Welcome!

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-1")`

In Excel: http://tinyurl.com/api-202-tf-2

EXCEL

What's the deal with regression?

API 202: TF Session 1

Nolan M. Kavanagh
January 26, 2024

Goals for today

1. **Get to know one another a little better.**
2. **Review regression notation, including the PRF vs. SRF.**
3. **Learn how to graph bivariate relationships.**
4. **Learn how to run regressions.**
5. **Review how to interpret regressions.**

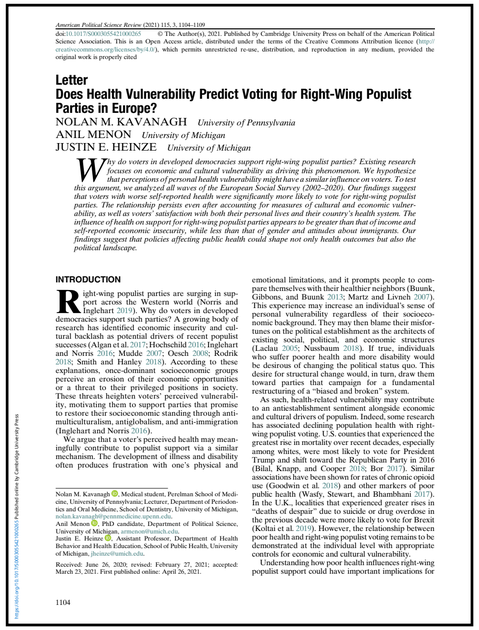
We'll treat this session like a workshop with interactive examples.

MD/PhD student in health policy.

“I don’t need backups. I’m going to Harvard.”

Hi, I’m Nolan.

GO BLUE!



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Letter

Does Health Vulnerability Predict Voting for Right-Wing Populist Parties in Europe?

NOLAN M. KAVANAGH *University of Pennsylvania*
ANIL MENON *University of Michigan*
JUSTIN E. HEINZE *University of Michigan*

Why do voters in developed democracies support right-wing populist parties? Existing research focuses on economic and cultural vulnerability as driving this phenomenon. We hypothesize that perceptions of personal health vulnerability might have a similar influence on voters. To test this argument, we analyzed all waves of the European Social Survey (2002–2020). Our findings suggest that voters with worse self-reported health were significantly more likely to vote for right-wing populist parties. The relationship persists even after accounting for measures of cultural and economic vulnerability, as well as voters’ satisfaction with both their personal lives and their country’s health system. The influence of health on support for right-wing populist parties appears to be greater than that of income and self-reported economic insecurity, while less than that of gender and attitudes about immigrants. Our findings suggest that policies affecting public health could shape not only health outcomes but also the political landscape.

INTRODUCTION

Right-wing populist parties are surging in support across the Western world (Norris and Inglehart 2019). Why do voters in developed democracies support such parties? A growing body of research has identified economic insecurity and cultural backlash as potential drivers of recent populist successes (Algan et al. 2017; Hochschild 2016; Inglehart and Norris 2016; Mudde 2007; Oesch 2008; Rodrik 2018; Smith and Hanley 2018). According to these explanations, once-dominant socioeconomic groups perceive an erosion of their economic opportunities or a threat to their privileged positions in society. These threats heighten voters’ perceived vulnerability, motivating them to support parties that promise to restore their socioeconomic standing through anti-multiculturalism, antiglobalism, and anti-immigration (Inglehart and Norris 2016).

We argue that a voter’s perceived health may meaningfully contribute to populist support via a similar mechanism. The development of illness and disability often produces frustration with one’s physical and emotional limitations, and it prompts people to compare themselves with their healthier neighbors (Buunk, Gibbons, and Buunk 2013; Martz and Livneh 2007). This experience may increase an individual’s sense of personal vulnerability regardless of their socioeconomic background. They may then blame their misfortunes on the political establishment as the architects of existing social, political, and economic structures (Laclau 2005; Nussbaum 2018). If true, individuals who suffer poorer health and more disability would be desirous of changing the political status quo. This desire for structural change would, in turn, draw them toward parties that campaign for a fundamental restructuring of a “biased and broken” system.

As such, health-related vulnerability may contribute to an antiestablishment sentiment alongside economic and cultural drivers of populism. Indeed, some research has associated declining population health with right-wing populist voting. U.S. counties that experienced the greatest rise in mortality over recent decades, especially among whites, were most likely to vote for President Trump and shift toward the Republican Party in 2016 (Bilal, Knapp, and Cooper 2018; Bor 2017). Similar associations have been shown for rates of chronic opioid use (Goodwin et al. 2018) and other markers of poor public health (Wasfy, Stewart, and Bhambhani 2017). In the U.K., localities that experienced greater rises in “deaths of despair” due to suicide or drug overdose in the previous decade were more likely to vote for Brexit (Koltai et al. 2019). However, the relationship between poor health and right-wing populist voting remains to be demonstrated at the individual level with appropriate controls for economic and cultural vulnerability.

Understanding how poor health influences right-wing populist support could have important implications for

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My research is on the politics of health.

My go-to karaoke song is “Since U Been Gone.”

