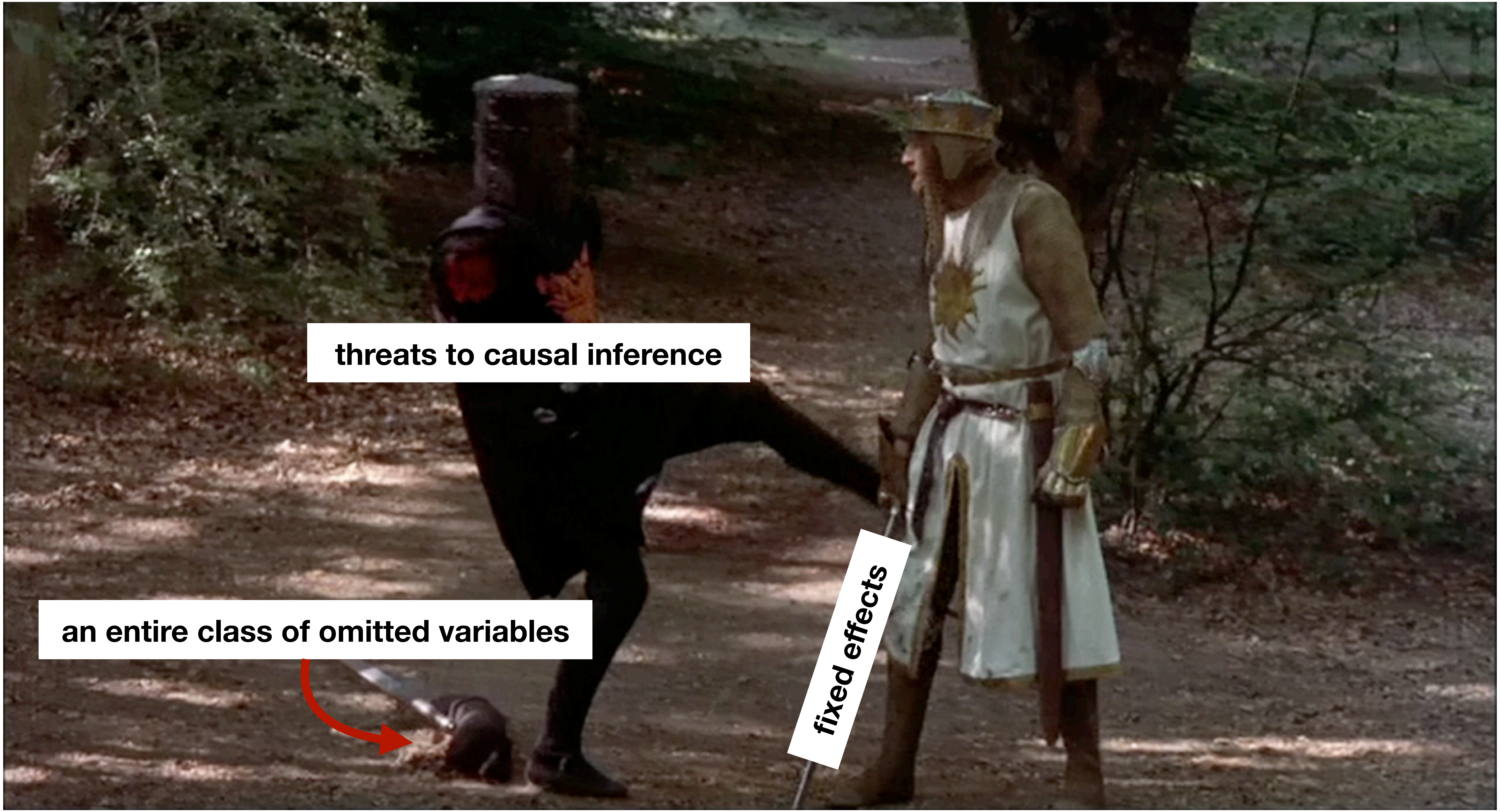
Enter: Fixed effects.

We want to know how changes in turnout *within a county* relate to votes.

Fixed effects let us control for entire classes of omitted variables.

A county fixed effect captures *all* time-invariant* characteristics of a county, e.g. geography, demographics, political inclinations, etc.
*meaning that they don't change meaningfully during our study period.

The result is a *within-county* estimate.


threats to causal inference
an entire class of omitted variables
fixed effects

A brief note on notation.

county fixed effects
Fixed effects are usually just written with one Greek letter and the appropriate subscript.

