How Different Were They Really? Republican and Democratic Counties in the Pandemic

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1 Introduction

During the pandemic there was a creeping suspicion in the US public: Republicans were less concerned about the pandemic than Democrats, and they treated social distancing and government mandates in a carefree manner. The suspicion may have been partly to do with media companies and politicians, who reinforced the idea for readership and political gain. For example, media companies frequently reported on spring breaks and summer vacation parties in Southern states like Florida and South Carolina,[1] which imparted the belief that people who disregarded the dangers of the pandemic knew they could venture into Republican territory without fear of enforcement. Similarly, Democratic and Republican governors were quick to claim credit for their rapid responses to the pandemic, with Democratic governors touting social lockdowns and Republican governors touting a lack thereof. But whether the suspicion is true is another matter. News organizations have an incentive to sensationalize stories, making outlier cases appear like a regular pattern. Moreover, it may be the case that Democratic and Republican locations have different COVID-19 risk factors such that we should not expect them to behave similarly anyway. This raises a handful of key questions about politics and the pandemic. Holding all else equal, did "being Republican" cause people to be more mobile? And if so, did it have any affect on public morbidity?

While many scholars have analyzed the relationship between partisanship and beliefs about the pandemic (Ternullo (2022); Adolph et al. (2022)), only a handful have studied how partisanship affected choices about "mobility" - or how much people ventured away from their homes and into retail stores, places of recreation, grocery stores, and pharmacies (Bisbee and Lee (2022); Grossman et al. (2020)). Mobility is a significant variable to study for a single key reason: it was the primary way people bought goods and services, engaged in social interaction, and got to work, but it was also the primary way that COVID-19 was

[1]See the New York Times article for an example. A web search for "COVID-19 spring break 2020" and similar entries yield thousands of results.

spread and sustained. This meant people had to trade-off the benefits and costs of mobility - more access to goods, services, and social interaction for a higher risk of contracting and spreading COVID-19 to other people.

In theory, there is good reason to believe that political ideology was a causal factor in affecting where people landed in this tradeoff space. First, conservative individuals tend to privilege individual freedom over collective action. This suggests that, all else equal, more conservative individuals may exhibit higher levels of mobility since they may disapprove of social lockdowns. Second, conservative individuals also select into Fox News at higher rates than liberal individuals. Since Fox News was more skeptical of COVID-19 than the major news outlets chosen by liberals, it stands to reason that more conservative individuals were consuming information that downplayed how infectious and medically damaging the COVID-19 disease was. In other words, conservatives and liberals were working with different sets of information about COVID-19. Figure 1 shows just how much of a difference this could have had on county behavior. It shows the distributions of how long counties survived in a depressed level of mobility after passing 10 cases per 100,000 people, based on whether voters in the county supported Donald Trump or Hilary Clinton more in the 2016 US Presidential Election. The figure shows that Republican counties were much likelier to survive less than 250 days with depressed mobility than Democratic counties. Nearly half the Republican observations survive with depressed mobility for less 50 days after passing the 10 case rate threshold.

There is, however, a catch. While it may be true that Republican and Democratic exhibited wildly different patterns of mobility during the pandemic, they were also in very different circumstances. Counties that voted for Donald Trump tend to be older, more rural, less densely populated, less educated, less ethnically diverse, and poorer than counties that voted for Hilary Clinton. For example, due to population sparsity, it may have been the case that the probability of infecting another person when going to grocery store in Republican counties was, on average, much lower than in Democratic counties. Similarly, due to lack of industrial heterogeneity in rural areas, Republican counties may not have had as many opportunities for remote work as Democratic counties, which could have forced individuals into being more mobile than they preferred. Many similar arguments can be made which highlight the fact that, without making sample adjustments, Republican and Democratic counties as groups are not comparable. The best comparison would be to find pairs of Democratic and Republican counties with similar social, economic, and demographic characteristics, such that the sole difference between them is their political beliefs.

In this paper, I use a research design which approaches my question from multiple angles. The design is split into three phases. The first stage is data collection and measurement. I

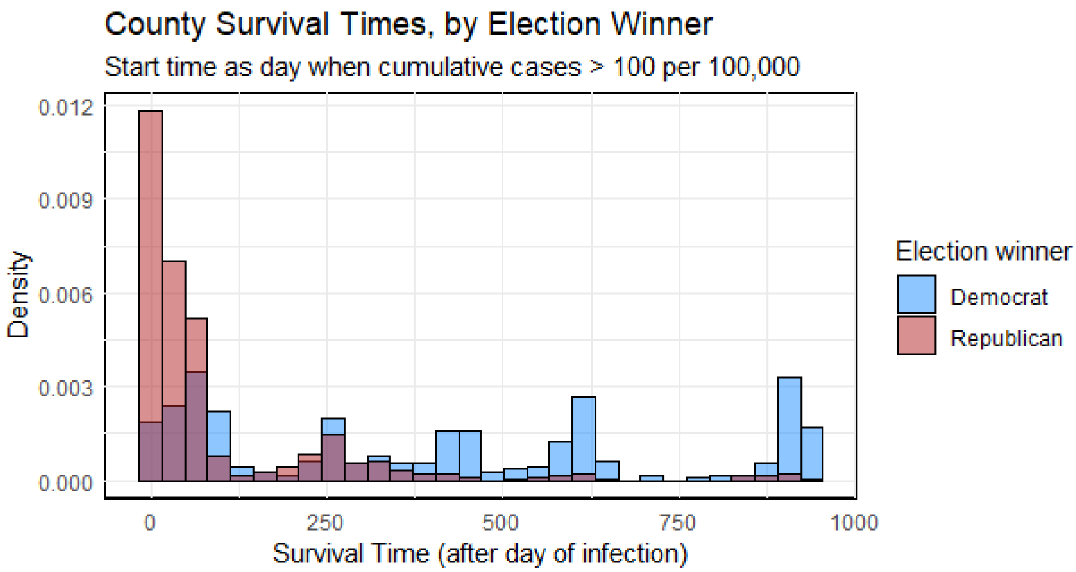

Figure 1: Histogram of county survival times, by political winner in a county. Political winners were defined as the party that received the most votes in a county. Survival times were calculated as the number of days it took a county to return to a pre-pandemic level of mobility after the day it passed 50 active cases per 100,000 individuals.

retrieved mobility data from Google, COVID-19 data from John Hopkins, and sociodemographic and election data from MIT Election Lab. I then used the Google mobility data and Johns Hopkins COVID-19 data to create aggregate variables relevant to the pandemic, like the day a county was first exposed to COVID-19, the length of time it survived with a depressed level of mobility, and other key variables.

The second stage is sample adjustment. In this stage, I empirically model the "decision" of a county to be Democratic or Republican. I do this so I can estimate selection weights, which I use to identify pairs of Democratic and Republican counties with similar characteristics. To ensure the selection model both (1) adequately accounts for all forms of pre-treatment variables and (2) does not include post-treatment factors that may be explained by the treatment, I create a directed acyclic graph (DAG). The DAG can be queried for the set of "admissible variables" which, when used to estimate selection weights for later use in outcome models, are sufficient for identifying the causal effect of county politics on county mobility. I use the matched pairs and selection weights from this step in every outcome model that follows.

The final stage is model estimation. I analyze three types of models, each of which is designed to address a unique aspect of mobility. The first model analyzes variation in county mobility for a short period after the Trump Administration declared a national emergency on March 13, 2020. I treat the period between March 13 and April 1 as the "preemption period," during which they could adjust their mobility in preparation for COVID-19. My hypothesis is that Democratic counties had lower average mobility levels than Republican counties, ostensibly in order to preempt the virus. I expect this to be the case because reliable information about the virus was scarce, and people largely had to behaved based on their predispositions toward scientific and government institutions. I refer to this model as the "preemption" model.

The second model analyzes how long counties were in a state of reduced mobility after they were initially infected. This corresponds to a survival setup where each county starts and ends on specific days, for a total survival time $t_{surv} = t_{end} - t_{start}$. I define the start time as the day a county passed a cumulative case threshold of 100 cases per 100,000 people, or a prevalence rate of 0.001; I define the end time as the first day a county had three consecutive days of pre-pandemic mobility levels. This setup intentionally allows for counties to fail out of the risk set quickly after they enter it (i.e., $t_{end} - t_{start} \approx \epsilon$, where $\epsilon > 0$ is small). I discuss the nuances of these measures later. My hypothesis is that, all else equal, Democratic counties on average survived in a state of reduced mobility for longer than Republican counties. The parameter of interest is a hazard ratio. I refer to this model as the "survival" model.

