Elections, Climate, Change

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Introduction

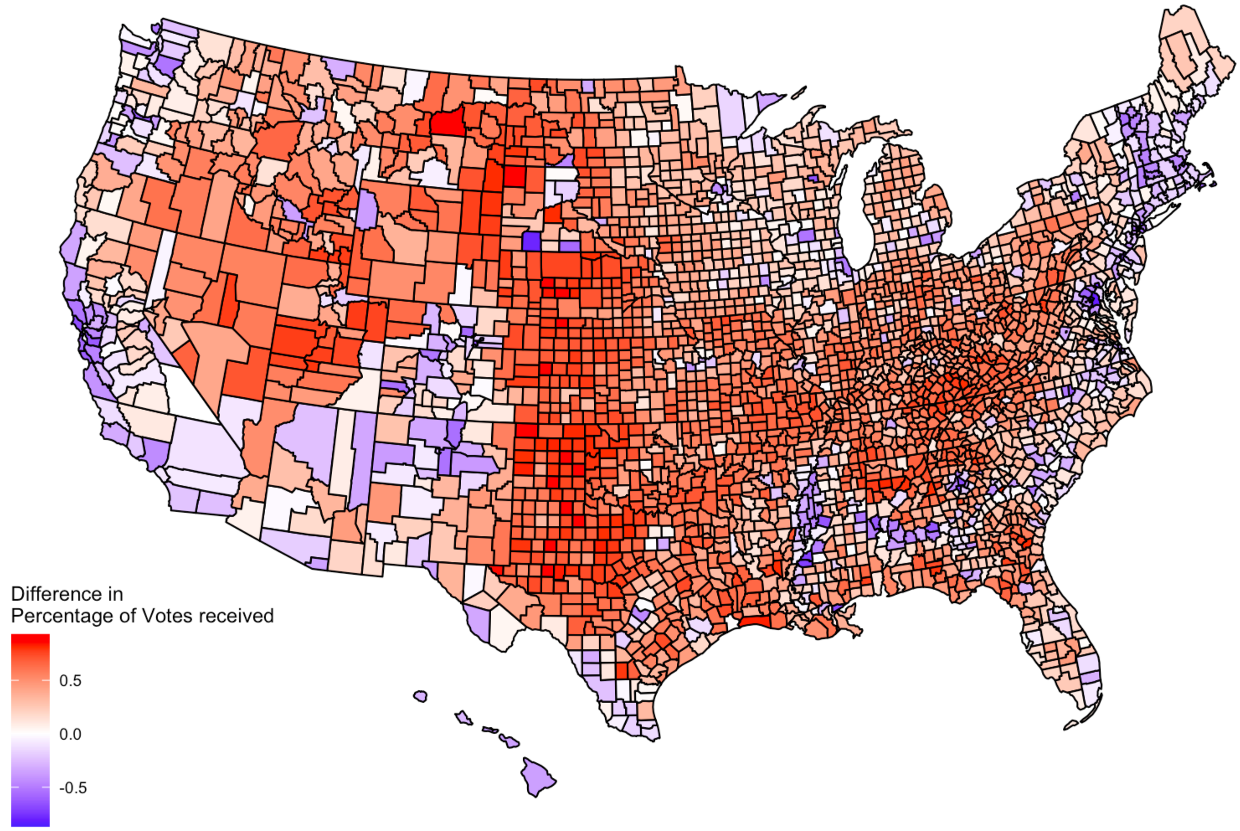

Figure 1. The difference in the percentage of votes received by a county. A positive (red) value means that Donald Trump received a larger percentage of votes in the county. A bluer value means Joe Biden received a higher percentage of votes. Alaska is left out of this map and any further analysis due to data availability issues. Data from (McGovern, 2020).

The US presidential election has officially concluded with the electoral college's election of Joe Biden (Fig. 1). The race for the country's most powerful office was heated with debates about economic plans, foreign policy, and not at last climate change. Donald Trump and Joe Biden's climate change action policies stand in clear opposition to one another. While Donald Trump has sympathized with climate change deniers, Biden is trying to capture progressive voters of the democratic that have lobbied for the Green New Deal (Tollefson, 2020). Trump left the Paris Climate Agreement, while Biden vows to rejoin it as soon as he is in office (Fig. 2). To what extent has this varying stance helped Biden claim victory in November? More specifically, is there a causal connection between the opinions on climate change and the vote share received by Joe Biden in the presidential election?

Climate change increases the risk of natural disasters that lead to death, conflicts, and economic hardship. The US experiences wildfires, tornados, cyclones, flooding, and other natural disasters, so regularly, there are tornado of wildfire "seasons." Men-made climate change stands in clear connection with the increased likelihood of natural disasters occurring (Van Aalst, 2006). Specifically, the rising temperatures caused by increased green-house emissions lead to stronger extreme weather phenomena, meaning hotter high-temperature peaks, lower cold-temperature peaks, intensified precipitation, or draughts (Van Aalst, 2006). In affected communities, natural disasters lower long term economic indicators such as human capital and growth (Toya, Skidmore, & Robertson, 2010). Further, the decreased GDP induced by natural disasters increases the likelihood of conflict in the region (Bergholt & Lujala, 2012). Recently, the younger generation has risen up with figureheads such as Greta Thunberg that led the charge in fighting climate change in both the streets and grand institutions such as the UN General Assembly (Kaplan, 2020). Hence, both literature and popular movements make climate change a political issue of gravitas. This analysis finds the connection between opinions on climate change and voting behavior in the US election. Specifically, I hypothesize that:

$H1$: *If a county has a high proportion of people believing in climate change, then a larger percentage will have voted for Joe Biden.*

Figure 2. *Contrasting views on the Paris Climate Agreement (Biden, 2020). Joe Biden vows to join the Paris Climate Agreement that was left by Donald Trump. The exit is symbolic for their different views on the importance of climate change.*

Modelling the Effects of Climate Change

To estimate the effect of climate change on the voting behavior in the U.S. presidential election, I use the exogeneity of a county's level natural disaster risk to instrument for the perception of climate change that drives the votes received by Donald Trump and Joe Biden.