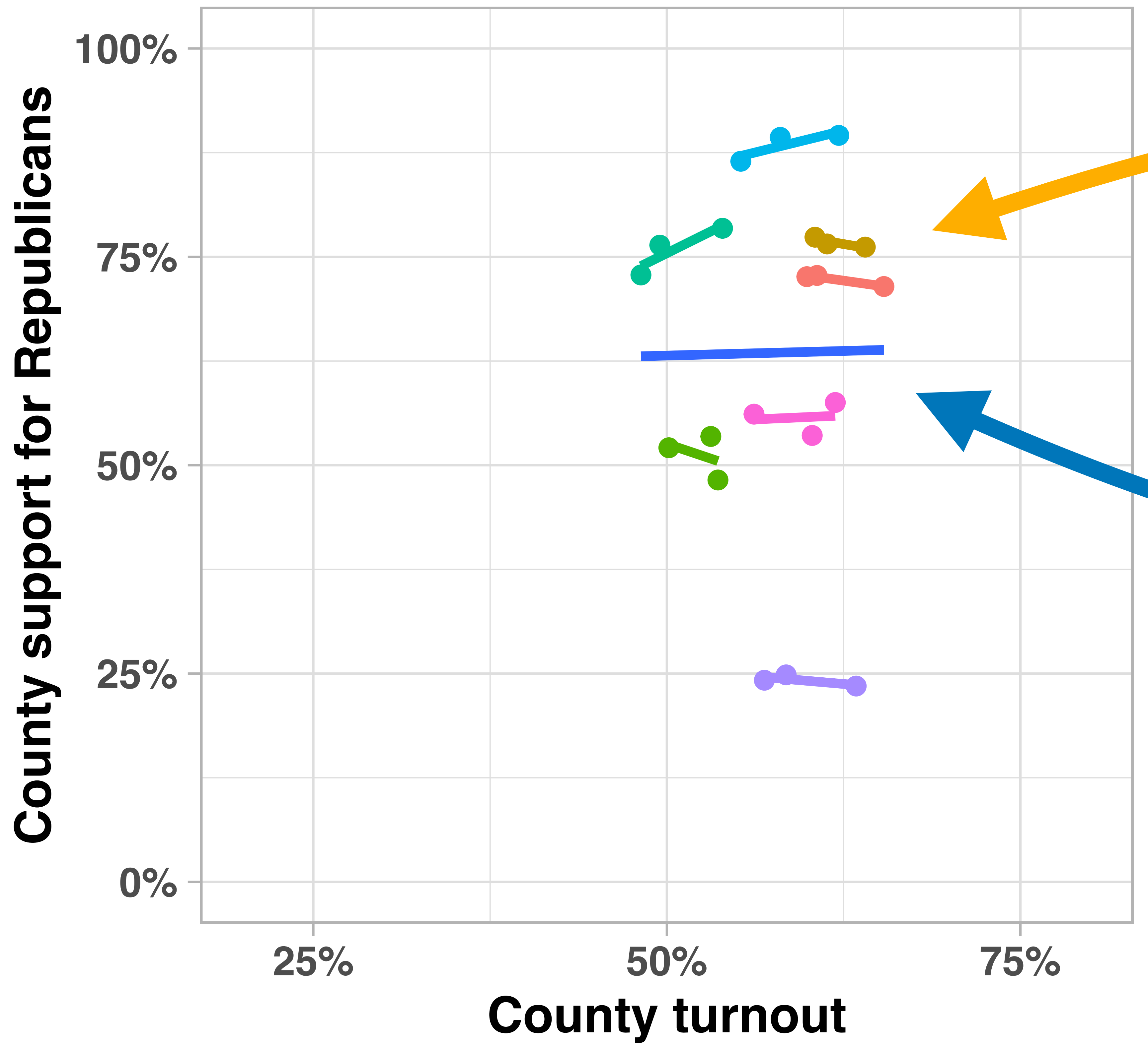
$$(pc\_Republican)_{ct} = \beta_0 + \beta_1(turnout)_{ct} + \lambda_c + u_{ct}$$

multiple indices for Xs and Y
Since we have the same county multiple times, we have to have enough indexes to identify each county-year.
c = county; t = time

residual (a.k.a. "error")
Also needs both indices!

Let’s look under the hood.

Here, I’ve selected a few counties in Alabama, each a different color.



Here is one county and the best-fit line for that county.

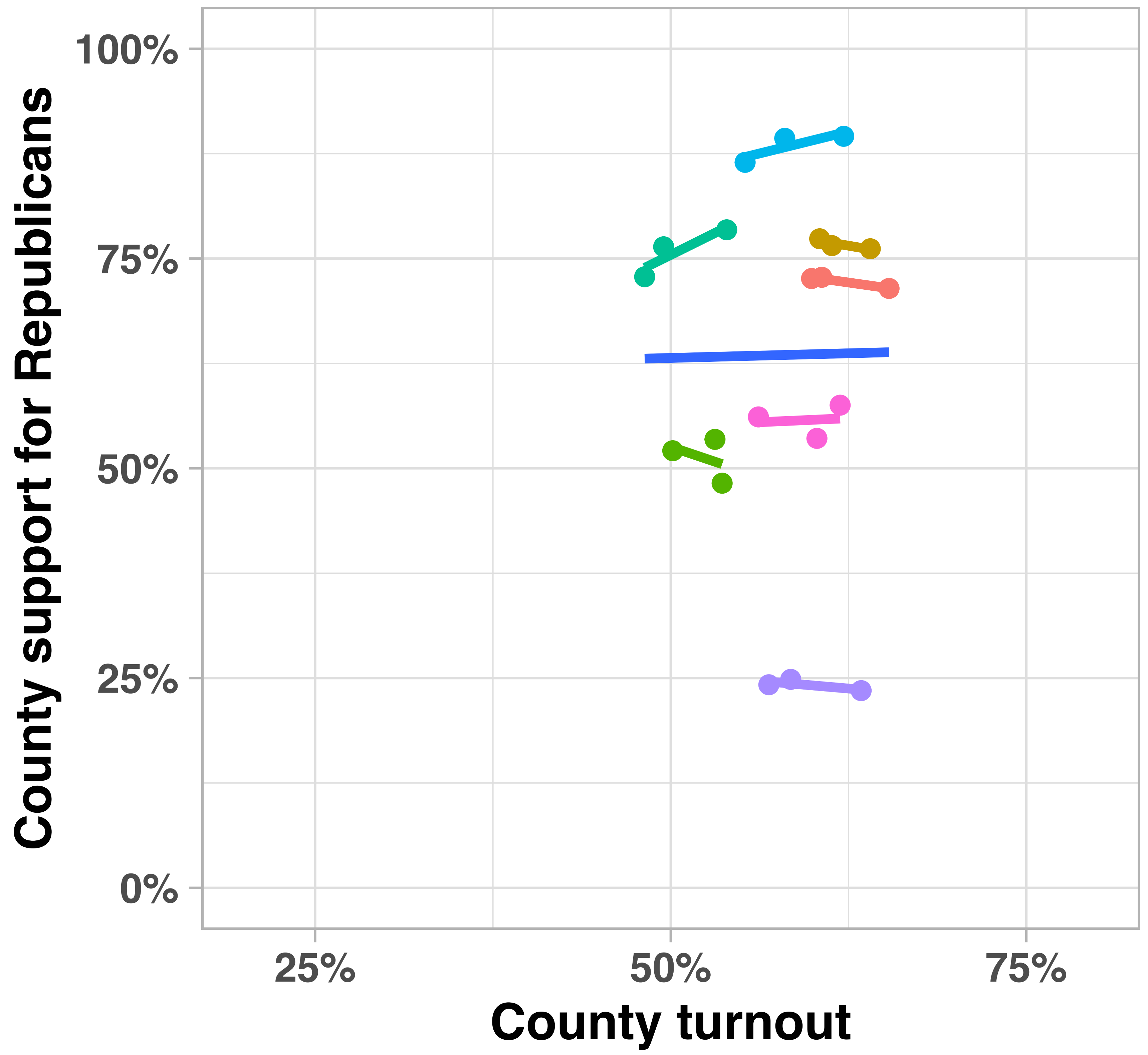
Here is the best-fit line for the pooled sample of a few Alabama counties.