The final model analyzes the time-series systems of county mobility and county COVID-

19 cases between Democratic and Republican counties. For each county with at least 800 observations of a possible 968, I estimate a unique vector autoregression (VAR) system to describe how its COVID-19 cases and mobility levels dynamically respond to each other over time. In each model I allow for seasonality, structural breaks, and long lag times. Then, once each county has a fitted time-series system, I compute an impulse response function (IRF) to measure how a county's mobility responds to a sudden shock by a standard deviation in its COVID-19 cases. I measure the average level of mobility for a county over a fourteen-day forecast horizon, and I group counties into their respective Democratic or Republican group. Finally, I use a simple t-test to compare the distributions of average mobility responses for the Democratic and Republican counties. I refer to this model as the "reaction" model.

I find multiple broad results of interest to social scientists. The most striking one is that, contrary to conventional wisdom, Republican and Democratic counties mostly behaved similarly. In the "survival" model, Democratic counties were, on average, just barely less likely than Republican counties to fail out of the risk set across the sample period. In the loosest models, the hazard ratio on the "Democratic status" variable is statistically significant and less than 1; in the strictest models, the hazard ratio loses its statistical significance, indicating that the negative effect of Democratic status on hazard may be due to model specification. Similarly, my time-series models find that Republican counties were actually *more responsive* to sudden shocks to COVID-19 rates than Democratic counties. Although both types of counties exhibited very similar response patterns, the mean of the distribution of average mobility responses for Republican counties was statistically less than the corresponding mean for the Democratic counties. This suggests that Republican counties were more responsive to sudden changes in COVID-19 rates.[2]

The only result I find consistent with conventional political wisdom is that Democratic counties were more likely to exhibit preemptive mobility behavior than Republican counties. The "Democratic status" treatment variable is highly significant and negative, indicating that Democratic counties had much lower levels of mobility than Republican counties between March 13 and April 1. In the matching-adjusted sample, the Democratic counties had an average mobility of -36.6606 and Republican counties an average mobility of -33.9823. This means Democratic counties were initially $100 * \frac{36.6606-33.9823}{33.9823} \approx 8$ percent more cautious than Republican counties in paying heed to the warnings of government authorities.

The statistical conclusions in my study are suggestive of a nuanced view of politics and the pandemic. They are consistent with the idea that Democrats and Republicans initially

[2]Later on I discuss how to interpret this result in light of the possibility that Democratic counties may have had lower levels of mobility on average than Republican counties when they got hit by new cases. If this were the cases, then Democratic counties would have already been at low mobility levels, such that there would have been less room for them to decrease their mobility further.

behaved differently when the set of medical information about COVID-19 was largely empty and shrouded in uncertainty, but that they later behaved similarly after more information was about COVID-19 was gathered. Although this is a new finding, it is not surprising from a political perspective. Conservatives tend to be less trustful of political authorities when they make social and scientific propositions which, if heeded, would coerce people to constrain their behavior. It is, essentially, a form of motivated reasoning, which happened to tilt in this case against the favor of conservatives. This is especially true when the information underlying the propositions is missing or unreliable, as was the case in the early days of COVID-19. The fact that Republican counties later on adjusted their behavior suggests that, once the set of information about COVID-19 was more reliable, conservatives and liberals were more similar.

My study unfortunately cannot explain *why* I observe Republican and Democratic counties converging in their mobility over time. There are multiple causal mechanisms which could be at play, but my study (nor its data) is capable of testing which mechanism is responsible. The criterion for a mechanism in this case is a variable that the treatment (political partisanship) may have caused after the pandemic started and which affected choices about mobility downstream (i.e., a post-treatment pathway). This criterion admits a large number of plausible mechanisms. For example, the shift in Republican behavior may have been due to large-scale exposure to COVID-19 deaths, a lack of supply of hospital beds, the observation of a global event, or other disease-related factors. It could also have been due to a change in the retrieval of information. As the pandemic progressed, Fox News covered fewer stories about COVID-19 being fake or not dangerous, and instead covered more factual stories listing the current state of affairs with the disease. Many more mechanisms can be postulated but not tested.

The remainder of my paper proceeds as follows. Section 2 synthesizes the literature on politics and the pandemic. Section 3 proposes a simple theoretical model to explain the decision to be mobile. I solve for the equilibrium and use the insights to structure my research design. Section 4 introduces my research design, and sections 5-7 cover my empirical models. Section 9 concludes with a discussion of my findings in light of other research, with particular attention to what political scientists should take away from research on politics and COVID-19.

2 Background

A small literature has started on politics and the pandemic. The best way to synthesize it is dividing it into research questions about politics and pandemic beliefs and politics and behavior (which may have been caused by beliefs).

Most studies fall into the category of politics and pandemic beliefs. These studies have the commonality of arguing that, through different mechanisms, a person's party preferences, beliefs about markets, or ideological position affected how they viewed the pandemic. For example, Lesschaeve, Glaurdic, and Mochtak (2021) studied whether political ideology and market preferences influenced the number of lives that people were willing to lose to keep the economy open. With a focus more on political institutions, TERNULLO (2022) used in-depth interviews to study whether an individual's trust in their political institutions was associated with how much they believed the pandemic was real. On the vaccine side of things, Ye (2023) studied aggregate patterns in the effect county political beliefs on county vaccination rates from January 2021 to August 2021. The general conclusion of this research is the conservative individuals were more skeptical of the vaccine, less supportive of government management of public behavior, and less likely to support social lockdowns and school and business closures.

The other category of research deals with political beliefs and pandemic behavior. These studies have the commonality of studying a dependent variable that is related to either a controversial form of mobility in the pandemic or a form of political behavior like voting. For example, BISBEE and HONIG (2022) studied how a person's exposure to COVID-19 made them more likely to vote for a mainstream candidate than an extremist candidate. Similarly, Bisbee and Lee (2022) studied whether voters chose to use partisan cues or facts about COVID-19 case rates on the ground to inform their choices about social distancing. Grossman et al. (2020) studied the conditions under which an individual's partisanship caused them to disobey behavioral recommendations made by their governor, like decreasing their movement outside their home to minimize contagion. These studies tend to find that (a) personal exposure to COVID-19 in the early stages of the pandemic (i.e., when the disease was least contagious but most medically harmful to an individual) makes a person more tolerant of lockdowns and mainstream politicians, and (b) politics influenced where a person retrieved their COVID-19 information and the type of information (e.g., political, medical) they used to make choices about mobility and voting.

My study falls into the latter category of research about politics and pandemic behavior. Like many scholars, I study politics and mobility. However, unlike other scholars, I make two new contributions. The first is that I use a research design premised on estimating, as best as possible given the data, the aggregate treatment effect of county Republican status on a mix of short-run and long-run county mobility outcomes. I do this by developing a decision-theoretic model of a person's mobility choice, which showcases how a variety of confounding variables may influence both political beliefs and mobility choices at the county aggregate -

which the spatial unit that most behavioral studies use. Other studies use research designs premised on unadjusted regression control models or time-series models. My design allows me to make more precise claims about the effect of politics on behavior.

The second contribution I make is studying multiple types of mobility. Instead of considering mobility as producing a single outcome of interest, I classify mobility into distinct types: preemption, hibernation, and reaction. Preemption refers to mobility just before and after the Trump administration declared a national emergency on March 13, 2020; hibernation refers the length of time a county was in a state of reduced mobility (relative to pre-pandemic levels) after first being infected; and reaction refers to the short-run response of a county to decrease its mobility after witnessing a case rate increase. These are analytically distinct types of mobility, and they happen to correspond to different points in the pandemic at which public information about the danger of COVID-19 was different. For example, preemption occurs at the start of the pandemic when the public's information set was incomplete and uncertain. By contrast, hibernation is a long-run pattern of mobility that can last several hundred days after the start of the pandemic. This gets into the time period where the public's information set was rich and more reliable.