Natural disasters are, as per definition, not controlled for humans. The risk effects of climate change from CO_2 emissions exacerbate the risk of natural disasters. Hence, the risk of a natural disaster can be seen as an exogenous variable to the system. The randomness allows the variable to be an instrument.

However, the effect of natural disaster risk is not unknown to the population, and counties may have adapted and evolved as a function of their risk to natural disasters in the past. Preparation is most likely in high-density areas and in areas of economic strength. Both factors make natural disasters less disruptive to voting behavior in economically strong areas (Gasper & Reeves, 2011). Indeed, these variables do not affect the risk of natural disaster, but they are able to affect the response to the risk of natural disaster, i.e., the attitudes towards climate change, which ultimately drive the voting behavior. Hence, these variables will have to be included for the instrument to be robust (Gasper & Reeves, 2011) (Autor, Dorn, Hanson, & Majlesi, 2020).

Experiencing natural disasters, climate change beliefs, and voting behavior have been previously linked, and mixed results for the causal relationship have been made. Hazlett & Mildenberger (2020) provide a brief overview. They, for example, find that experiencing a wildfire changes the voting behavior, with regard to climate policy, of Californians living near the fire, yet they employ no technique for causal inference. Hazlett & Mildenberger (2020) find that wildfires only affects voting behavior in areas typically voting for the Democratic Party. Further, the experience of a natural hazard is a persistent driver of voting behavior in rewarding/punishing politicians for their actions (Bechtel & Hainmueller, 2011) (Gasper & Reeves, 2011). I add to the literature with by examining recent federal results for the United States.

The instrumental variable (IV) approach allows the isolation of a causal effect by blocking spurious relationships between the treatment and outcome variable. Practically the IV approach estimates a first-stage model that is used to predict the treatment variable. The predicted variable is then used to estimate the second stage model of the outcome variable. By instrumenting for the treatment variable (here the perception of climate change), the variables in the first stage become the only determinants of the treatment variable, blocking all other lines of associations. The instrument has to fulfill the relevance, independence, exclusion restriction, and assumptions (Hernán & Robins, 2006). The relevance assumption states that the instrument strongly affects the treatment variable, which is given here as the risk of natural disasters clearly affects the perception of climate change. The exclusion restriction means that the instrument does not causally affect the outcome variable other than through the treatment variable. The independence assumption requires that the instrument does not share common confounders with the outcome or treatment variable. Independence assumption and exclusion restriction are both untestable and would be violated if the only first stage variable was the risk score for natural disaster. However, I block the causal paths of population density, unemployment rate, education, and income by controlling for them in the first stage. Therefore, using the risk of natural disaster is still a valid instrument under the assumption that there are no other causal pathways between the risk of natural disaster and the outcome variable.

The directed acyclic graph (DAG) in Fig. 2 outlines the connections between the different variables. Each arrow describes the causal connection between the two variables. Any variable that is a cause of both treatment ("Worried about climate change") and outcome ("Margin of J.

Biden"), is a confounder that could introduce spurious correlations or change the sign of the effect. By controlling for the confounders, the causal path becomes blocked. For clarity, I have left out some of the connections between the confounders such as the link between income and unemployment. The links are rendered irrelevant as each confounder is controlled for. The ideal instrument would only affect the treatment variable, but the risk of natural disasters is similarly relevant as it affects few variables that can be controlled for. To summarize the DAG, the two stages of the IV approach can be formulated as:

Stage II
$$Biden = \beta_1 \overline{Opinion} + \beta_2 Income + \beta_3 Edu + \beta_4 Unemployment + \beta_5 PopDensity + \beta_6 State + \varepsilon$$

Stage I
$$Opinion = \gamma_1 NaturalDisaster + \gamma_2 Income + \gamma_3 Edu + \gamma_4 Unemployment + \gamma_5 PopDensity + \gamma_6 State + \varepsilon$$

, where $\overline{Opinion}$ is the predicted value for the opinion on climate change estimated by the first stage. $State$ refers to fixed effects added for the individual US states. Both stages observations are weighted by the total number of votes casted in each county which ensures that each opinion is equally relevant (Autor, Dorn, Hanson, & Majlesi, 2020).