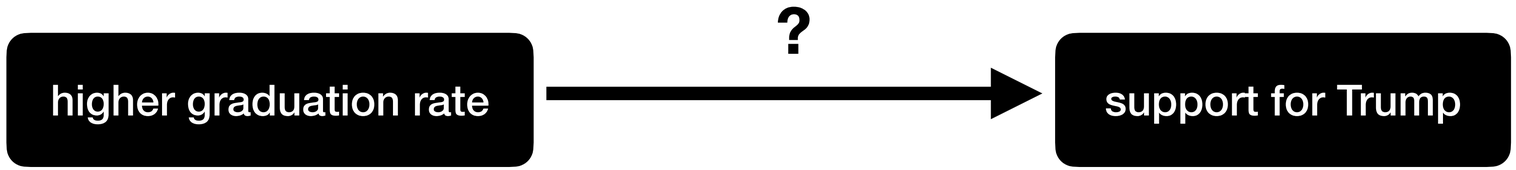
Overview of our sample data

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

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

Tell me a story.

Let's say we're interested in the relationship between high school graduation and support for Trump.

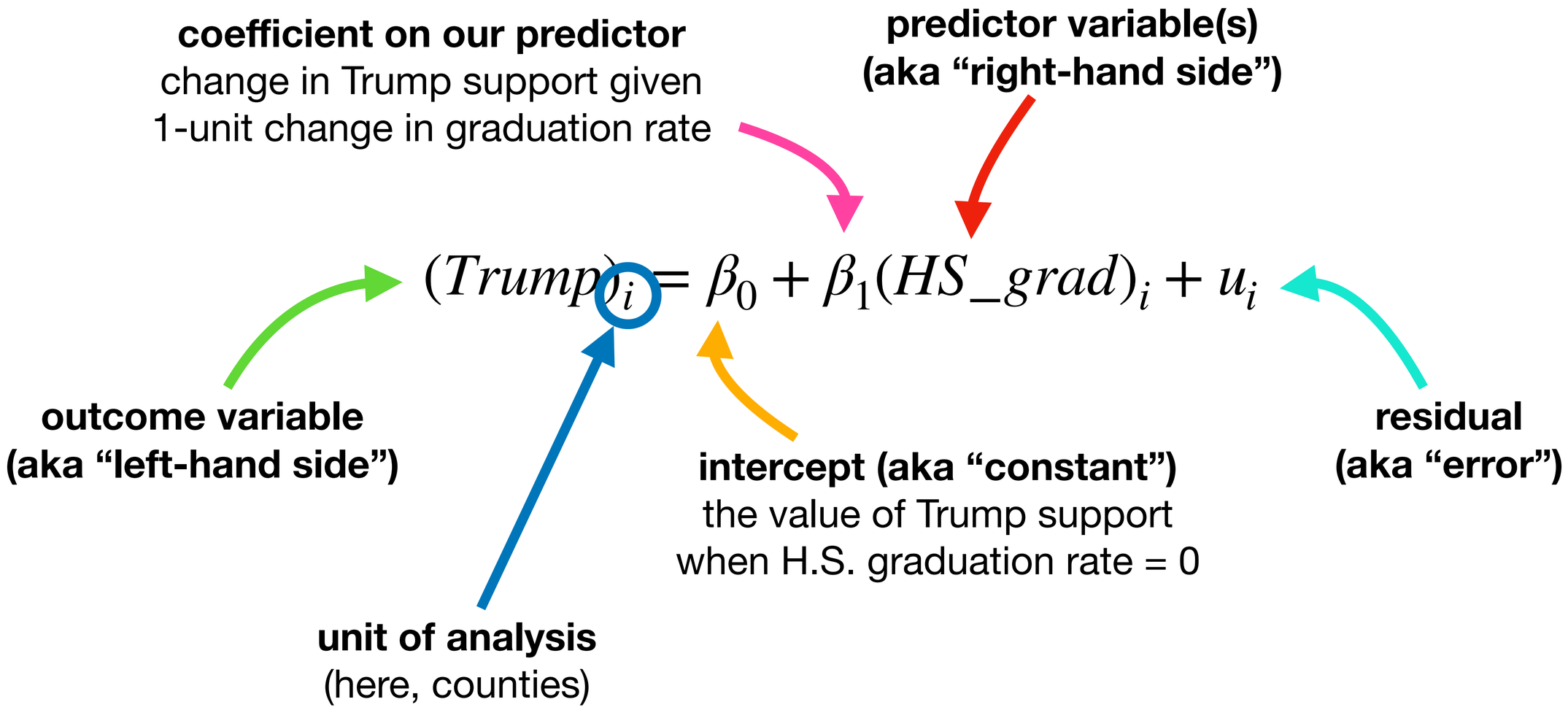


What might be the mechanism?

More education = liberal values = prefer multiculturalism?

More education = more income = prefer lower taxes?

Population regression function



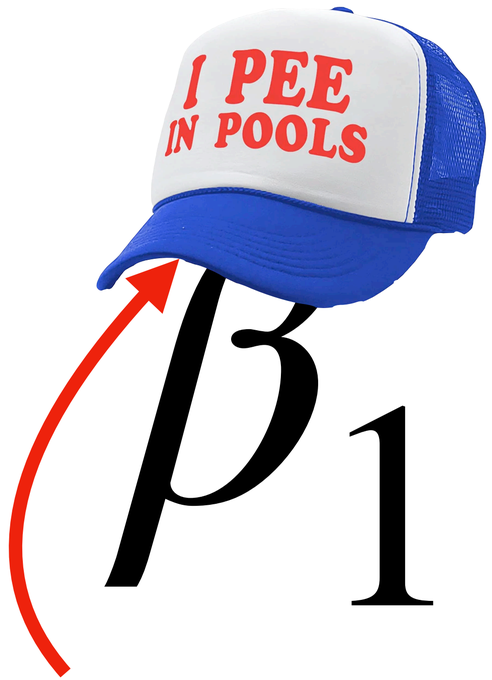
Population regression function

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

We add "hats" to signify estimated values in our sample.