To summarize, my study contributes to the literature on politics and the pandemic by studying three types of mobility: preemption, hibernation, and reaction. I use a research design premised on comparing Democratic and Republican counties that were as similar as possible before the pandemic. This research design is informed by a theoretical model which explains how likely it is that failing to account for non-randomness in how "Democratic" and "Republican" county statuses is highly biasing in a statistical sense. I hope my study is able to shed more light on the question of whether, and how much, Democrats and Republicans behaved differently during the pandemic.

3 Theory

Why would political ideology be related to mobility choices? There are multiple plausible pathways. Some are direct and other indirect. A couple indirect pathways are naturally obvious. For example, conservatives tend to live in more rural locations. Rural locations tend to be more sparsely populated and less industrially diverse. This suggests that, holding all else equal, people in rural locations had a lower chance of being exposed to COVID-19 from going outside, as well as fewer opportunities to generate income from remote technological work. This suggests the following causal chain:

$$\text{rural status} \rightarrow \text{conservatism} \rightarrow \text{medical risk, alternative work} \rightarrow \text{mobility choice.}$$

More generally, there are several variables which may confound the relationship between politics and mobility at the aggregate level. Figure 2 shows how some of these variables are related to political ideology at the county level. In particular, it shows how county vote patterns are strongly related to college education, median household income, the share of foreign-born in the population, the share of a county as being "rural," the population of a county, and the age composition of a county. A county is coded as "Democrat" if more voters in the county supported Hilary Clinton than Donald Trump in the 2016 US Presidential Election. Clearly, when aggregated to the county level, political ideology is strongly explained by a variety of social and economic variables.

From a research design perspective, these relationships are troubling. If a mix of social, economic, and demographic variables explain political ideology and COVID-19 mobility at the county level, then any statistical association discovered between ideology and mobility may be spurious. Political ideology at the county level may not, in fact, have anything to do with mobility choices. The fact that Republican counties exhibited more mobility than Democratic counties in the pandemic may simply be due to the fact that Republican counties were socially, economically, and demographically distinct in ways that tilted their decision calculus. This begs the following counterfactual - if Democratic counties had the same characteristics as Republican counties, would they have behaved the same?

To both explain why this question is valid and to put forward a mechanism for how "Republicanship" may be related to mobility choices *independent*, I develop a formal theoretical model of a person's mobility choice. My theory is predicated on news media and partisan bias. I argue that, prior to pandemic, a person selects into a media firm, and hence a news bubble, based on their social, economic, and racial characteristics. Since this occurred before the pandemic, a person was "stuck" with slanted coverage of the pandemic reflecting their ideological views. The slant stereotype during the pandemic was that Fox news supplied listeners with skepticism about the virus and vaccine while CNN and MSNBC supplied listeners with caution about the virus and support for the vaccine. In broader terms, this can be simplified to the statement that Fox News downplayed the probability of infection and medical risks of the virus while CNN and MSNBC exaggerated them. Both types of media providers had an incentive to cater to their listeners by supplying them with information that conformed to their preexisting beliefs.

To justify my beliefs that politics, media choice, and beliefs about the pandemic are

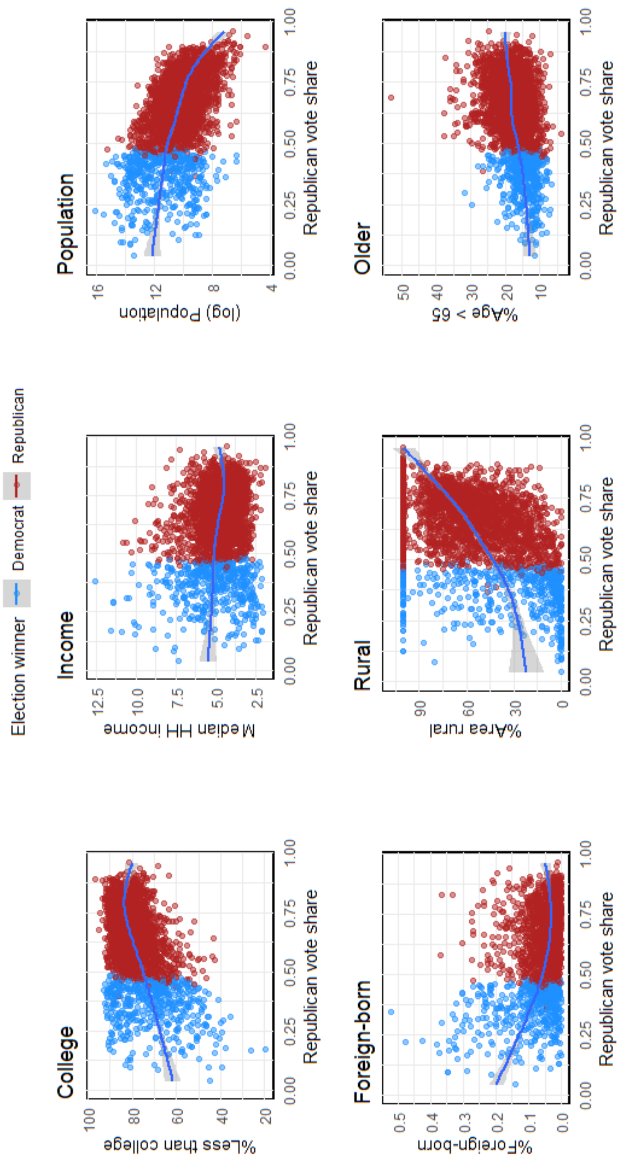

Figure 2: Multiple scatterplots showing the relationship between political preferences and a mix of socioeconomic characteristics, at the aggregate county level. Political preferences were measured as the share of voters in a county who voted for Donald Trump in the 2016 US Presidential Election.

related, figure 3 shows the relationship between these variables from the ANES Social Media survey fielded in 2020. The plots clearly show that higher conservatism is associated with higher trust in Fox News. Political ideology is measured on a 1-7 scale, with 7 being more conservative; trust in Fox News is measured on a 1-5 scale, with 5 being most trusting. The plots also show that trust in Fox News is strongly related to how worried a person was about COVID-19. How worried a person was is measured on a 1-5 scale, with 5 being very worried. The more a person trusted Fox News, the less worried they were about COVID-19.