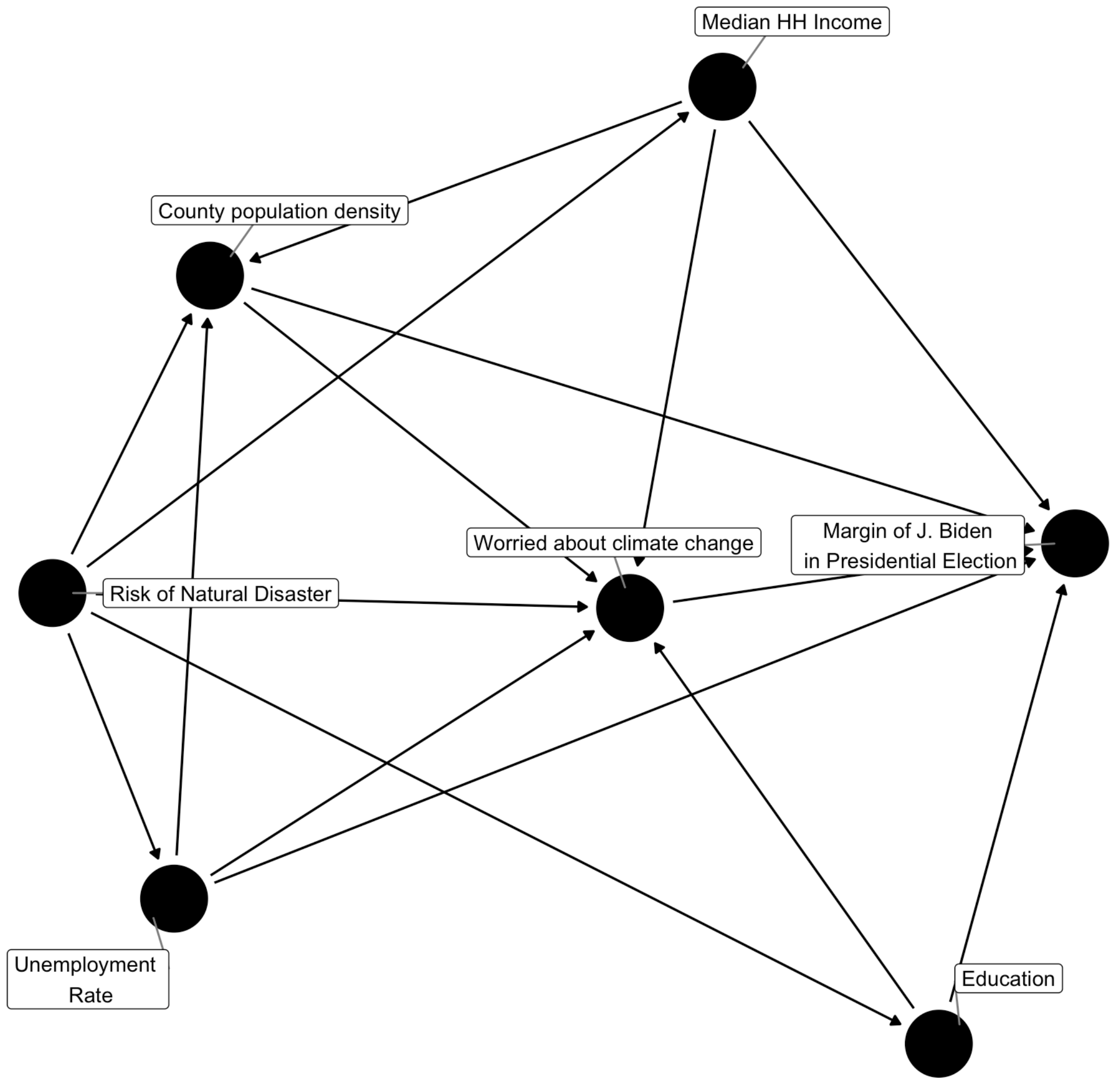

Figure 3. *Directed Acyclic Graph showing the relationship of demographic variables, the risk of natural disasters, opinion on climate change the votes received by Joe Biden. Risk of natural disaster can be seen as an instrument for the opinion on climate change under the assumption that there are no other causal linkages when controlling for the demographic variables.*

Data

To estimate the model outlined above, I draw county-level data to achieve a final sample size of 3121 counties. Because the election only concluded a month ago, no official county-level data has been aggregated. Therefore, I use data scraped from the New York Times (McGovern, 2020). Data on economic covariates are taken from the United States Department of Agriculture (2020).. The natural hazard risk score data looks at exposure to natural hazards and the relative harm they may cause in a county and is compiled by the Federal Agency for Emergency Management (FEMA) (2020) (Fig. 4). The opinion on climate change is taken from the Yale Progam on Climate Change Communication (Howe, Mildenberger, Marlon, & Leiserowitz, 2015), which is as recent as September 2020. The opinion asks questions on an increasing scale of controversy from asking for a factual statement of whether climate change is happening, to whether the respondent is worried about it, to whether the president should do more about it, and further to specific policies. I use the question of whether climate change is happening as it is the least influenced by other political opinions. A summary of the variables chosen is shown in Tab 1.

Table 2 gives summary statistics for each variable, grouped by which candidate won in the respective county. The difference in counties in the dataset won by each candidate (Trump: 2580, Biden: 541) illustrates the importance of weighing the observations by the total votes cast as Biden's counties have a significantly higher population density. As shown in Fig. 5, when reweighting the counties, the vote margin distribution shifts from positive (Trump winning) to negative (Biden winning). In all variables other than the unemployment rate in 2019, the two candidates are statistically significantly different. Biden's counties are more densely populated, have higher median household incomes, and have more people with bachelor's degrees. Fig. 6 illustrates the relationship between belief in climate change and Biden's margin and shows a clear correlation between the two. The disentanglement of the correlation and the causal effects follows in the next section.

Table 1. Variables used and their relative descriptions. Biden Votes is the dependent variable, Opinion is the treatment variable, Risk Score functions as the instrument. The other variables control for possible confounders.

Variable	**Definition**	**Source**
Biden votes	Difference between percentage of votes received by Donald Trump and Joe Biden in 2020 presidential election.	McGovern (2020)
Opinion	Variable "happening" is the estimated percentage who think that global warming is happening in each county.	(Howe, Mildenberger, Marlon, & Leiserowitz, 2015). Data from 2020.
Risk Score	The national risk score "calculates a baseline relative risk measurement for each United States county and census tract for 18 natural hazards, based on Expected Annual Loss, Social Vulnerability, and Community Resilience" FEMA (2020).	FEMA
Income	Median Household Income in county	USDA
Education	Percentage of county residents with at least a Bachelor's degree between 2014 and 2018	USDA
Unemployment	Unemployment rate (%) in 2019	USDA
PopDensity	Population divided by Area	USDA, FEMA