Sample regression function

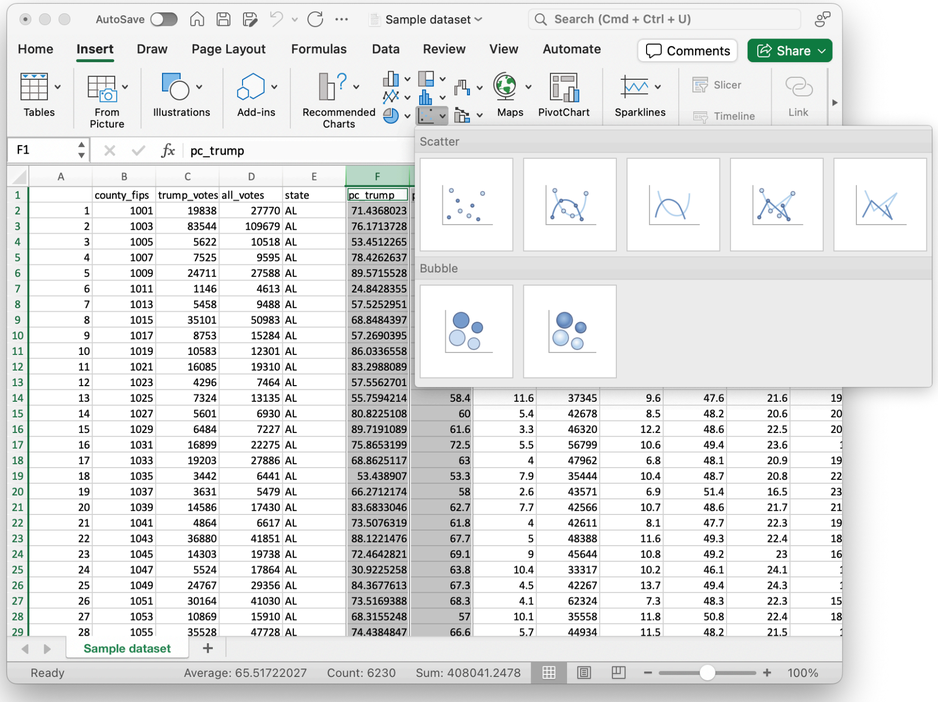
$$(Trump)_i = \hat{\beta}_0 + \hat{\beta}_1(HS\_grad)_i + \hat{u}_i$$



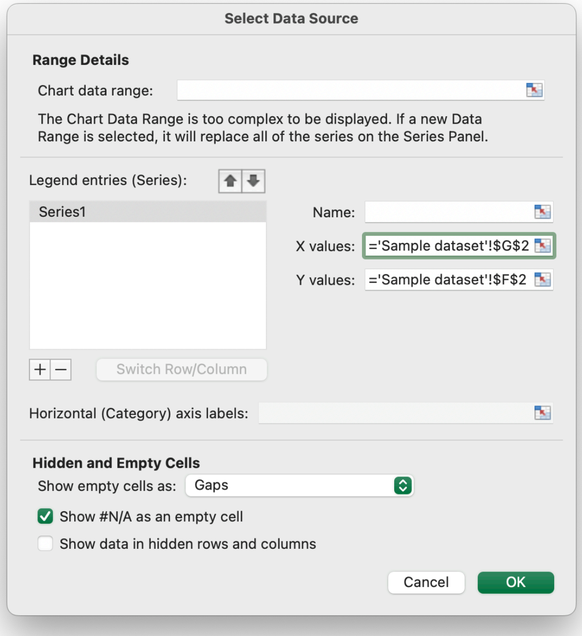
Only a <u>specific</u> sample would ever wear this hat.

Let’s graph our data.

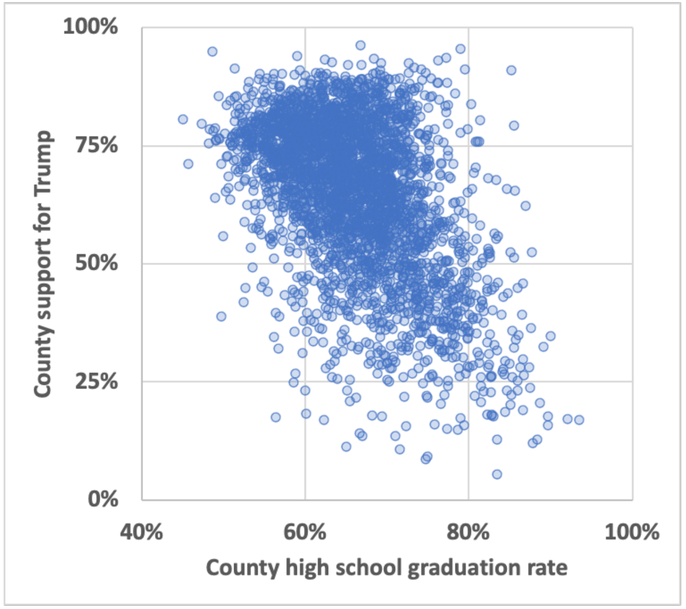
1. Insert a scatterplot.