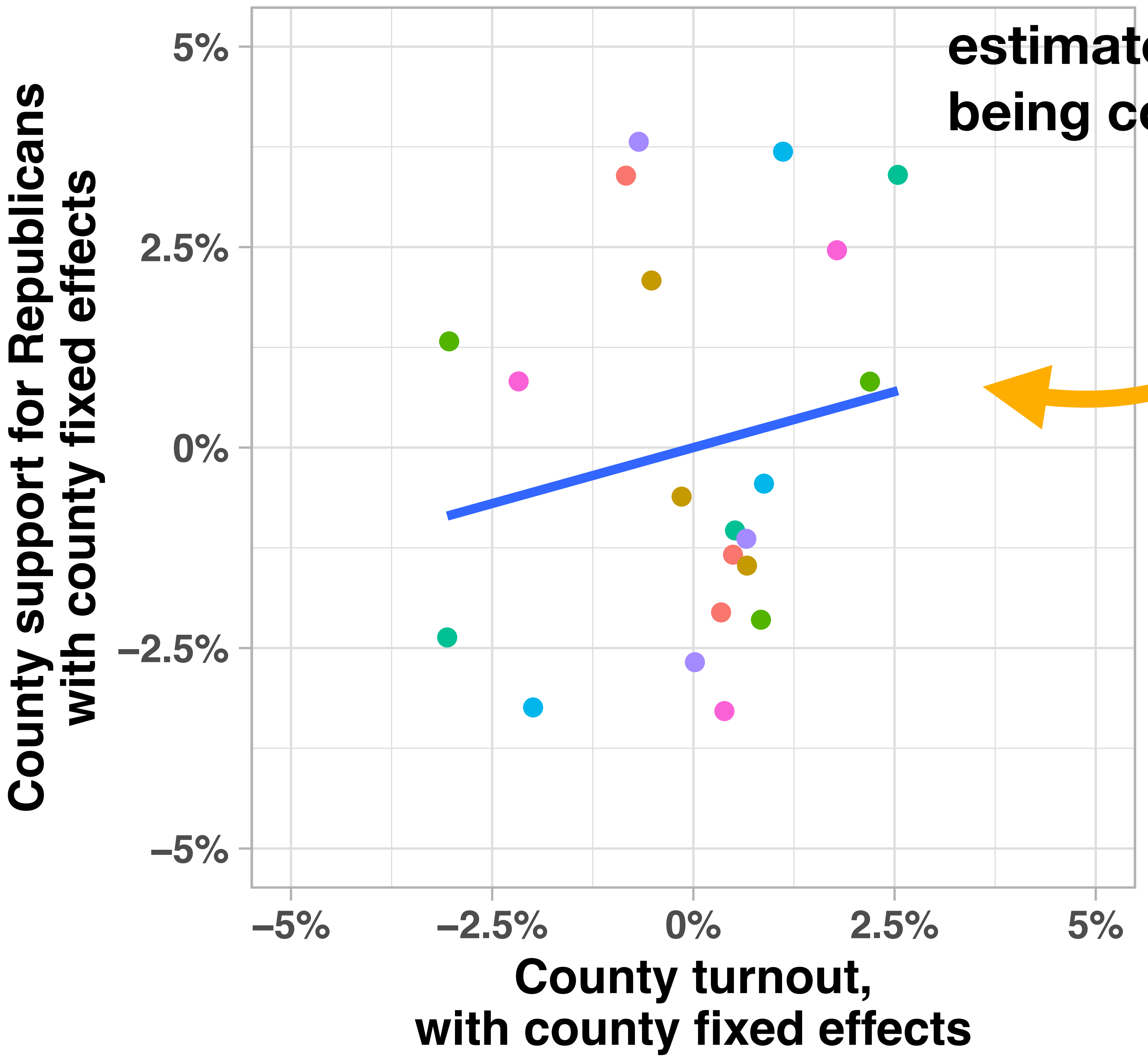
We can see that the association across counties is not necessarily the same as the association within counties!