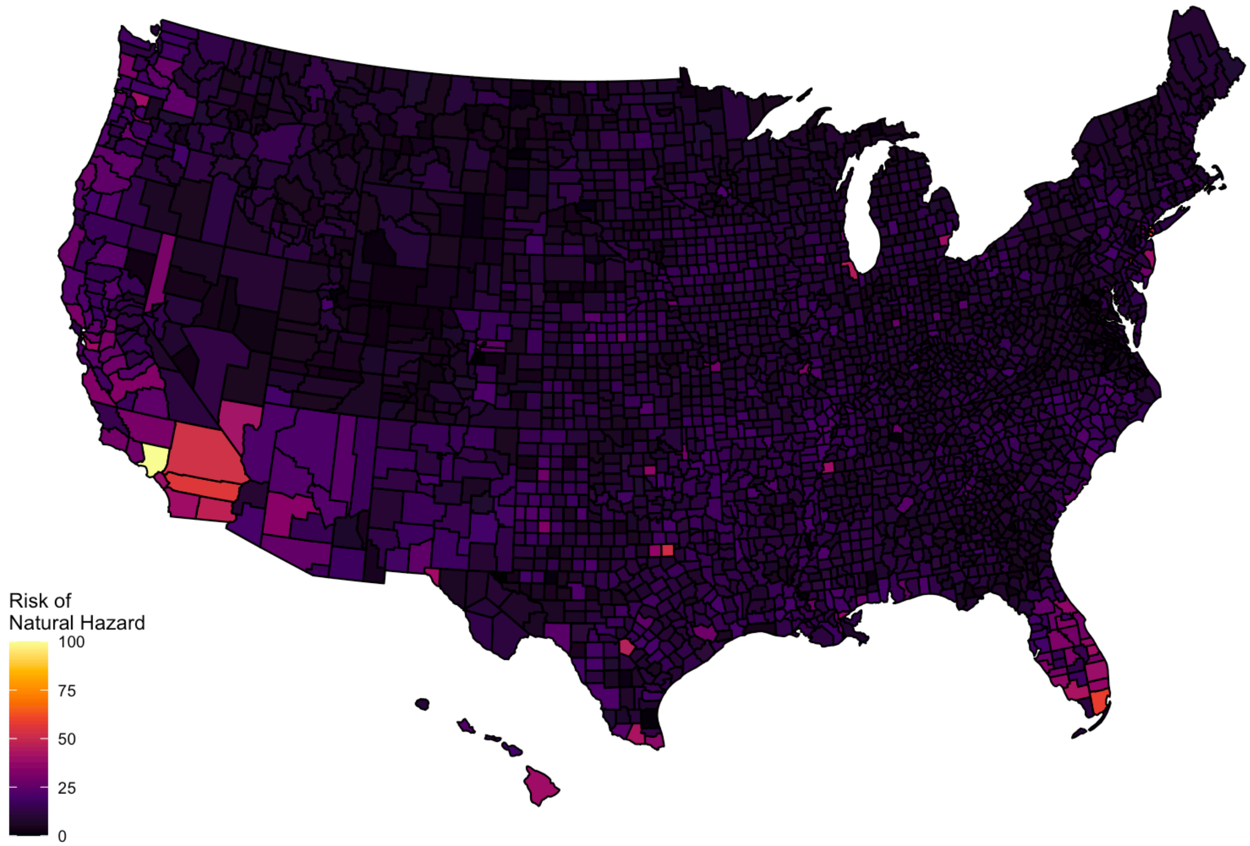

Figure 4. *Risk of natural disaster by counties. Data from FEMA (2020). The risk score.is higher on the coasts (flooding, tornados, tsunamis) and towards the very central regions of the country. The national risk score "calculates a baseline relative risk measurement for each United States county and census tract for 18 natural hazards, based on Expected Annual Loss, Social Vulnerability, and Community Resilience" FEMA (2020).*

Table 2. Summary statistics for covariates, grouped by winner of county. The counties are statistically significantly different in all variables, but unemployment, as shown by the p-value. Biden votes generally seem to care more about climate change. They are also live in more densely populated areas, are richer, and more educated. Due to issues with the region naming had to be left out.

	BidenWon	N	Mean	SD	Min	Q1	Median	Q3	Max	p.value
per_point_diff	0	2580	0.43	0.20	0.00	0.27	0.45	0.59	0.93	<0.001
	1	541	−0.23	0.18	−0.87	−0.34	−0.19	−0.09	−0.00	
happening	0	2580	62.94	4.33	48.94	60.05	62.92	65.81	80.43	<0.001
	1	541	73.90	4.16	63.42	71.04	73.50	76.43	86.53	
worried	0	2580	53.69	4.25	39.13	50.61	53.35	56.35	77.84	<0.001
	1	541	65.80	4.70	55.17	62.20	65.27	68.78	81.00	
president	0	2580	52.50	3.73	38.06	49.78	52.30	55.00	71.04	<0.001
	1	541	62.95	3.86	53.80	60.17	62.74	65.39	74.53	
RISK_SCORE	0	2580	10.27	4.57	0.02	7.39	9.53	12.35	42.93	<0.001
	1	541	15.65	10.95	0.00	8.79	12.84	19.12	100.00	
density	0	2580	91.88	228.60	0.24	14.76	38.77	89.68	8278.06	<0.001
	1	541	1148.25	4197.89	0.57	38.40	223.54	972.44	71885.40	
Income	0	2580	51401.50	11483.91	26278.00	43705.00	49843.00	56979.50	120670.00	<0.001
	1	541	58620.21	20822.49	25385.00	42568.00	56141.00	69753.00	140382.00	
Unemployment	0	2580	3.92	1.29	0.70	3.00	3.70	4.60	16.40	0.003
	1	541	4.17	1.79	1.80	3.00	3.70	4.80	18.30	
MinBachelor	0	2580	0.13	0.05	0.00	0.10	0.13	0.16	0.39	<0.001
	1	541	0.21	0.09	0.05	0.13	0.21	0.26	0.54	