2. Modify X and Y data ranges, as necessary.



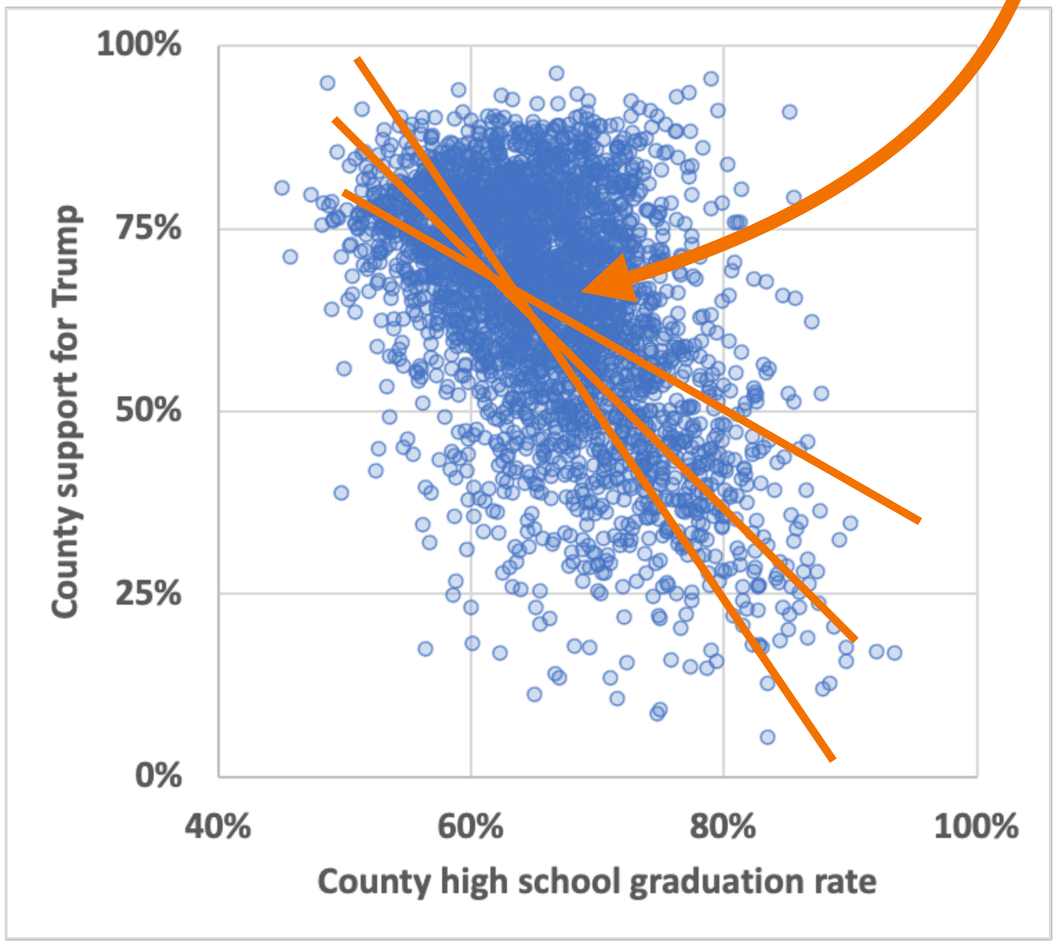
3. Chart Design > Add Chart Element, like axis labels.



To modify an existing element, double-click on it and a formatting window will pop up on the right.

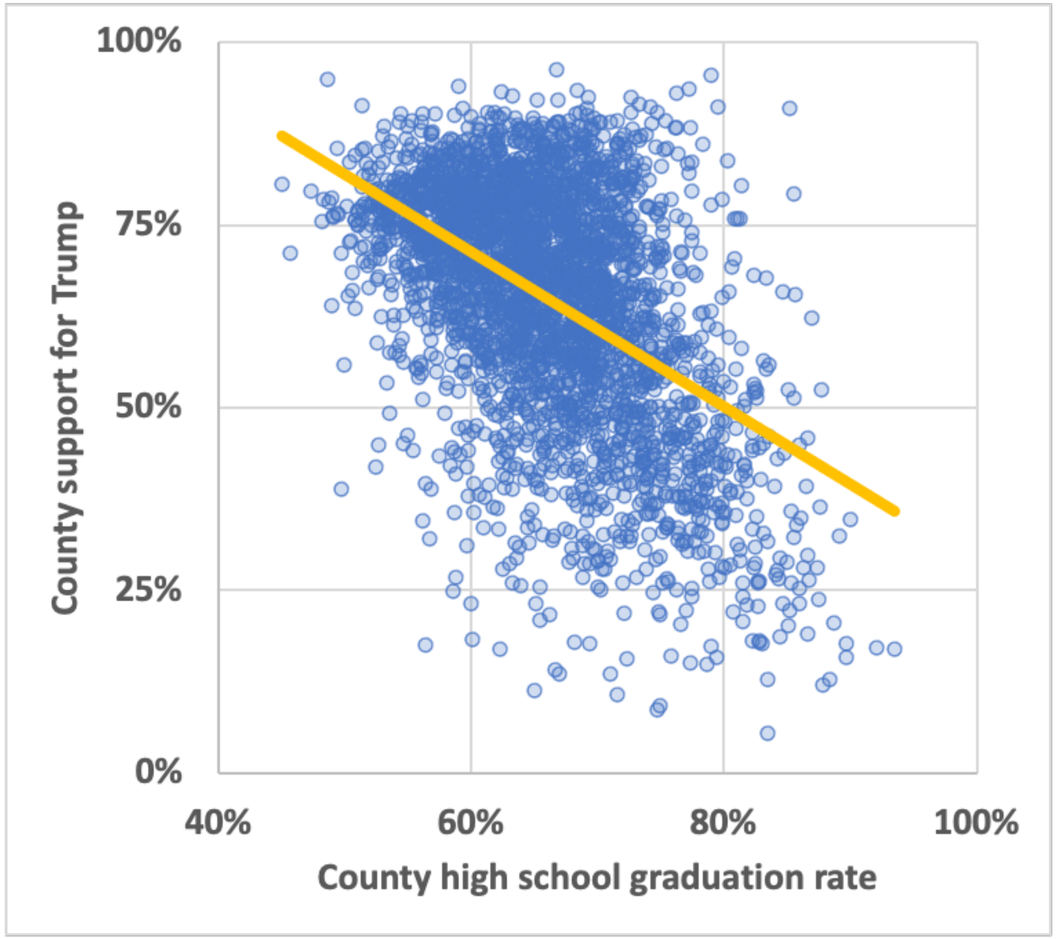
Let’s graph our data.