The code for these analyses is all on GitHub.

Let’s “take out” the fixed effects.

Each county gets re-centered, and the best-fine line is refit.





The result is a “within-county” estimate since each county is being compared to itself!

This line is different than the pooled line!

The code for these analyses is all on GitHub.

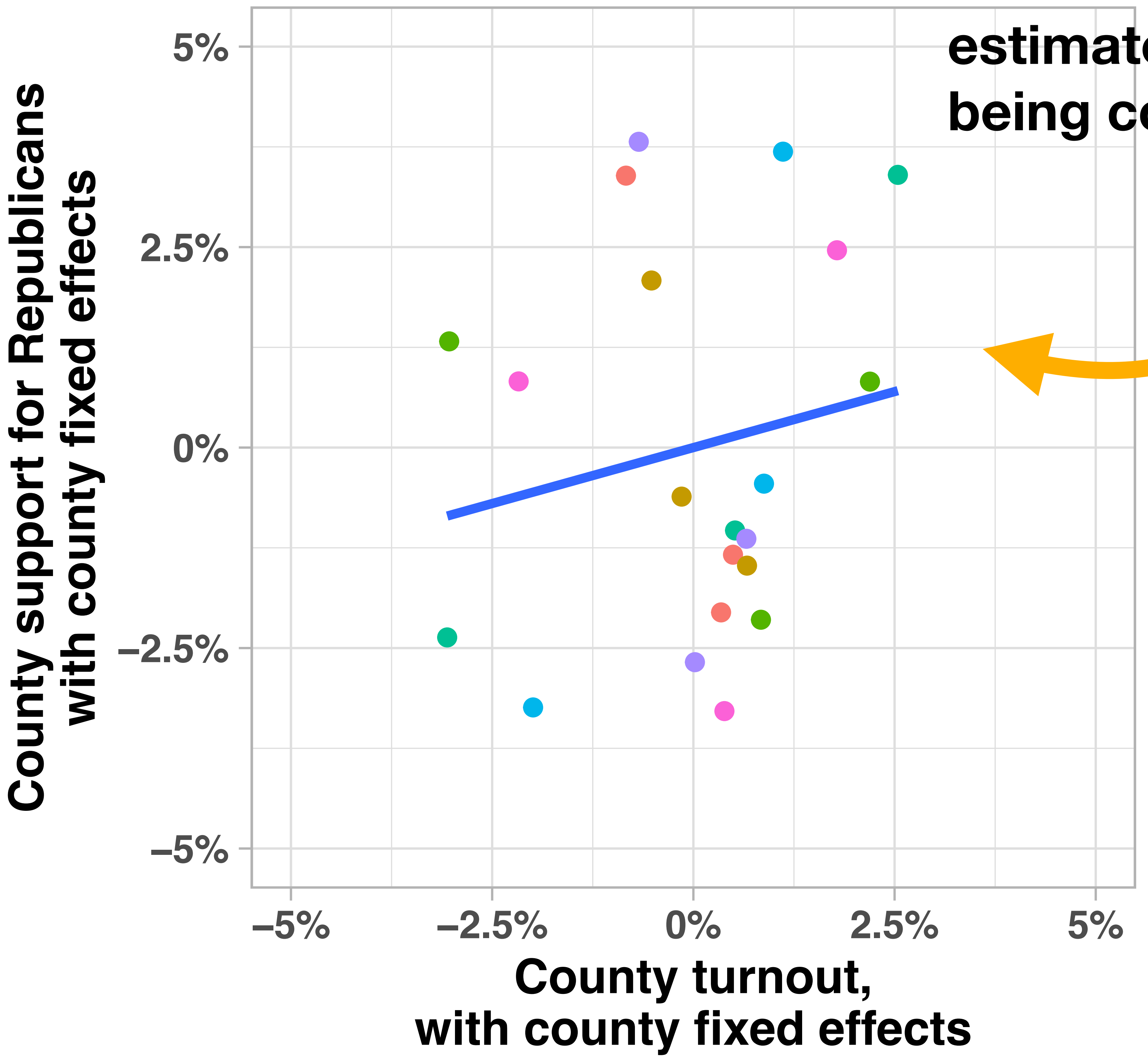
Let’s “take out” the fixed effects.

Each county gets re-centered, and the best-fine line is refit.

This process removes the differences between each county and leaves only the differences within counties over time!

Note: The fixed effects get “taken out” of both the X and Y variables.

So it’s a re-centering on both dimensions, not just one. Hence, it’s not as visually obvious as expected.