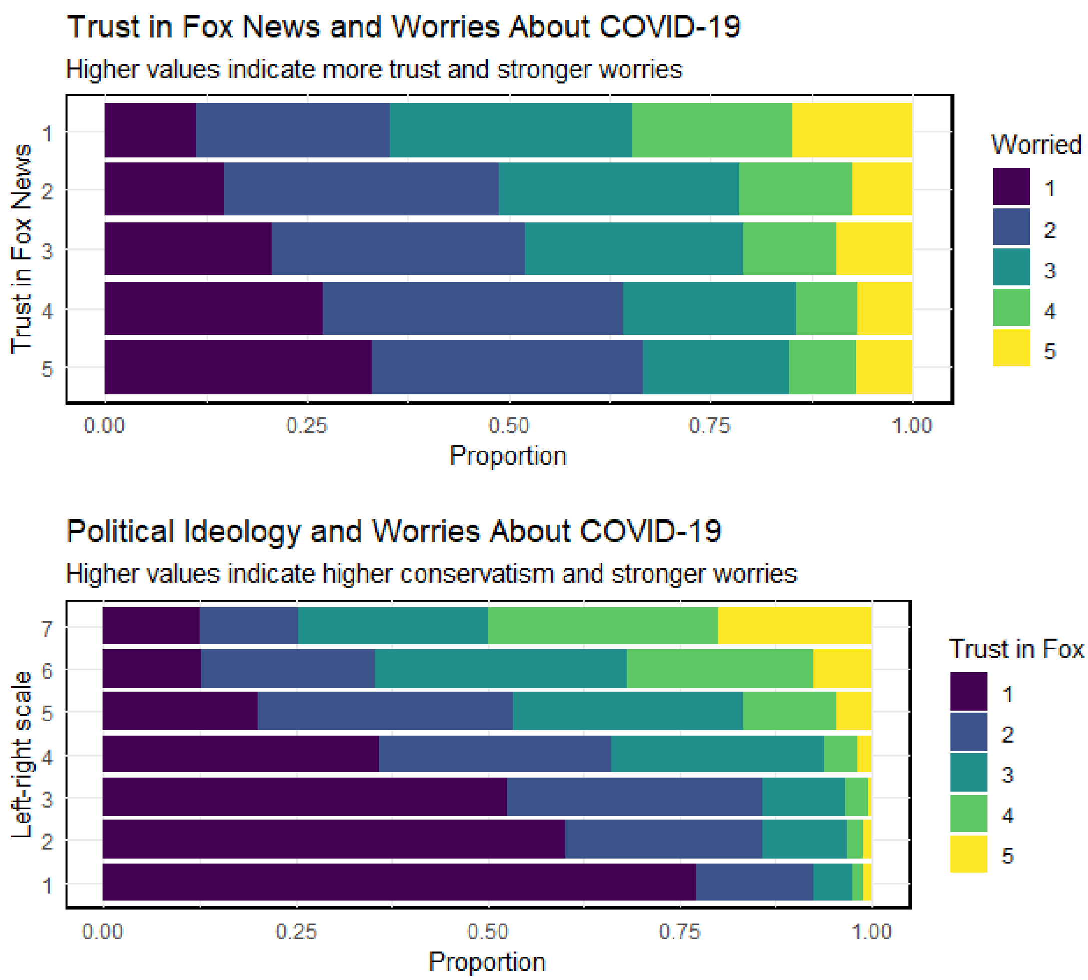

Figure 3: Plots of how in 2020 trust in Fox News, ideological conservatism, and fears about COVID-19 were related. The general trend is that more conservatism is associated with more trust in Fox News, and more trust in Fox News is associated with less fear about COVID-19.

3.1 Model

Consider a person during the pandemic choosing to stay inside or go outside. Their payoff to staying inside is normalized to zero. Their payoff to going outside is a wage $w_i > 0$ and a social benefit $s_i > 0$. However, they also risk exposing themselves to COVID-19. The chance they get infected is p, and the medical consequence of infection is $c_i(a_i, m_i)$, where a_i is age and m_i is medical vulnerability. I assume this cost function $c_i(\cdot)$ increases with respect to both age and vulnerability, such that $\frac{\partial c_i(a_i,m_i)}{\partial a_i}, \frac{\partial c_i(a_i,m_i)}{\partial m_i} > 0$ and $\frac{\partial^2 c_i(a_i,m_i)}{\partial a_i^2}, \frac{\partial^2 c_i(a_i,m_i)}{\partial m_i^2} > 0$. With this setup, the person chooses to go outside when

$$\begin{gathered} EU(\text{go outside}) \geq EU(\text{stay inside}) \\ -c_i(a_i, m_i)p_i + (w_i + s_i)(1 - p_i) \geq 0. \end{gathered} \tag{1}$$

As age a_i and medical vulnerability m_i increase, the justification for going outside retreats. Conversely, as the wage w_i and social benefit s_i from going outside increase, the justification returns.

Suppose now that political ideology enters the decision model through media consumption. Let $v_i \geq 0$ be the number of minutes the person watches Fox news. My premise is that the more Fox News a person watches, the more they will think that the chance of infection is low and that the health cost of getting infected is negligible. I justify this by noting that Fox News reported far more stories that were skeptical about COVID-19 than CNN or MSNBC. Keeping the framework of expression (1), we can update the p_i and $c_i(\cdot)$ terms to depend on how much Fox News the person watches. Specifically, I adjust the equation to

$$\begin{gathered} EU(\text{go outside}) \geq EU(\text{stay inside}) \\ -c_i(a_i, m_i, v_i)p_i(v_i) + (w_i + s_i)(1 - p_i(v_i)) \geq 0, \end{gathered} \tag{2}$$

where $c_i(a_i, m_i, v_i)$ and $p_i(v_i)$ have replaced $c_i(a_i, m_i)$ and p_i. Per my argument about consuming Fox News, both $p_i(\cdot)$ and $c_i(\cdot)$ decrease with v_i. The formal equivalent is the set of assumptions $p_i\prime(v_i), \frac{\partial c_i(a_i,m_i,v_i)}{\partial v_i} < 0$.

We can use the adjusted model in equation (2) to study how a person's choice to be mobile depends on their social, economic, and medical characteristics. For each variable, I take a partial derivative of the expression in (2):

$$
\begin{aligned}
&\frac{\partial F()}{\partial w} = \frac{\partial F()}{\partial s} = 1 - p(v) > 0 \\
&\frac{\partial F()}{\partial a} = -c_a(a, m, v)p(v) < 0 \\
&\frac{\partial F()}{\partial m} = -c_m(a, m, v)p(v) < 0 \\
&\frac{\partial F()}{\partial v} = c_v(a, m, v)p(v) + c(a, m, v)p\prime(v) + p\prime(v)(w + s) > 0.
\end{aligned} \tag{3}
$$

This system of partial derivatives (3) exhaustively describes how changes in a person's political, social, and economic characteristics affect their mobility. It reveals four insights. The first is that the more wages and social engagement a person stands to earn from going outside, the more likely they are to be mobile. This implies that if a person can obtain their wages *without* going outside, like through remote work, they have less of a reason to be mobile. This suggests that, all else equal, people with jobs that have no option for remote work should be more mobile than people with jobs that do.

The second insight is that a person's age and medical vulnerability should prevent them from being mobile. Within the scope of my model, this happens because both age and medical vulnerability raise the medical consequences of contracting COVID-19, or that $\frac{\partial c_i(a_i,m_i,v_i)}{\partial a_i}, \frac{\partial c_i(a_i,m_i,v_i)}{\partial m_i} > 0$ per my earlier assumptions. Even if the probability of infection is low, the damages to a person's health could be bad enough that they choose to stay inside.

The third insight is that variation in a person's perception of the chance of infection $p_i(v_i)$ greatly influences their mobility choice. The more a person believes the chance of infection is low, the likelier they are to be mobile because they believe that basic trips to the grocery store, pharmacy, retail stores, and other locations are safe. This idea can be extended to counties to consider what mobility patterns would look like in sparsely populated and densely populated locations. Since it is reasonable to believe that p was lower in sparsely populated counties than in densely populated counties, it should be the case that mobility in sparsely populated counties was higher.

The final insight is that watching more Fox News - or rather, being more conservative - tilts the decision calculus toward going outside. There are two mechanisms responsible, and both are about information. The first is that more Fox News makes a person believe that the medical consequences of getting COVID-19 is smaller. This decreases the cost of contracting the disease. The second is that more Fox news makes a person believe the chance of getting infected from going outside is also smaller. This decreases the likelihood of getting the disease in the first place, which lowers the cost of going outside. Both mechanisms effectively discount the medical risks of COVID-19. This insight leads to the conventional wisdom, stated as a hypothesis, held by the public:

H1: All else equal, Democratic counties will reduce their mobility more than Republican counties in response to COVID-19.

A couple other hypotheses can be generated from the model. Recall that the primary mechanism through which Republican counties may be more mobile than Democratic counties is news coverage by Fox News. If it were the case that Fox News became less skeptical of how contagious and medically damaging COVID-19 was over time (without necessarily endorsing the vaccine or lockdowns), then it would also be the case that viewers of Fox News would converge in their mobility behavior toward viewers of other media providers. The formal justification for this informal proposition is that both the chance of infection $p_i(v_i)$ and the medical cost of COVID-19 $c_i(a_i, m_i, v_i)$ would no longer depend on how much Fox News a person watches v_i. Since coverage of COVID-19 by Fox News would become more like coverage by alternative media channels, v_i would cease to have an effect on either p_i or c_i. This leads to the following proposition:

H2: All else equal, due to shifts in coverage of COVID-19 by Fox News over the course of pandemic, Democratic and Republican counties will display similar long-run mobility patterns.

My final hypothesis concerns short-run mobility. Under the premise that Democratic counties start from lower levels of mobility than Republican counties, as well as the premise that Republican counties may have been less fearful of COVID-19 due to their sources of information, it may be the case that Republican counties actually exhibit *more* reactive mobility patterns to sudden COVID-19 shocks than Democratic counties. The reason for this counter-intuitive result is rather simple - since Democratic counties may already be less mobile due to their trustfulness of government and scientific institutions, they may not be shocked when they observe that COVID-19 hits their counties. By contrast, Republican counties may be shocked to see the damage of COVID-19 when it arrives, and they may adapt their behavior in response to a surprising reality. This leads to my final hypothesis:

H3: All else equal, Republican counties should display more reactive mobility changes to an uptick in COVID-19 cases than Democratic counties.