Which line fits best?



Let’s graph our data.

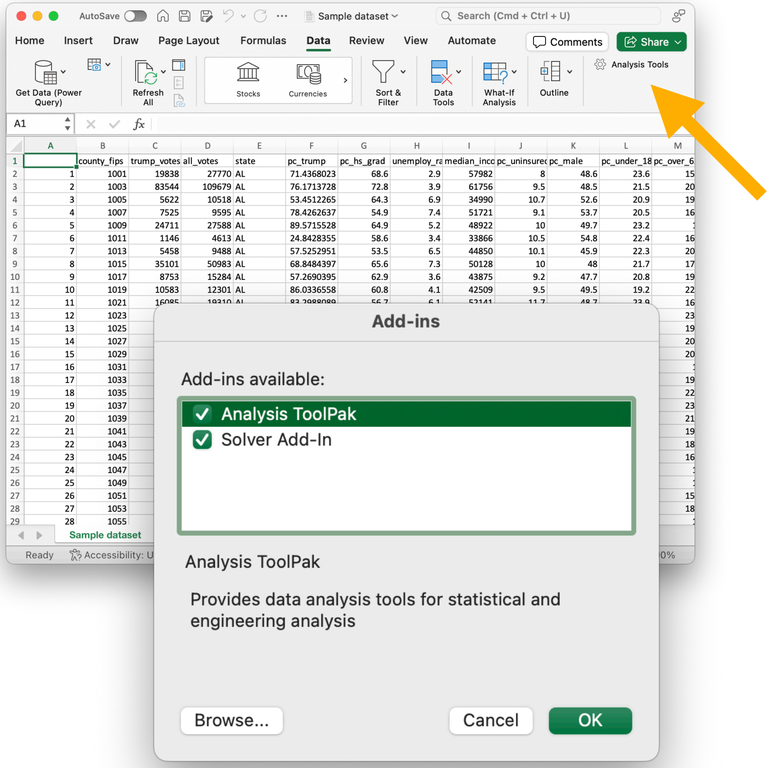
We can add a linear model under Add Chart Element > Trendline > Linear.



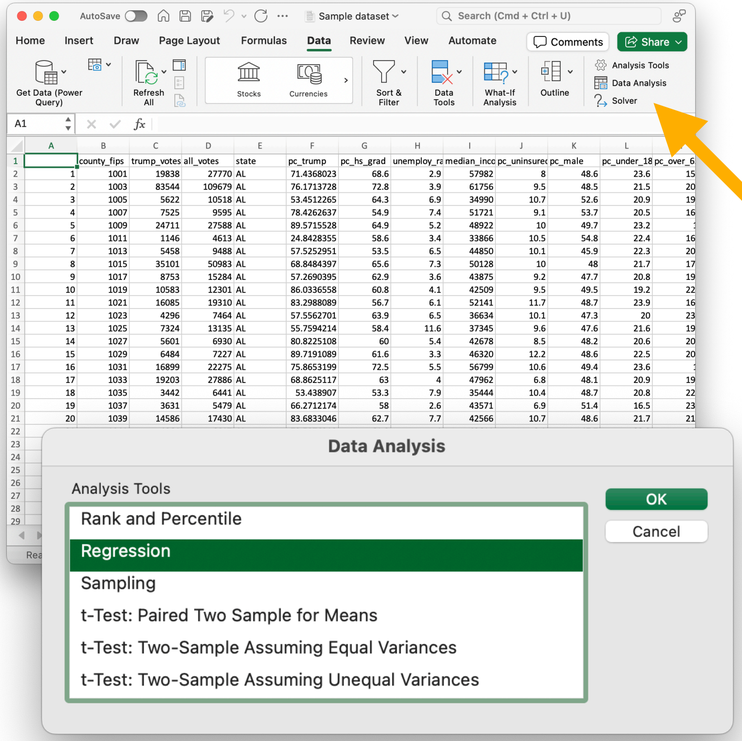
…but we still want to run the regression.

OK fine, let's run a regression.