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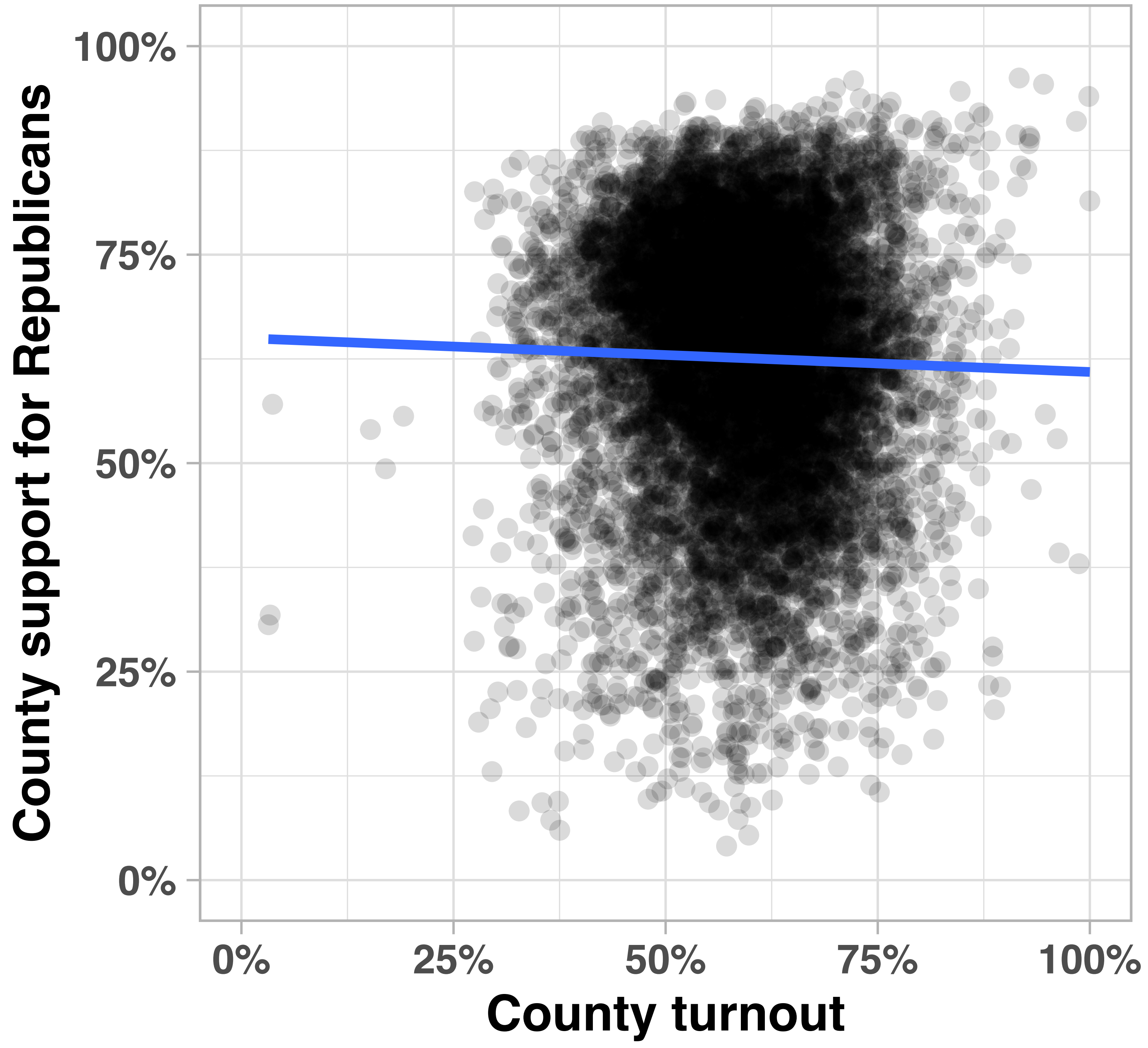