4 Data and Research Design

To test my hypotheses, I collected data on aggregate mobility patterns, COVID-19 infections, election outcomes, and socioeconomic data on the county level. The mobility and COVID-

19 data come from Google in the form of daily time-series. For the COVID-19 data, I used the average number of people newly infected with COVID-19 over the last fourteen days, per 100,000 people in the county. This number varied by day in reflection of how many new people became infected. For the mobility data, daily observations are aggregates from individual-level GPS data from mobile phones. Records began on February 20, 2020, and the date of collection was October 15, 2022 making the total number of possible observations 968 days. I discarded counties from my sample if they had fewer than 800 of the possible 968 observations, which left around 1,100 counties in the sample. Figure 4 shows a daily time-series plot of the COVID-19 rate and mobility level observed in King County, Washington (which contains Seattle). The horizontal axis is time and the vertical axis is both the mobility level and the COVID-19 case rate. The patterns in both the COVID-19 and mobility series are largely common to other counties, though with more or less time delay from when a county was first infected. The shaded areas of the plot describe summer months when temperatures were warmer and people became more mobile.

The mobility data from Google is measured in a slightly hidden way. Given a county c and weekday d, the observed mobility levels were calculated relative to how mobile county c was on weekday d between the first weeks of January 2020 and February 2020. That is, the observed data is explicitly a *relative* representation of what county mobility was just before the pandemic. To be formal, given a county c and weekday d, the observed level of mobility is

$$\hat{y}^d_{t,c} = \frac{y^d_{t,c} - \bar{y}^d_c}{y^d_{t,c}}, \tag{4}$$

where $\bar{y}^d_c$ is the median aggregate level of mobility between the first weeks of January 2020 and February 2020.[3] Based on equation (4), and relative to pre-pandemic mobility levels, a county is in a state of reduced mobility when $\hat{y}^d_{t,c} < 0$, and a state of recovered mobility when $\hat{y}^d_{t,c} > 0$.

My source of data for county election outcomes and sociodemographics is MIT Election Lab.[4] Among other variables, the dataset contains electoral information on the share of votes cast for Donald Trump and Hilary Clinton in the 2016 US Presidential Election, as well as sociodemographic information like county population, the number of college-educated people, the number of foreign-born people, the number of white, black, Hispanic, Asian, and Native American people, and the median household income. A key variable in this dataset is the share of voters in a county who voted for Donald Trump. Letting V_c be the number

[3] Notice from equation (4) that the "true," non-normalized level of mobility $y^d_{t,c}$ is not available in the dataset. Neither can it be backed out, since we do not know the median weekday level of mobility $\bar{y}^d_{t,c}$.

[4] See the MIT Election Lab's homepage here.

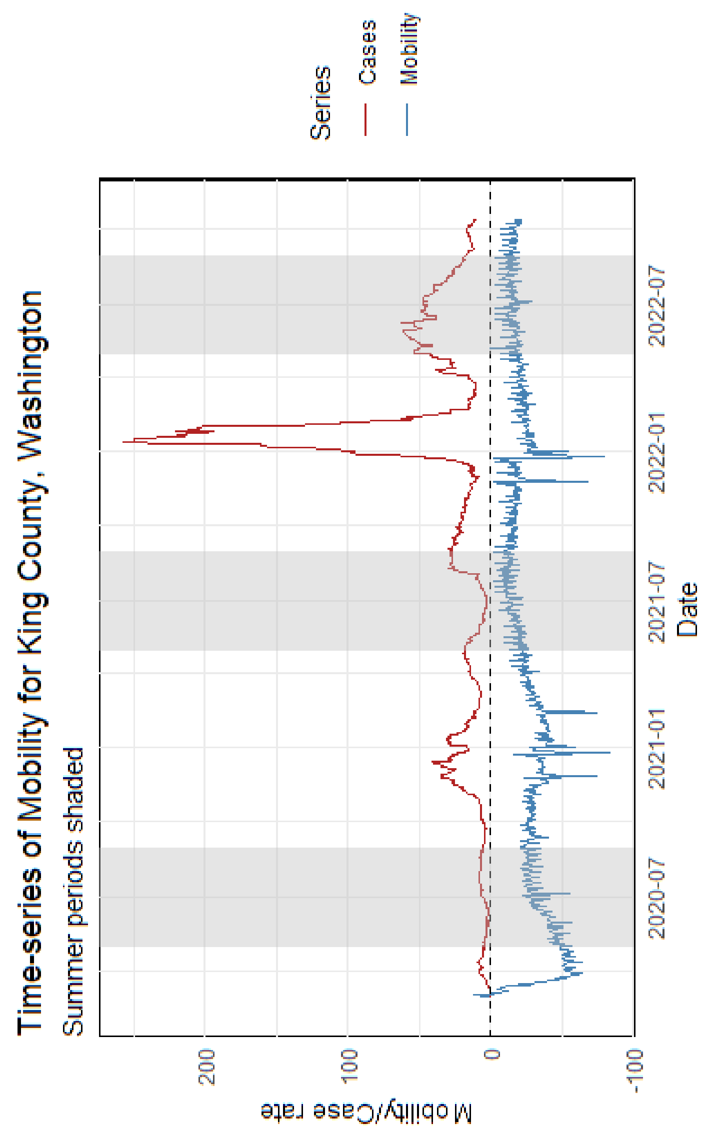

Figure 4: Time-series of county mobility for King County, Washington. The horizontal axis refers is time while the vertical axis is mobility level. Negative mobility scores on a specific weekday indicate that mobility that weekday was less than the median level of mobility on that same weekday before the pandemic. The shaded regions indicate summer months.

of voters in county c and R_c the number of voters who voted for Donald Trump, the share of Republican voters is

$$r_c = \frac{R_c}{V_C}, \tag{5}$$

while the corresponding share of Democratic voters is

$$d_c = \frac{D_c}{V_C}. \tag{6}$$

I then used equations (5)-(6) to measure the treatment variable T_c, "Democratic status," as

$$T_c = \begin{cases} \text{Democratic (1) if } \ d_c > r_c \\ \text{Republican (0) otherwise.} \end{cases} \tag{7}$$

5 Research Design

My objective was to test hypotheses H1-H3. However, due to selection bias in which counties were Democratic or Republican, I needed to adjust my sample. Specifically, I needed to identify Democratic and Republican counties for whom, before COVID-19 hit, the sole observable difference was their voting behavior. In other words, I needed to find counties that had similar pre-treatment characteristics. To help with this process, I built a causal graph following Pearl (2009). Figure 5 shows my hypothesized causal model. The arrows indicate causal directions while the labels refer to variables. The graph shows that partisanship is a selection variable, but also that media bias, mobility, and COVID-19 rates are downstream post-treatment variables. Based on Pearl's back-door criterion, the set of variables with a box around them constitutes an "admissible set" ((2009)) of adjustors - variables that, if used as controls in an empirical model, are enough to identify the causal effect of partisanship on mobility. The intuitive explanation for this is that the boxed variables occur *before* the political treatment, while the other variables are the consequence of the treatment. If we find counties with similar values on the pre-treatment variables but that happened to vote differently, then we feel comfortable believing that whatever vote differences remain are mostly due to randomness or unobserved variables.

Based on the admissible set of adjustors identified by figure 5, I specified a propensity score model (PSM) with the Democratic treatment variable T_c as the dependent variable and a vector $\boldsymbol{x}_c$ of K social, economic, and demographic variables $\boldsymbol{x}_c = \{x_{c1}, x_{c2}, ..., x_{cK}\}$ as

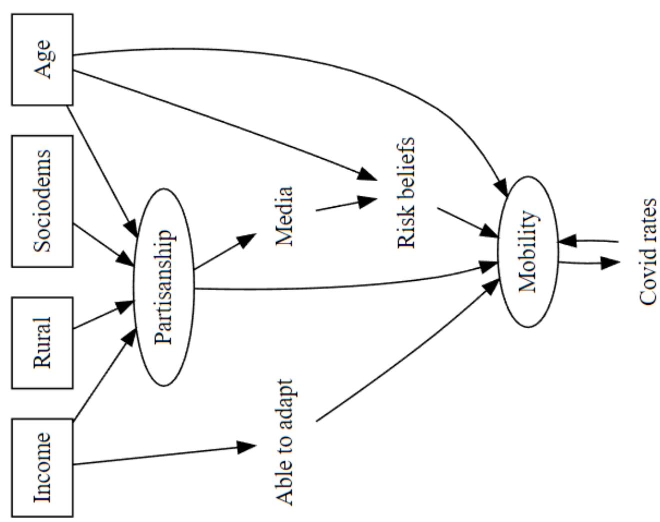

Figure 5: A Causal Graph representing the causal relations behind county partisanship and county mobility during the pandemic. Variables with a box surrounding them constitute an admissible set for identifying the causal of partisanship on mobility.

explanatory variables. Among the vector of explanatory variables were the boxed variables in the figure. My empirical specification for the PSM was a generalized linear model (GLM) with a logit link function,

$$e_c = \Pr(T_c = 1|\boldsymbol{x}_c) = \frac{1}{1 + e^{-\boldsymbol{x}_c^T \boldsymbol{\beta}}}. \tag{8}$$

The e_c term in equation (8) is the estimated "propensity" for county c to receive the Democratic treatment, which is just the fitted value for county c.