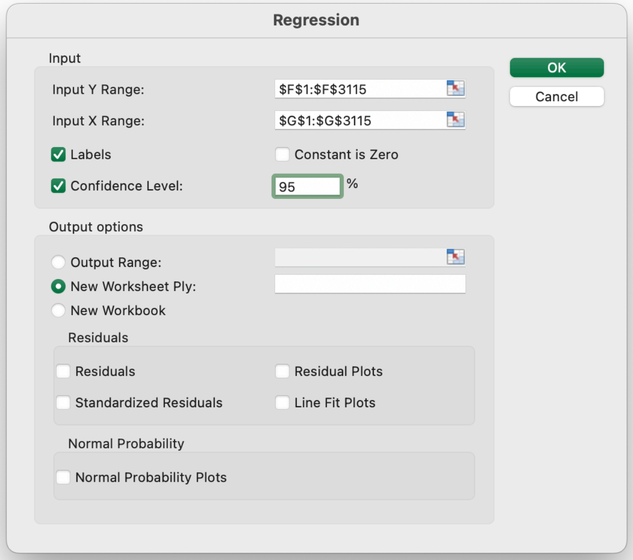
1. Data > Analysis Tools. Add the Analysis ToolPak.



2. Click Data Analysis. Then, select Regression.



3. Modify X and Y ranges. Add labels and 95% C.I.s.



Other tidbits

- Constant should not be 0.
- Can ask for residuals if you plan to use them for another analysis.
- For ranges, have to give first and last cell in the range: "$F$1:$F$3115". Can't just name the column.

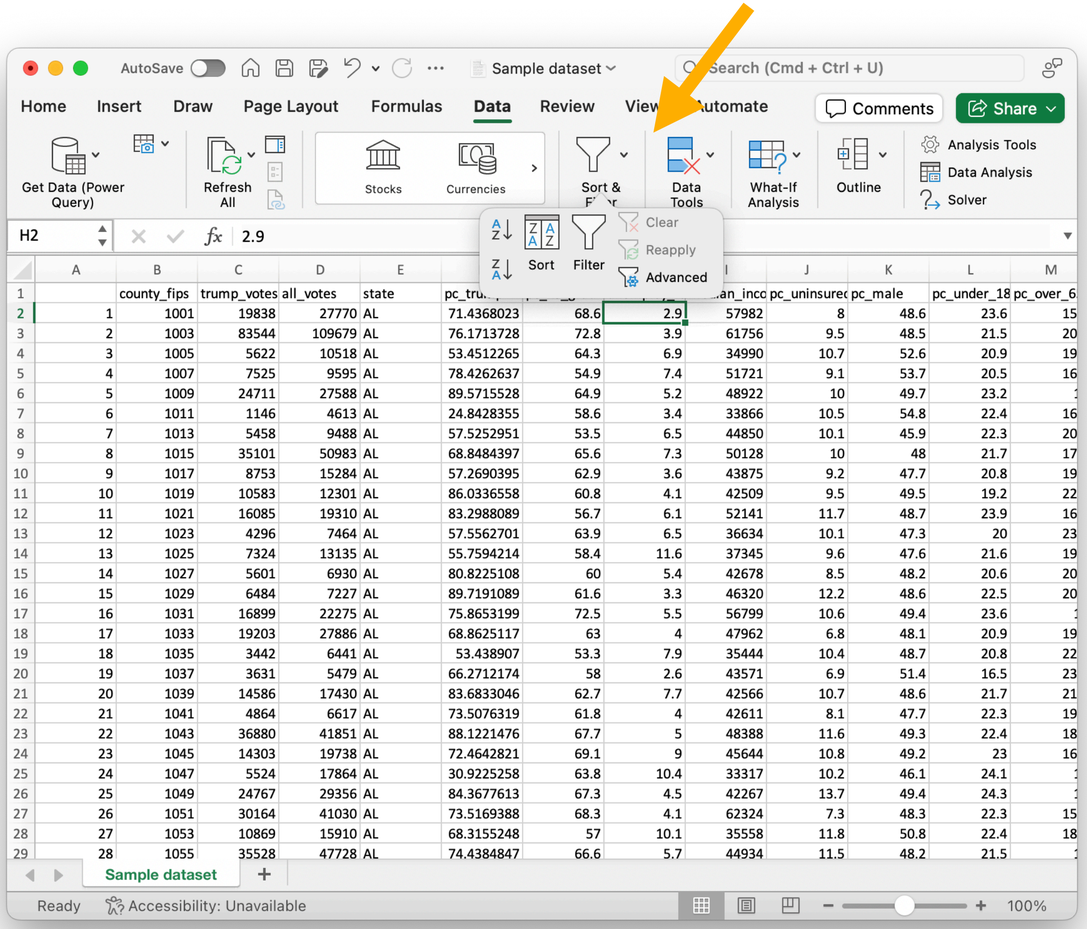
OK fine, let's run a regression.

If your X or Y columns have missing data (e.g. blank cells or "NAs"), you'll get an error and the regression won't run.

We have a few options for dealing with it:

- "Sort" the column(s) with missing data so that the NAs go to the bottom. Then, specify a range that excludes the missing rows.

- Use "Filter" and uncheck the NAs. Then, copy the remaining rows into a new sheet and run the regression on these rows.