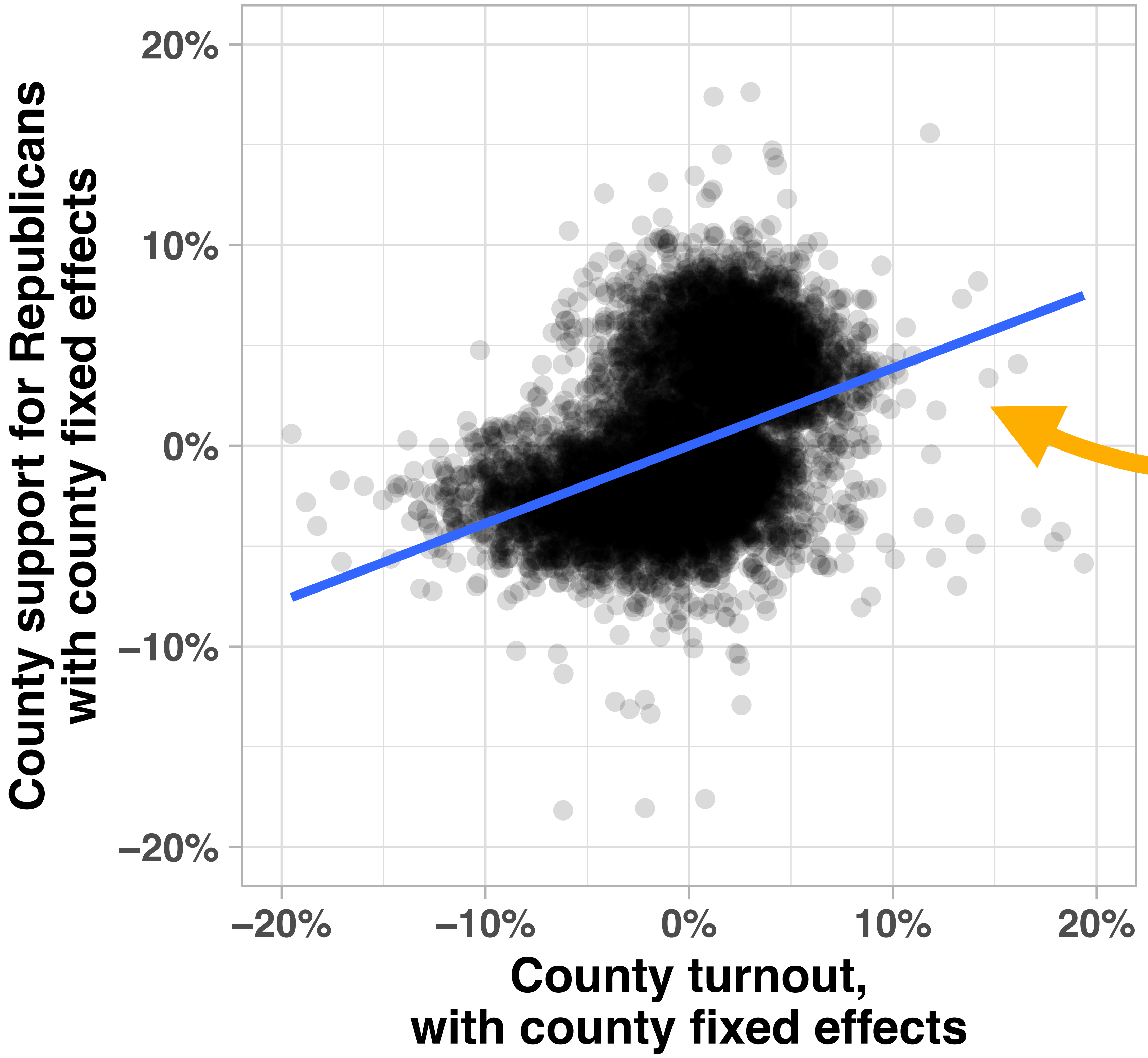

When we look within all counties, Republicans appear to benefit big from higher turnout!

The code for these analyses is all on GitHub.

Let’s “take out” the fixed effects.

```
# Estimate within-county regressions
model_3 <- feols(pc_rep ~ turnout | county_fips, df)
summary(model_3)

OLS estimation, Dep. Var.: pc_rep
Observations: 9,345
Fixed-effects: county_fips: 3,117
Standard-errors: Clustered (county_fips)
        Estimate Std. Error t value  Pr(>|t|)
turnout 0.370447   0.013371 27.7063 < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
RMSE: 3.48412     Adj. R2: 0.926479
                Within R2: 0.144134
```

To add our fixed effect, we place it after the bar.

Note that our output does not show the estimates for the individual fixed effects or intercept.

The fixed effects get estimated by a clever de-meaning procedure behind the scenes, and the intercept gets wrapped up with them.

Note: `turnout` and `pc_rep` are coded 0–100.

Let's "take out" the fixed effects.

```
# Estimate within-county regressions
model_3 <- feols(pc_rep ~ turnout | county_fips, df)
summary(model_3)

OLS estimation, Dep. Var.: pc_rep
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RMSE: 3.48412     Adj. R2: 0.926479
                Within R2: 0.144134
```

A 1 pp increase <u>in a given county's</u> turnout was associated with a statistically significant 0.37 pp <u>increase</u> in support for the Republican presidential candidate from 2012 to 2020.

Note: `turnout` and `pc_rep` are coded 0–100.

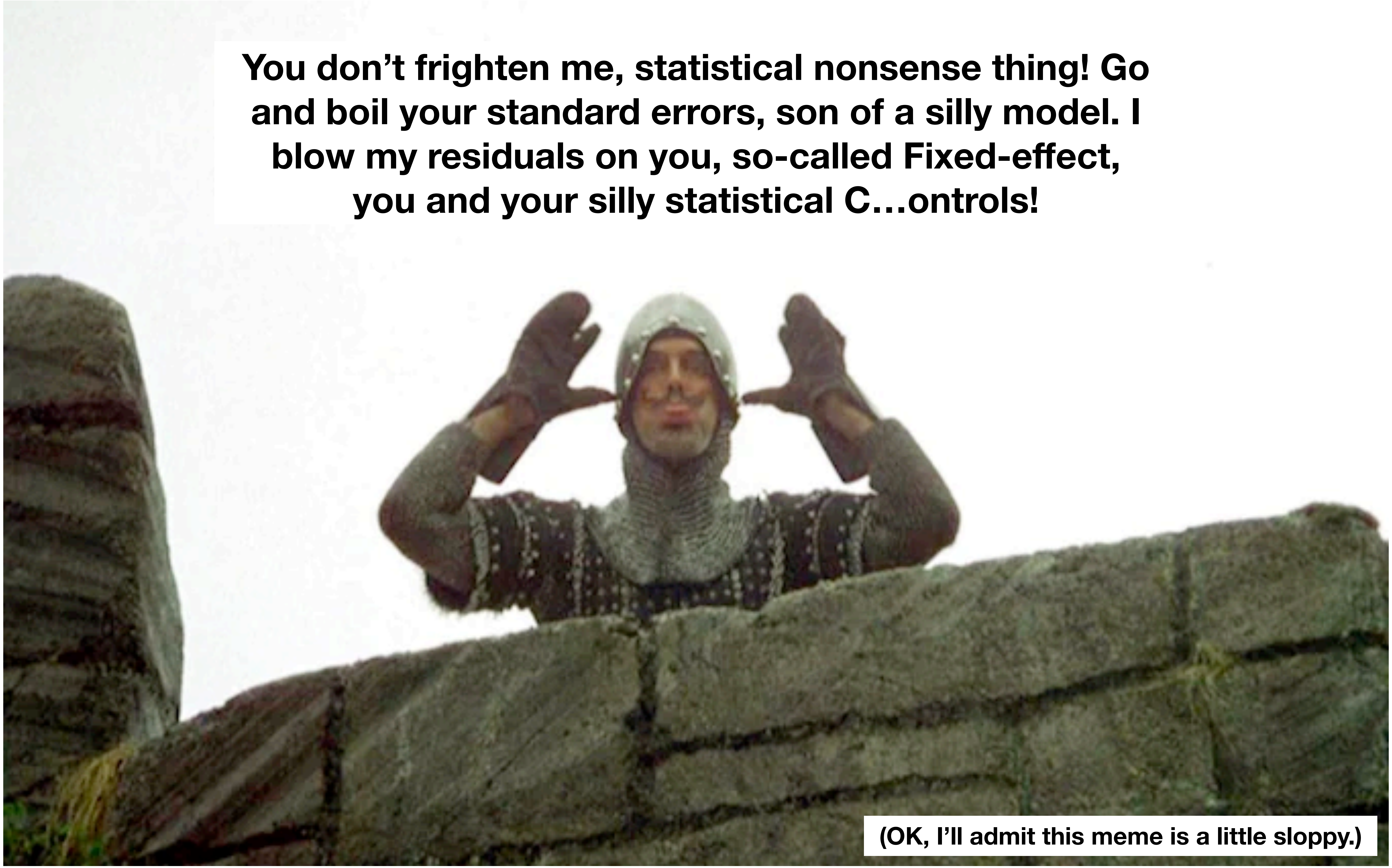
Let's "take out" the fixed effects.