With the vector of estimated propensity scores $\boldsymbol{e}_c$, I then used a matching algorithm to determine which counties from the Democratic and Republican subsamples should be paired for comparison. My algorithm of choice was a nearest-neighbor model with a 2:1 matching ratio and a varying caliper. The 2:1 ratio means that each treated unit is assigned two control units, while the caliper means that matches between counties could only include counties that were less than the caliper distance apart in propensity score space (e.g., 0.05). To be formal, a match between county i and county j would only be considered if $|e_i - e_j| < \tau$, where τ is the caliper. To ensure robustness, I performed ten different matching algorithms, each with a different caliper spaced between 0.001 and 0.01. For the remaining empirical models except the time-series analysis, I ran 10 different models corresponding to the 10 calipers used in the matching algorithm as a form of sensitivity analysis to see how the statistical results change under more or less stringent conditions.

Figure 6 shows a diagnostic plot to describe the similarity the treatment (Democratic) and control (Republican) subsamples after matching. The diagnostics are from the 5th caliper value of the possible 10. In the figure, each panel represents one of explanatory variables from the propensity score model. The panels show the distributions of an explanatory variable by treatment group before and after sample adjustment. For a given variable, the goal is for the distributions in the "Adjusted Sample" panel to look more similar than the distributions in the "Unadjusted Sample" panel. This indicates that, after using the matching algorithm the sample of Democratic and Republican counties became *more similar* on that particular explanatory variable. In statistical terms, Rubin (2007) suggests that the standardized mean difference between the treatment and control groups after matching should, in the real world, be around 0.1, while the variance ratio should be around 2. For all but the "%Area as rural" variable, this holds true (this variable has a near-zero standardized mean difference but slightly more than a 2.0 variance ratio).

The following sections use the adjusted sample from the PSM and matching algorithm to empirically model the preemption, hibernation, and reaction types of mobility data.

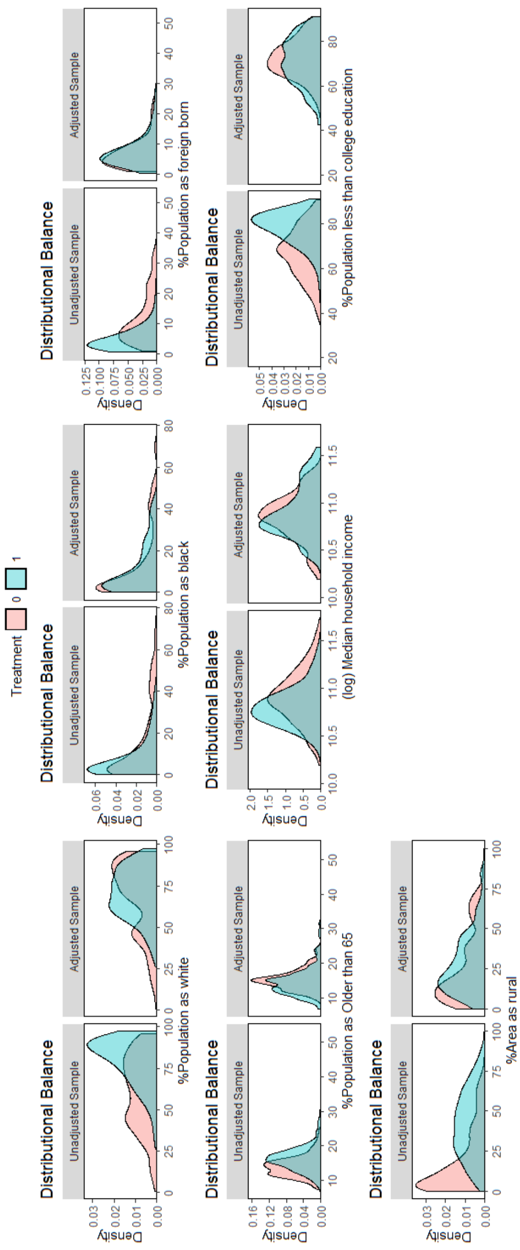

Figure 6: Distributions of selection covariates across treatment and control groups, before and after adjustment by matching. The panels that represent the data before matching show that Democratic and Republican counties are highly different on the selection covariates. This is visually clear in how much the distributions do not overlap. The panels that represent that adjusted data after matching show that Democratic and Republican counties are much more similar.

6 Preemption Analysis

My first analysis is of politics on preemption. On March 13, 2020, the Trump administration declared a national emergency in response to the COVID-19 disease. Very little was known about the virus (SARS-CoV-2), how it spread, how quickly it reproduced, or how the disease it led to (i.e., COVID-19) operated within the human body. People therefore had a large degree of uncertainty over key pieces of information. They had a choice - reduce mobility to preempt the virus for the *possible* benefit of increased safety at the *sure* cost of inconvenience, or maintain mobility at the risk of getting infected with a virus about which little was known. This choice to preempt the virus in the early stages of the pandemic may have fallen along political lines, as it was primarily the government and scientific organizations that were urging caution and lockdowns. Per my first hypothesis **H1**, I expect that Democratic counties exhibited more preemption thatn Republican counties.

I measure the aggregate level of "preemption" in a county as its average mobility level over a set of early pandemic days. Let this set of early days Q be defined as the days which fall between March 13 and April 1, or $Q = \{t : t \in [\text{March 13}, \text{April 1}]\}$. I chose March 13 and April 1 as the boundaries for convenience. Many counties did not have their first observation until late March, while going too far past the start of April would enter a period in which people were starting to gain more information about the virus (such that preemption would no longer apply). Marginal changes to the start and end dates do not have a significant effect on my results. Continuing with this time span, the average preemption mobility of a county c is

$$Y_c = O_c^{-1} \sum_{t \in Q} -y_{t,c}, \tag{9}$$

where $y_{t,c}$ is mobility on day t and O_c is the number of times a county was observed in the set of early days. I multiplied county mobility levels by -1 to make the preemption variable positive. This means that counties with higher values on equation (9) are more preemtive - that is, they reduced their mobility more in the early days period.

Figure 7 plots a county's average preemption against its share of votes for Donald Trump in the 2016 election. The plot is composed of the unadjusted sample, where none of the observations are weighted. The horizontal axis is the fraction of votes for Donald Trump while the vertical axis is average preemption. The plot clearly shows that Republican counties were less preemptive. As a county votes for Donald Trump more, it gradually becomes less preemptive. However, this conclusion is misleading because it does not account for the fact that most Democratic and Republican are not comparable. It describes the true trend between partisanship and preemption, but it is not causal in any sense. Therefore, using it alone to test H1 is invalid.

To make a better test of H1, I set up a simple linear regression model of preemption and county political status. The empirical model is

$$Y_c = \alpha + \delta T_c + \epsilon_c, \tag{10}$$

where α is the intercept, δ is the average treatment effect (ATE) of Democratic status on preemption, ϵ_c is the residual. The ATE is the best guess for how much Democratic status affected preemption - the average gain in preemption for a Republican county if, holding all else equal, it were instead Democratic. An alternative estimator which gets the same result is calculating the difference in the weighted averages of the preemption variable between the treatment (Democratic) and control (Republican) group. The weights are from the matching algorithm. This corresponds to

$$\delta = \frac{1}{N_T} \sum_{c:T_c=1} w_c Y_c - \frac{1}{N_C} \sum_{c:T_c=0} w_c Y_c,$$

where N_T is the number of treatment units and N_C is the number of control units.