	A	B	C	D	E	J	K	L	M
1		county_fips	trump_votes	all_votes	state	pc_uninsured	pc_male	pc_under_18	pc_over_6
2	1	1001	19838	27770	AL	8	48.6	23.6	15
3	2	1003	83544	109679	AL	9.5	48.5	21.5	20
4	3	1005	5622	10518	AL	10.7	52.6	20.9	19
5	4	1007	7525	9595	AL	9.1	53.7	20.5	16
6	5	1009	24711	27588	AL	10	49.7	23.2	1
7	6	1011	1146	4613	AL	10.5	54.8	22.4	16
8	7	1013	5458	9488	AL	10.1	45.9	22.3	20
9	8	1015	35101	50983	AL	10	48	21.7	17
10	9	1017	8753	15284	AL	9.2	47.7	20.8	19
11	10	1019	10583	12301	AL	9.5	49.5	19.2	22
12	11	1021	16085	19310	AL	11.7	48.7	23.9	16
13	12	1023	4296	7464	AL	10.1	47.3	20	23
14	13	1025	7324	13135	AL	9.6	47.6	21.6	19
15	14	1027	5601	6930	AL	8.5	48.2	20.6	20
16	15	1029	6484	7227	AL	12.2	48.6	22.5	20
17	16	1031	16899	22275	AL	10.6	49.4	23.6	1
18	17	1033	19203	27886	AL	6.8	48.1	20.9	19
19	18	1035	3442	6441	AL	10.4	48.7	20.8	22
20	19	1037	3631	5479	AL	6.9	51.4	16.5	23
21	20	1039	14586	17430	AL	10.7	48.6	21.7	21
22	21	1041	4864	6617	AL	8.1	47.7	22.3	19
23	22	1043	36880	41851	AL	11.6	49.3	22.4	18
24	23	1045	14303	19738	AL	10.8	49.2	23	16
25	24	1047	5524	17864	AL	10.2	46.1	24.1	1
26	25	1049	24767	29356	AL	13.7	49.4	24.3	1
27	26	1051	30164	41030	AL	7.3	48.3	22.3	15
28	27	1053	10869	15910	AL	11.8	50.8	22.4	18
29	28	1055	35528	47728	AL	11.5	48.2	21.5	1

OK fine, let's interpret a regression.

SUMMARY OUTPUT								
Regression Statistics								
Multiple R	0.4832049							
R Square	0.23348698							
Adjusted R S	0.23324067							
Standard Err	14.1346772							
Observations	3114							
ANOVA								
	df	*SS*	*MS*	*F*	*Significance F*			
Regression	1	189388.892	189388.892	947.944069	6.07E-182			
Residual	3112	621743.678	199.7891					
Total	3113	811132.57						
	Coefficients	*tandard Erro*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	134.921115	2.28637329	59.0109742	0	130.438162	139.404068	130.438162	139.404068
pc_hs_grad	-1.0588226	0.03438998	-30.7887	6.07E-182	-1.126252	-0.9913933	-1.126252	-0.9913933

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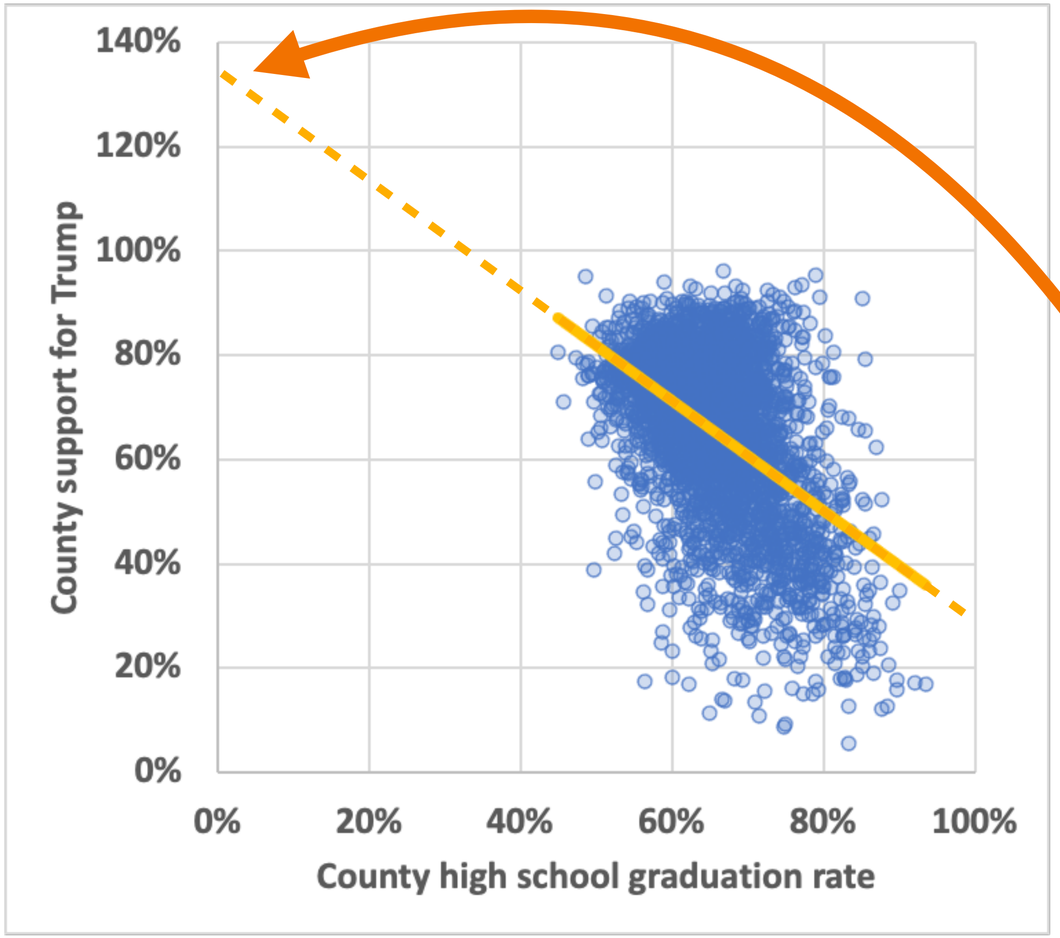
We'll start with the intercept.