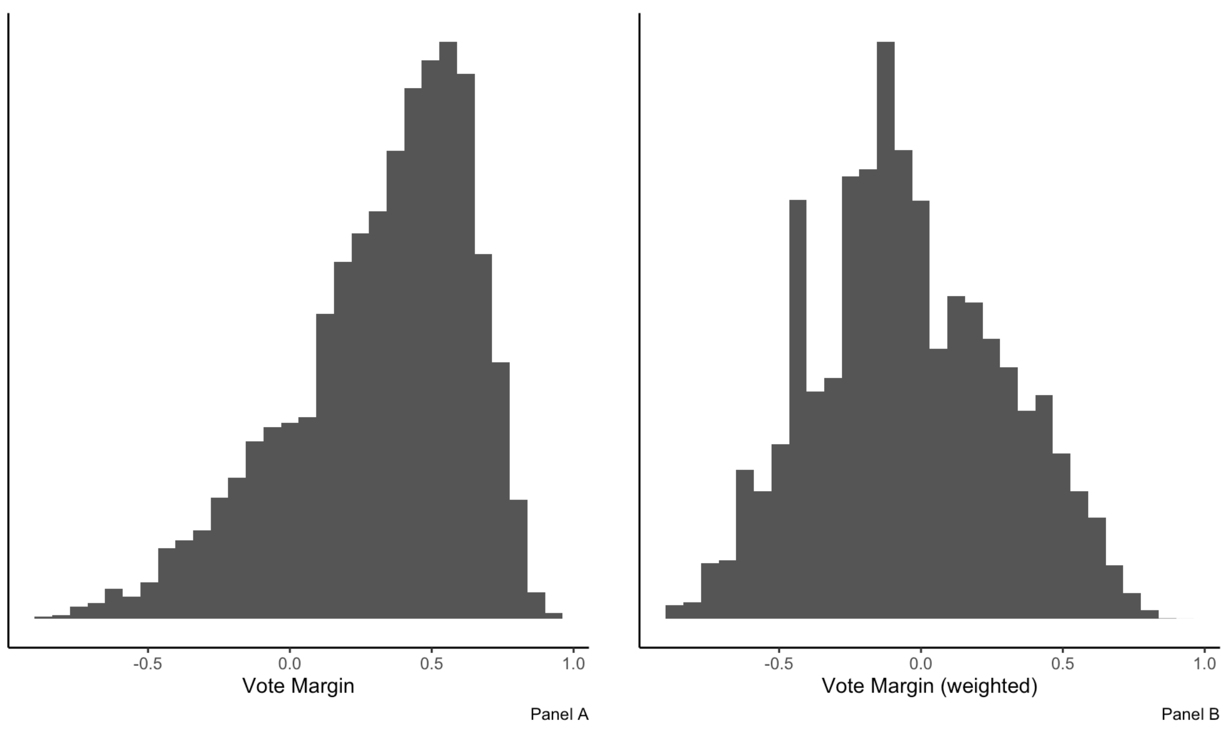

Figure 5. Weighing the votes by the total votes casted shifts the distribution from Trump winning (Panel A) to Biden winning (Panel B). y-axes are left blank as the distribution not the frequencies matter.