	Model 1	Model 2	Model 3	Model 4
County turnout (0–100)	**–0.04****	**–0.09*****	**0.37*****	**0.15*****
	(0.01)	(0.01)	(0.01)	(0.02)
County median income ($1,000s)		**–0.40*****		**0.09*****
		(0.01)		(0.02)
County unemployment rate (0–100)		**–2.17*****		**–0.50*****
		(0.05)		(0.03)
Num.Obs.	9345	9345	9345	9345
County fixed effects	No	No	Yes	Yes
R2	0.001	0.202	0.951	0.955
R2 Adj.	0.001	0.201	0.926	0.933

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

Collectively, the time-invariant differences between counties added enough omitted variable bias to flip the sign of the relationship!

Note: `pc_rep` is coded 0–100.


You don’t frighten me, statistical nonsense thing! Go and boil your standard errors, son of a silly model. I blow my residuals on you, so-called Fixed-effect, you and your silly statistical C…ontrols!
(OK, I’ll admit this meme is a little sloppy.)

Consider what the fixed effect captures.

For example, what about <u>state-level</u> omitted variables?

What happens when we include <u>state</u> fixed effects?

Consider what the fixed effect captures.

For example, what about <u>state-level</u> omitted variables?

What happens when we include <u>state</u> fixed effects?

No worries!

Each state fixed effect is just the sum of all the county fixed effects in that state, so the state FEs get dropped from the regression.

Consider what the fixed effect captures.

But what about time-variant omitted variables?

Consider what the fixed effect captures.

But what about time-variant omitted variables?

These are not covered by our county fixed effects.

We might consider adding year fixed effects, which would address national trends that affect all counties in our sample.

We could add time-county-varying controls, like unemployment rate.

Consider what the fixed effect captures.

Can we add county-year fixed effects?

Consider what the fixed effect captures.

Can we add county-year fixed effects?

No, because that's the source of all our variation!

```
# Estimate regression with county-year FEs
feols(pc_rep ~ turnout + med_inc_000s + unemploy_rate | county_fips*year, df)

Error: in feols(pc_rep ~ turnout + med_inc_000s + unemploy_...:
All variables'turnout', 'med_inc_000s' and 'unemploy_rate' are collinear with
the fixed effects. In such circumstances, the estimation is void.
```

Is it causal?

Causality is a spectrum.

Fixed effects eliminate entire classes of potential omitted variables.

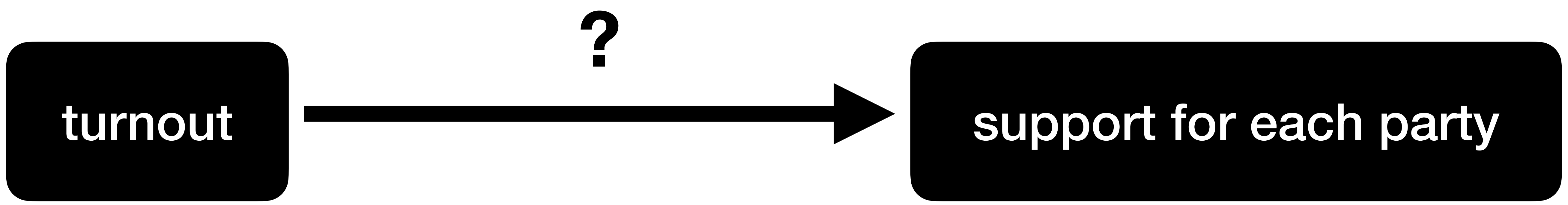
We consider a study “causal” if the most worrisome classes of omitted variables (and other biases) have been adequately addressed.

In this case, probably no. But in other fixed effects regressions, maybe yes.

AND NOW FOR SOMETHING COMPLETELY DIFFERENT

What’s up with instrumental variables?