6.1 Results

Figure 8 plots the average treatment effects from equation (10) under each of the 10 caliper settings from the matching algorithm. The closed circles are point estimates and the bars as the boundaries on a 95 percent confidence interval. Depending on how strict the caliper values were, the ATE varies between 5.601 and 2.705. Across all the caliper settings, the average of the ATEs was 3.778. Notice that each of the estimates for the ATE are statistically significant - none of the confidence intervals are even close to zero. This is strong evidence in favor of my first hypothesis.

Interpreting the effect is straightforward. An estimate of 3.77 for the ATE can be taken to mean the following: holding all else equal, if a Republican county were instead Democratic before the pandemic, it on average would have been 3.77 points less mobile during the early days of the pandemic. But this effect large? To judge the overall size of the effect, consider the fact that the average mobility of Republican counties in the adjusted sample was -33.0074. From this baseline, a shift of 4.4 points is equal to a $\frac{3.77}{33.0074} \approx 11$ percent change in mobility. In other words, in the early days of the pandemic, the average effect on preemption of being Democratic relative to being Republican was to increase preemption by about 11 percent.

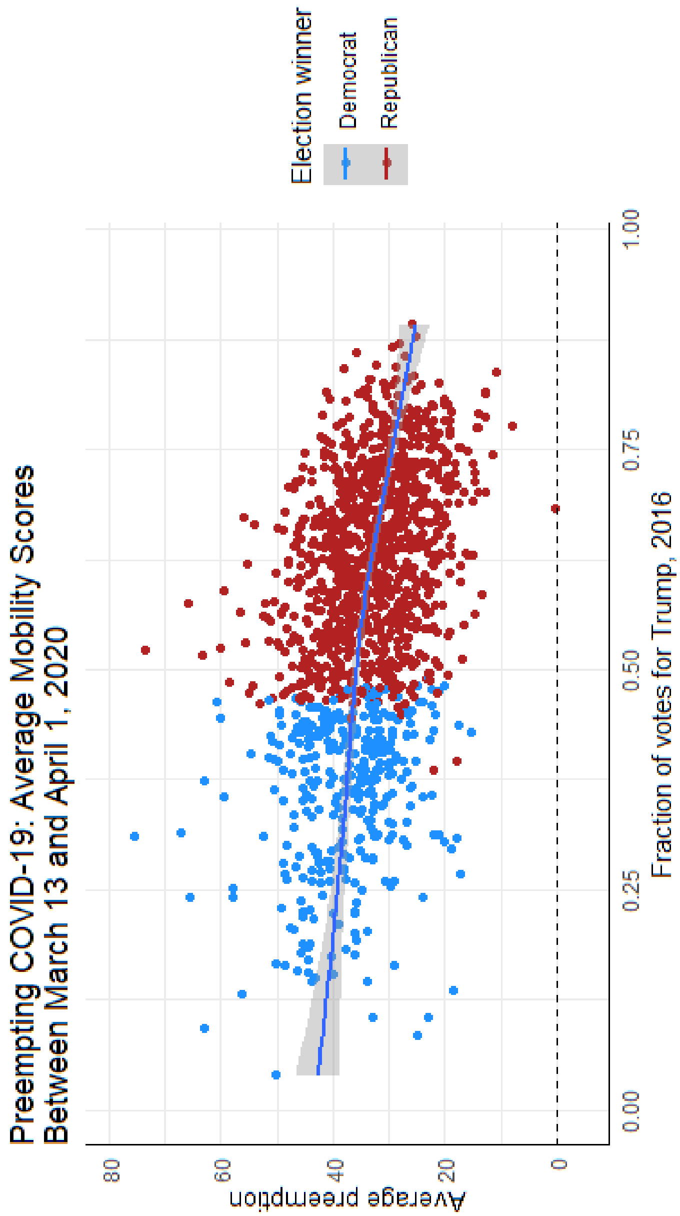

Figure 7: Scatter plot of county average mobility responses as a function of county Republican vote share. County Republican vote shares range between 0 and 1, while average mobility responses can take on any real number. Mobility responses below 0 indicate that a county decreased mobility after a case rate shock, whereas mobility responses above 0 indicate that a county increased mobility.

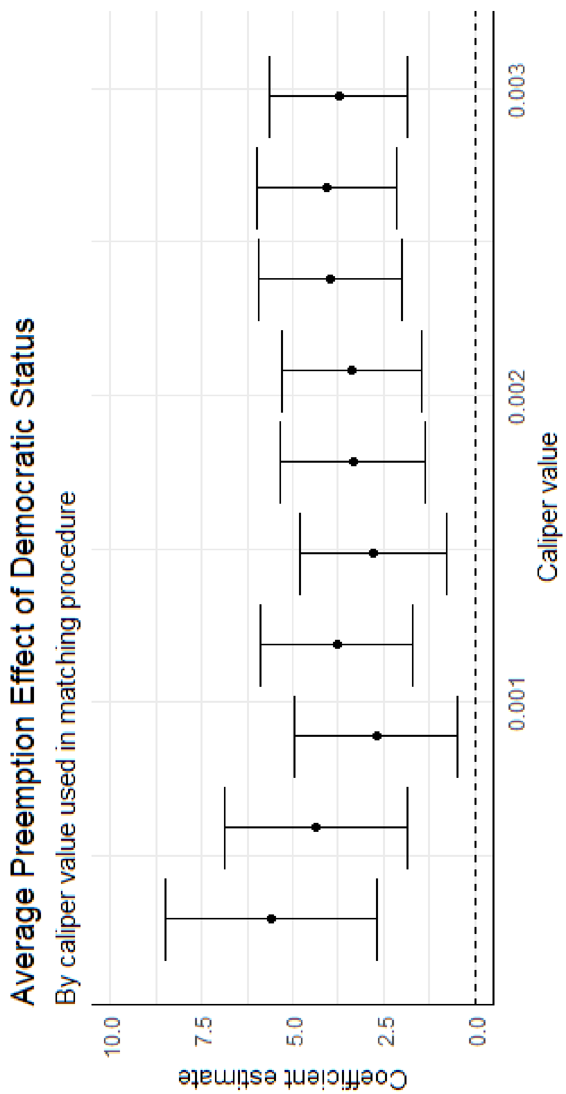

Figure 8: Coefficient plot for the results of a linear regression model of county preemption on county Democratic status. The horizontal axis describes the caliper value used in the pre-estimation matching procedure while the vertical axis describes the estimate for the average treatment of Democratic status on preemption. The bars on the graph represent 95-percent confidence intervals around the treatment effect.

This is a surprisingly large effect.

7 Reaction Analysis

My second analysis is of how counties adapted their mobility in reaction to sudden increases in case rates. My objective was to test hypothesis **H3** - that Republican counties would exhibit a *larger* mobility reaction to COVID-19 than Democratic counties. Although I cannot test for a mechanism behind this hypothesis, my hunch was that Republicans were less fearful than Democrats of both the chance of a COVID-19 infection and the medical consequences of an infection, due to their self-selection into distinct information environments (e.g., Fox News, CNN, MSNBC).

To analyze reactive behavior, I used a vector autoregression (VAR) model of mobility and case rates for each county. In the context of this study, a VAR is a set of time series equations in which the present and past time-series observations of the COVID-19 case rate and mobility levels influence each other. I chose to use VAR models for specific reasons. First, VARs use all available time-series data. Second, VARs are particularly a-theoretic. Other than assuming linearity in parameters, they make very few assumptions about the data-generation process. Third, due to the lag structure in VAR models, they are capable of capturing dependencies between present behavior and past behavior over both short and long runs. In the models I specify, I allow for lags up to fourteen days. Fourth, VARs can be "shocked" with an impulse response function (IRF) to simulate how a county's mobility levels responds when COVID-19 cases increase. This is useful for studying how counties behaved in the real world when they experienced case rate increases.