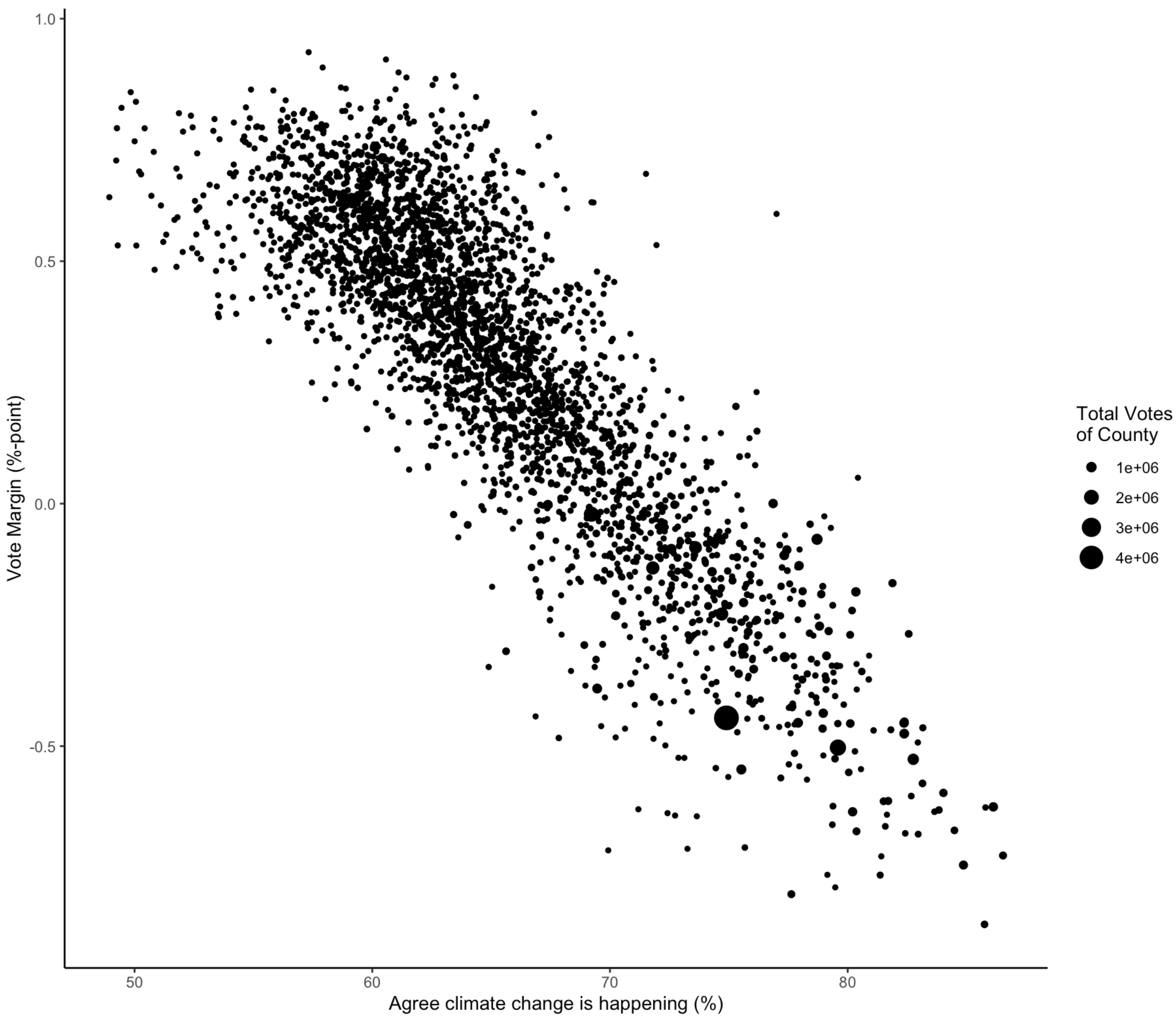

Figure 6. *Clear correlation between the belief in climate change and voting for Joe Biden. The higher the percentage of people in a county agreeing that climate change is happening, the higher the vote margin that Biden wins by (i.e., the more negative the percentage point difference). Each county is represented by its relative weight. See Appendix A for a more colorful visualization.*

Results

Running the two-stage least squares estimation gives strong evidence that Joe Biden's vote counts were influenced by people believing in climate change.

Tab. 3 gives the results of the first and second stage model, which show that a one percentage point increase in the county's belief in climate change, adds 0.06 percentage points (SD: 0.002) to the difference between the percentage of votes received by Donald Trump and Joe Biden. This allows us to reject the null hypothesis that climate change did not affect the election results in favor of H1.[1] Looking at the spread of margins in Fig. 5 and Fig. 6, this means that ten percentage points of agreement, the vote margin can tilt towards Joe Biden's favor. The p-value is very close to 0 and the coefficient statistically significant. Both stages have high R^2 values indicating a strong fit of the model.

The main predictors of the vote margin are the state fixed effects of which almost all are highly significant and have plausible coefficients (see Appendix A). For example, being a county in California decreases the vote margin by an average of 0.356. This coefficient is plausible as the lower the margin, the more pro-Biden is the state. Of the remaining covariates, only the unemployment rate is statistically significant, illustrating while the effects of income and education are swallowed by the effects of the states, unemployment, and climate change opinion.

Similarly, in the first stage, the risk score is highly statistically significant and a strong instrument. The F-statistic (242.432) tests if for the relevance assumption to check if the instrument

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[1] #hypothesisdevelopment: From initial observations that the democratic left is rallying to fight climate change, I develop a hypothesis that opinions on climate change influenced the voting behavior. Throughout make and hypothesis that are used to find the answer to H1, such as that the risk of natural hazards, can be used to predict the climate change opinion. By using this HC, I constantly thought about: what is the hypothesis I am making, how can I test it, did I find support for it in the data.

is a strong enough predictor of the treatment variable. Commonly the first stage is considered strong if the F-statistic is at least ten. The instrument used here even passes more the more rigorous threshold of 104 proposed in the recent literature with flying colors (Lee, McCrary, Moreira, & Porter, 2020).

Table 3. Climate change happening and the national risk score are relevant predictors in the second and first stage, respectively. The weak instrument statistic and its p-value are strong indicators of the strength of the approach. The fixed effects of the states are given in Appendix A. The sample size is 3121 counties in all columns. All estimations are weighted by votes per county.

	Second Stage	**First Stage**	**Second Stage**	**First Stage**
Dependent Variable	**Diff Percentage point**	**Happening**	**Diff Percentage point**	**Happening**
happening	-0.060***	-	-0.040***	
	[0.002]	-	[0.002]	
Risk Score	-	0.189***		0.185***
	-	[0.012]		[0.010]
density	0	0.000***	-0.000***	0.000***
	[0.000]	[0.000]	[0.000]	[0.000]
Median_Household_Income_2018	0.000***	0.000***	0	0.000***
	[0.000]	[0.000]	[0.000]	[0.000]
Unemployment_rate_2019	-0.027***	-0.565***	-0.012***	0.033
	[0.004]	[0.120]	[0.003]	[0.101]
`Bachelor's degree or higher, 2014-18`	-0.000***	-0.000***	-0.000***	-0.000***
	[0.000]	[0.000]	[0.000]	[0.000]
(Intercept)	4.009***	55.176***	2.900***	55.414***
	[0.131]	[1.014]	[0.096]	[0.704]
Fixed Effects	True	True	False	False
R2	0.779	0.506	0.807	
adj R2	0.776	0.497	0.807	
Wu-Hasuman stat	125.256	-	0.043	
Wu-Hasuman pval	0	-	0.835	
Weak instr stat	242.432		317.068	
Weak instr p-value	0		0	

Discussion

Through the IV approach, I was able to disentangle the causal effect of understanding climate change on the general election results. Yet, the model could be improved and adjusted to include further covariates.

One such covariate could be the racial make-up of the county as African-Americans, Hispanic-Americans, Asian-Americans, and Caucasians have different voting preferences. However, there is no clear indication that one's ethnic group influences whether one believes in climate change. Still, it might be a relevant predictor.

Another potential covariate could be religious affiliation shares within a county. Some religious groups may reject that climate change is happening or that it would be connected to humans. At the same time, religious groups may also have varying voting preferences. Having county-level granularity would be beneficial.

Further, previous election results are a relevant confounder. Previous voting behavior has been shown to affect one's climate change views (McCrea, Leviston, & Walker, 2015). Hence, in our example also adding the percentage of votes Donald Trump received in the previous year in the respective counties could be a predictor of the climate change attitudes now. Adding this would also allow checking for heterogeneous treatment effects similar to the ones in (Hazlett & Mildenberger, 2020). Using this variable would require the assumption that Joe Biden is similar enough to Hillary Clinton that the two elections are comparable.