When 0% of a county has graduated high school, support for Trump is an estimated 134.9%.

(Is a graduation rate of 0% meaningful?)

OK fine, let's interpret a regression.



We'll start with the intercept.

When 0% of a county has graduated high school, support for Trump is an estimated 134.9%.

(Is a graduation rate of 0% meaningful?)

That looks about right!

…but here, it's not meaningful. We don't have any counties near 0% graduation rates, and we can't ever have 135% support!

OK fine, let's interpret a regression.

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Multiple R	0.4832049							
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We'll start with the intercept.

When 0% of a county has graduated high school, support for Trump is an estimated 134.9%.

(Is a graduation rate of 0% meaningful?)

The standard error is 2.3%. This gives us a 95% C.I. of 134.9 ± 1.96*2.3 = [130.4% to 139.4%].

The t-statistic is 59.0. The p-value is <0.05.

Thus, we can conclude that the intercept is significantly different from 0.

OK fine, let's interpret a regression.

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Regression Statistics								
Multiple R	0.4832049							
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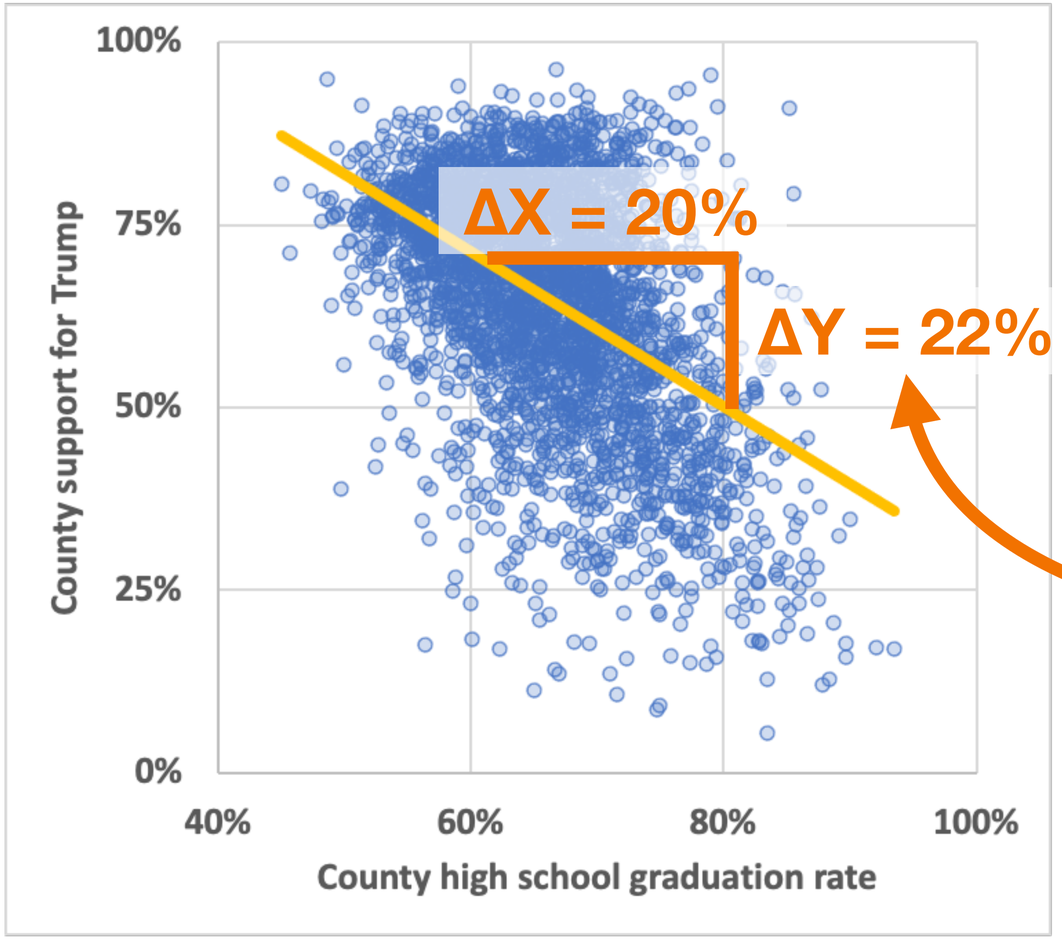
pc_hs_grad	-1.0588226	0.03438998	-30.7887	6.07E-182	-1.126252	-0.9913933	-1.126252	-0.9913933

Now for the coefficient on `pc_hs_grad`.

For each 1 percentage point (pp) increase in a county's high school graduation rate, the estimated support for Trump decreases by 1.1 pp.

OK fine, let's interpret a regression.



That looks about right!

Now for the coefficient on `pc_hs_grad`.

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pc_hs_grad	-1.0588226	0.03438998	-30.7887	6.07E-182	-1.126252	-0.9913933	-1.126252	-0.9913933

Now for the coefficient on `pc_hs_grad`.

For each 1 percentage point (pp) increase in a county's high school graduation rate, the estimated support for Trump decreases by 1.1 pp.

The standard error is 0.03%. This gives us a 95% C.I. of –1.06 ± 1.96*0.03 = [–1.13% to –0.99%].

The t-statistic is –30.8. The p-value is <0.05.

Thus, the coefficient is significantly different from 0. There's a negative association between graduation rates and Trump support.

That’s all good. But is it causal?

We’ll spend lots of time in API 202 asking this very question.

What problems with a causal interpretation come to mind?

What variables/influences are we missing?