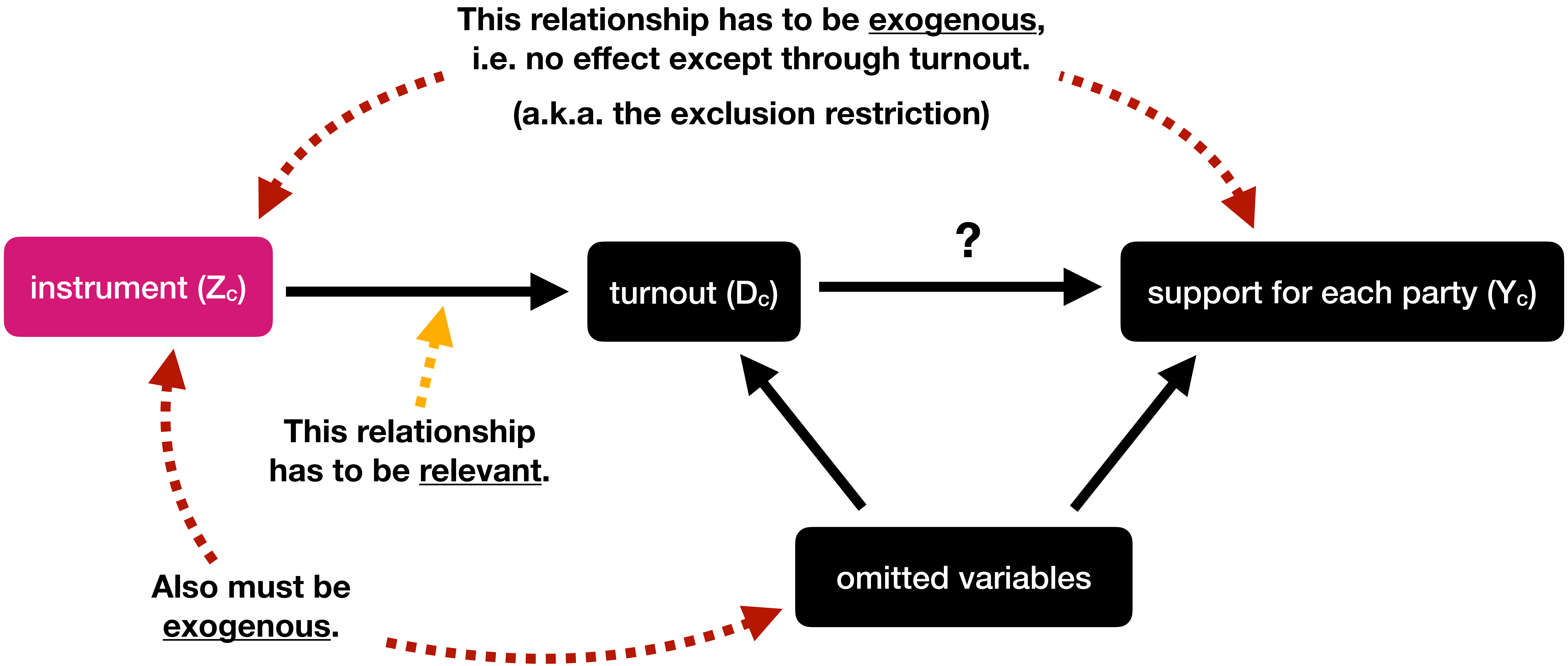
We still want to know about turnout and Republican support.



Some of this relationship is causal; some is due to omitted variables.

IVs basically split the relationship into causal and non-causal parts by taking advantage of random variation in a third variable.

What's up with instrumental variables?



Let’s say our instrument is rain.

The idea is that random variation in rain = random variation in turnout.

<u>Stage 1:</u> Regress D on Z and take the predicted values of D.
This captures the part of our predictor that is “random.”

$$(turnout)_c = \alpha_0 + \alpha_{FS}(rain)_c + \alpha_2(average\_rain)_c + v_c$$

I’ve included a control for the average rainy-ness of each county.

Let's say our instrument is rain.

The idea is that random variation in rain = random variation in turnout.

<u>Stage 1:</u> Regress D on Z and take the predicted values of D.
This captures the part of our predictor that is "random."

I've included a control for the average rainy-ness of each county.

$$(turnout)_c = \alpha_0 + \alpha_{FS}(rain)_c + \alpha_2(average\_rain)_c + v_c$$

<u>Stage 2:</u> Then, regress Y on the <u>predicted</u> values of D.
This estimates the change in our outcome due to random variation in our predictor.

$$(pc\_Republican)_c = \beta_0 + \beta_{IV}\widehat{(turnout)}_c + \beta_2(average\_rain)_c + u_c$$

This process is called "two-stage least squares."


Phillip G. Wright when people rediscovered instrumental variables after he casually invented them in 1928 while writing about vegetable oil tariffs, only for the method to be forgotten for several decades.
Of course it's a good idea

What can go wrong?

As it turns out, potentially a lot:

1. Weak IV: The first stage just isn't very strong ("irrelevant").

2. Violations of exclusion restriction: Does rain *only* affect turnout?

3. Not "independent": The instrument might not actually be random.

Unfortunately, we can only prove 1 and maybe 3.

Where do we go from here?

Next week, we will dive deeper into IVs.

We will also learn how to estimate them in R.

For now, focus on your understanding.

IVs fundamentally hinge on whether we “buy” that their assumptions are met.