However, having an instrument and including state-level fixed effects mitigates the threats to confounding. As shown by the coefficients on the states are able to capture some of the demographic and socio-economic differences between the different counties. As there are 50 states and a high R^2, I was worried there could be overfitting. However, as shown in columns three and four in Tab. 3, the effect is robust to excluding the fixed effects and the R^2 even increases. Hence, it is unlikely that the fixed effects have caused stark overfitting. However, the Wu-Hausmann p-value becomes which tests for endogeneity becomes insignificant when removing the fixed effects. This means that without the fixed effects, the treatment is not seen as endogenous and no instrument would be needed. However, because states are a relevant variable to include, the IV results, including fixed effects, are still preferable.

The instrument is employed to avoid the threats of confounding but is volatile to violations of the exclusion restriction. As stated in the methods section the instrument is only valid in case there is no other confounding variable that opens a forward or backward path between the instrument and the treatment or outcome variable. A factor rending the instrument endogenous could be the amount of investment capital available to alter the natural landscape to risks of natural hazards, which also influences, for example, incomes. With the exclusion restriction untestable, the only checks available are to use different instruments for exposure evidence for climate change. One example could include the accessibility of information to climate change related material. However, this is likely to be influenced by similar confounding factors as the opinion. Another instrument could be the change in exposure to natural hazards and lagged variables of the covariates. This would ensure that the underlying risk of natural disasters does not affect the socio-economic and demographic covariates. An extension to this paper should certainly use this instrument as a robustness check. Using this instrument, I would also be able to extend the findings and see if more natural disasters could have been the reason Joe Biden won in the so-called swing states. The advantage of the risk score, however, is that it values exposure to different natural disasters and the relative exposure, loss, and historic risk associated with them. Using just the change natural disaster incidence rate does not allow to capture the gravity of various hazards.

To improve the robustness, using official data for the election results from one source. It would also mean that Alaska could be included into the results.

The results have no external validity as the sheer existence of climate change is a political issue already in the United States. Almost every country has acknowledged it and candidates differ on policy issues that are more nuanced than sheer acceptance of the issue. Still, testing how relevant these results are in various other nations such as developing countries with less fiscal space and institutional power to implement policies would be a valuable extension.[2]

Conclusion

The results shown above give reason to believe that the climate change has been a significant contributor to Joe Bidens victory over Donald Trump and that H1 is true. He may not be perceived as the climate warrior by the progressive left that is demanding a sharp turn in US climate policy, but it seems like his acknowledgement of climate change has gained him some votes. To estimate the effect of climate change opinions, I instrument for them using the risk of natural hazards and control for county level covariates. Threats to causality of these results remain in the validity of the exclusion restriction and the possible endogeneity of the natural risk score. Possible extensions include further covariate controlling and using different instruments as robustness check.

[2] #cognitivepersuasion: Any application of the IV-approach needs to argue for why the instrument is relevant. In the section describing the model, I can discuss reason that speak for the instrument and make sure to address the assumptions and concerns. I continue to address relevant counterarguments to the validity of the instrument in the Discussion section and go into how relevant, realistic, or plausible are. By addressing them openly, I am able to convince the reader that I am not trying to sell the approach.

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Appendix A

All code can be found at:

https://gist.github.com/Halkenhaeusser/3acb8b89e9dc6b539fa0a6150011d2bf

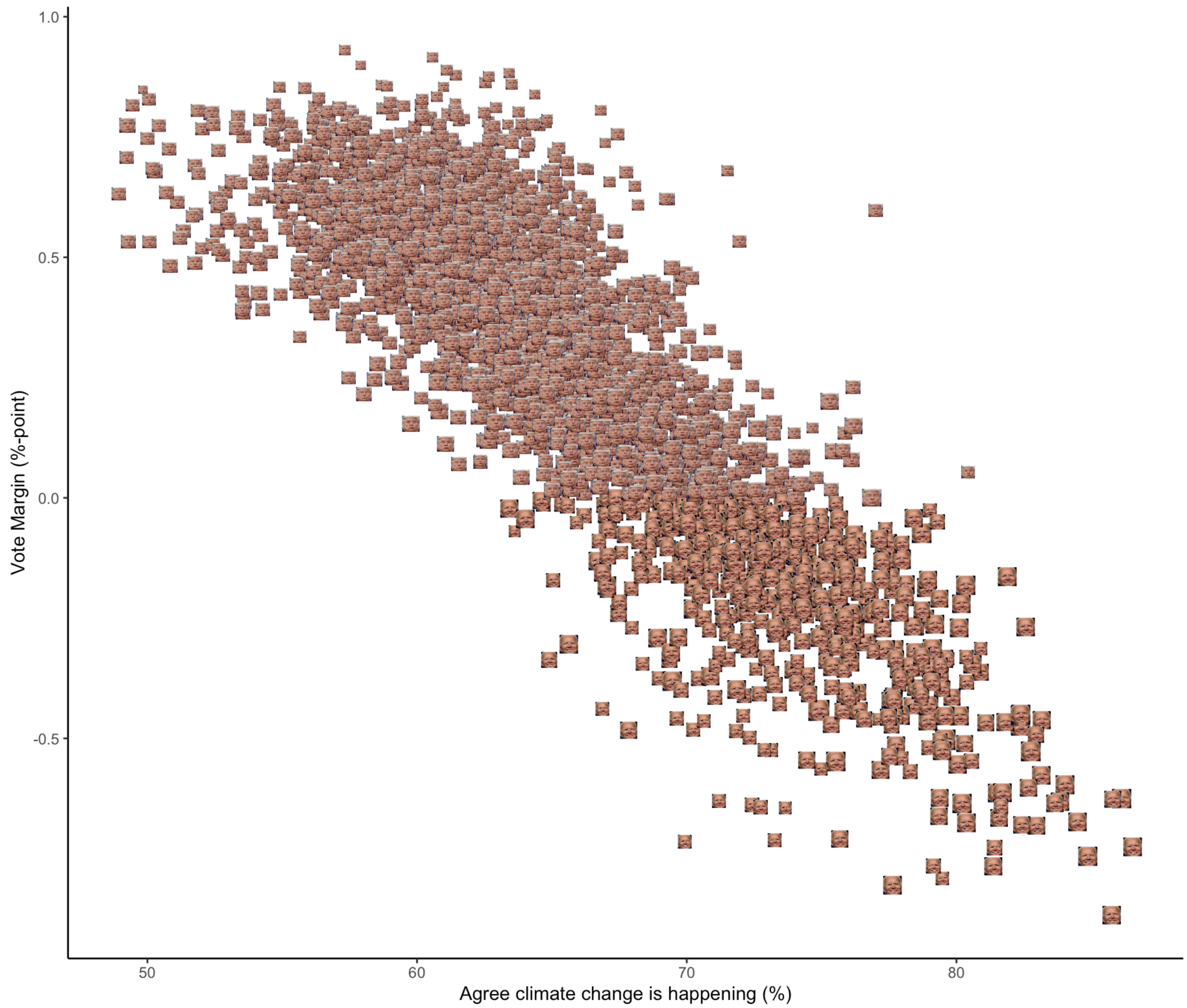

Figure 7. *Fig. 6 but each marker is either Donald Trump's or Joe Biden's face. Images from Deutsche Welle (2020) and A&E Television Networks (2020). Each marker is scaled by the log of total votes cast in the county.*

Table 4. State fixed effects results as extension to Tab.

	Second Stage	**First Stage**
I(state_name)Arizona	0.282***	6.120***
	[0.034]	[0.957]
I(state_name)Arkansas	0.246***	3.671***
	[0.040]	[1.197]
I(state_name)California	0.356***	6.239***
	[0.035]	[0.866]
I(state_name)Colorado	0.160***	5.917***
	[0.035]	[0.945]
I(state_name)Connecticut	0.196***	8.357***
	[0.041]	[1.098]
I(state_name)Delaware	0.042	6.723***
	[0.058]	[1.686]
I(state_name)District of Columbia	0.338***	18.023***
	[0.078]	[2.038]
I(state_name)Florida	0.394***	6.732***
	[0.032]	[0.796]
I(state_name)Georgia	0.188***	6.194***
	[0.032]	[0.865]
I(state_name)Hawaii	0.566***	13.725***
	[0.063]	[1.610]
I(state_name)Idaho	0.272***	3.705***
	[0.045]	[1.359]
I(state_name)Illinois	0.296***	8.656***
	[0.034]	[0.873]
I(state_name)Indiana	0.077**	2.052**
	[0.032]	[0.945]
I(state_name)Iowa	0.119***	3.808***
	[0.037]	[1.094]
I(state_name)Kansas	0.277***	5.122***
	[0.040]	[1.173]
I(state_name)Kentucky	0.084**	1.378
	[0.034]	[1.038]
I(state_name)Louisiana	0.218***	3.920***
	[0.036]	[1.047]
I(state_name)Maine	0.222***	9.224***
	[0.050]	[1.391]
I(state_name)Maryland	0.210***	10.184***
	[0.040]	[0.988]

I(state_name)Massachusetts	0.236***	10.844***
	[0.038]	[0.933]
I(state_name)Michigan	0.145***	5.747***
	[0.031]	[0.863]
I(state_name)Minnesota	0.189***	6.406***
	[0.034]	[0.943]
I(state_name)Mississippi	0.062	3.231***
	[0.040]	[1.212]
I(state_name)Missouri	0.231***	3.686***
	[0.033]	[0.948]
I(state_name)Montana	0.247***	6.084***
	[0.053]	[1.560]
I(state_name)Nebraska	0.180***	2.059
	[0.044]	[1.317]
I(state_name)Nevada	0.344***	5.693***
	[0.043]	[1.185]
I(state_name)New Hampshire	0.158***	6.389***
	[0.048]	[1.405]
I(state_name)New Jersey	0.435***	9.202***
	[0.039]	[0.927]
I(state_name)New Mexico	0.309***	10.902***
	[0.050]	[1.345]
I(state_name)New York	0.377***	8.213***
	[0.034]	[0.870]
I(state_name)North Carolina	0.267***	7.656***
	[0.033]	[0.855]
I(state_name)North Dakota	0.134**	0.019
	[0.064]	[1.931]
I(state_name)Ohio	0.202***	5.288***
	[0.030]	[0.853]
I(state_name)Oklahoma	0.172***	0.066
	[0.037]	[1.121]
I(state_name)Oregon	0.302***	8.974***
	[0.041]	[1.020]
I(state_name)Pennsylvania	0.271***	6.995***
	[0.032]	[0.851]
I(state_name)Rhode Island	0.171***	8.604***
	[0.058]	[1.669]
I(state_name)South Carolina	0.236***	5.527***
	[0.035]	[0.983]

I(state_name)South Dakota	0.248***	3.768**
	[0.060]	[1.807]
I(state_name)Tennessee	0.023	-0.248
	[0.031]	[0.943]
I(state_name)Texas	0.339***	5.659***
	[0.030]	[0.797]
I(state_name)Utah	0.272***	3.054***
	[0.038]	[1.142]
I(state_name)Vermont	0.023	10.513***
	[0.067]	[1.918]
I(state_name)Virginia	0.188***	6.857***
	[0.033]	[0.896]
I(state_name)Washington	0.368***	9.957***
	[0.039]	[0.945]
I(state_name)West Virginia	0.191***	2.271
	[0.047]	[1.420]
I(state_name)Wisconsin	0.112***	5.161***
	[0.033]	[0.932]
I(state_name)Wyoming	0.157**	-0.511
	[0.072]	[2.176]