My VARs had the following setup. Using c_t as the case rate and m_t as mobility, my VAR(p) systems had the empirical representation

$$\begin{aligned} r_t &= \alpha_{01} + \sum_{s=1}^{p} \alpha_{t-s} r_{t-s} + \sum_{l=0}^{q} \beta_{t-l} m_{t-l} + \epsilon_{0t} \\ m_t &= \alpha_{11} + \sum_{u=1}^{v} \gamma_{t-u} m_{t-u} + \sum_{m=0}^{n} \kappa_{t-m} r_{t-m} + \epsilon_{1t}, \end{aligned} \tag{11}$$

where $\boldsymbol{\theta} = \{\{\alpha\}, \{\beta\}, \{\gamma\}, \{\kappa\}\}$ are model parameters and P is the number of past values (i.e., lags) of a series included in the system. When estimating a VAR for a county, I determined the number of lags based on the Bayesian information criteria. I estimated the VAR system in equation (11) for every county in the dataset with at least 800 observations, making for a total of more than 900 unique VARs. The fitted VARs can be viewed and downloaded as model objects from the Online Appendix, as well as their plots, diagnostics, and impulse responses functions.

To test my third hypothesis **H3**, I use the VAR models to compute impulse response functions. An impulse response function is a simulation used to calculate what happens to a time-series system when one of the series experiences a large, unanticipated increase in its error term. It uses the estimated parameters from equation (11) to make the calculations. I used it to calculate how the mobility time series $\hat{m}_t$ would respond to a shock to COVID-19 cases through the residual of the COVID-19 cases series ϵ_{0t}. The idea is simple - the shock to ϵ_{0t} propagates to mobility m_t by affecting c_t. The short-run and long-run mobility effects over H time steps are captured by the α, β, γ, and κ parameters. More formally, it is a forecast for how m_t would evolve over H future time steps from a shock to ϵ_{0t}. For county c, this evolution is captured by the set of predictions $\{\hat{m}_{t+h,c}\}_{h=1}^{h=H}$. This can be used to calculate the average mobility response of a county, accounting for non-random selection into the treatment:

$$\boldsymbol{m}_c^H = \sum_{h=1}^{H} w_c \hat{m}_{t+h,c}. \tag{12}$$

I use equation (12) to compare how Democratic and Republican counties would have responded to a sudden shock to COVID-19 case rates.

7.1 Results

Figure 9 plots values from the fitted vector autoregression model for King County, Seattle against its observed values. Notice that the fitted values are very close to the observed values. This is unsurprising, since VAR models tend to overfit the data by using copious amounts of past information. For example, using the Bayesian information criteria, the models chose to use a lag length of 14. This was the typical outcome for the vast majority of other counties in the sample. Although this degree of overfitting would be harmful for predicting how counties would respond to a COVID-19 shock in 2023, it is very useful for describing how counties responded to COVID-19 shocks during the pandemic.

Figure 10 moves from the VAR model in equation (11) to impulse response functions. It calculates equation (12) using a county's unique VAR model, and plots the results by whether a county voted Republican or Democratic in the 2016 election. My hypothesis was that the distributions should be clearly different, with Republicans being *more* reactive in their mobility than Democrats. However, this is not the case. Visually, it appears as if the Democratic and Republican distributions could have been generated from the same underlying process. They seem to have roughly the same means and variances.

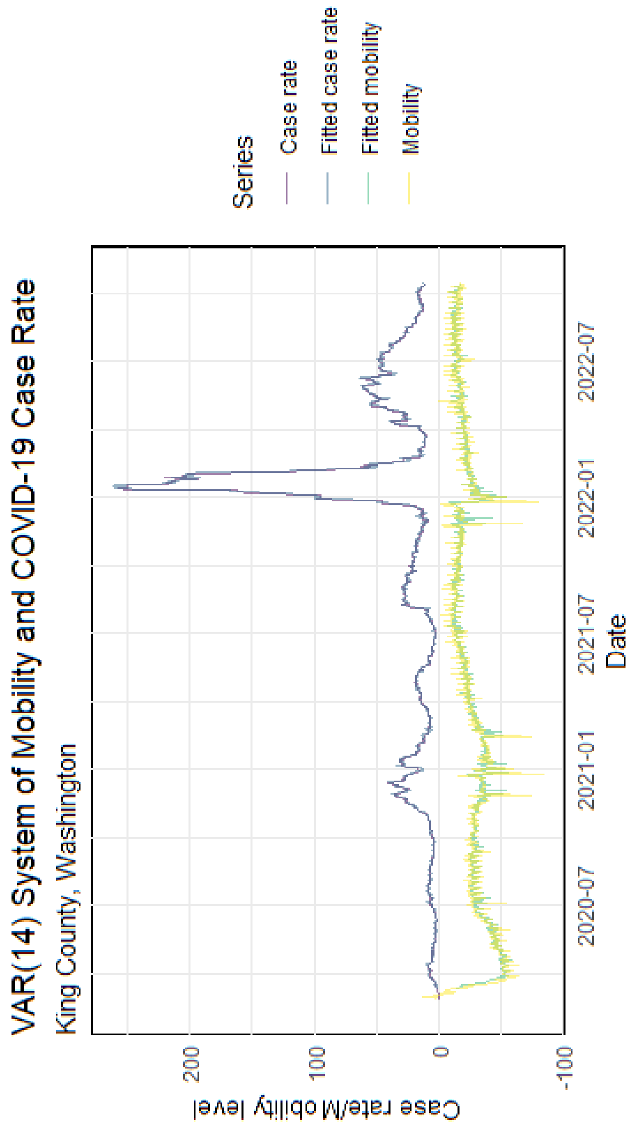

Figure 9: Fitted values for the VAR(14) system of the COVID-19 case rate and mobility levels for King County, Seattle. The close fit between the observed values and the fitted values reflects the overfitting tendency of VAR models.

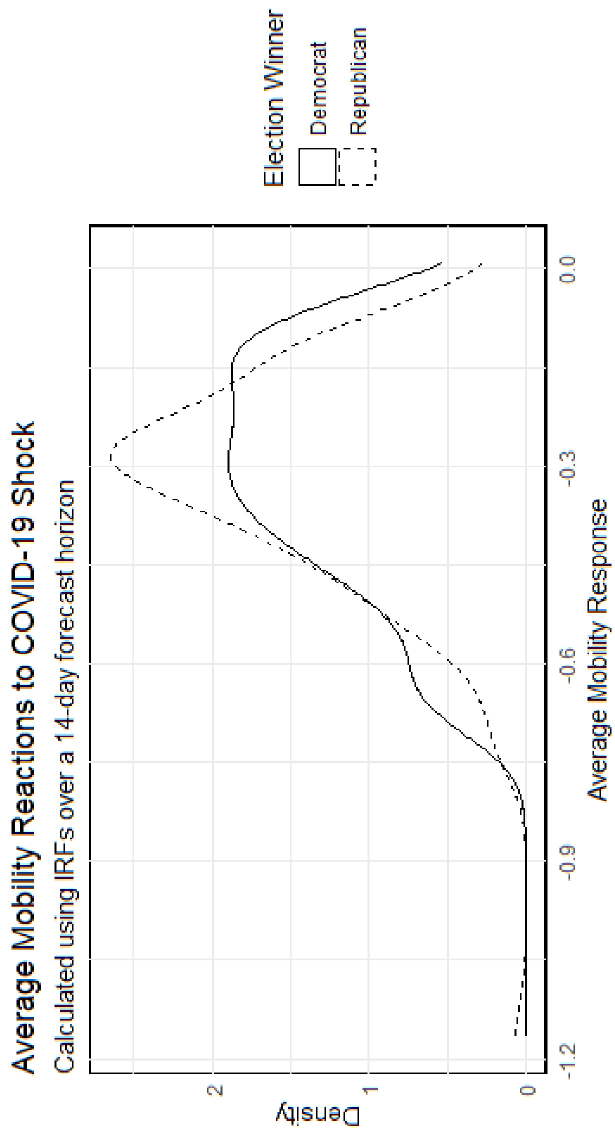

Figure 10: Distributions of average county mobility reactions from impulse response simulations. The averages were calculated from a 14-day impulse response horizon, and weighted according to sample adjustment weights from a matching algorithm.

A t-test confirmed that the distributions are indistinguishable. With a sample mean of -0.3141 for Republican counties and -0.3051 for Democratic counties, the 95-percent confidence interval around the true difference of means is $\mu^{95}_{x-y} \in [-0.0503, 0.0323]$. This result implies that I should reject my third hypothesis **H3** that Republican counties would have been more reactive in changing their mobility than Democratic counties. It is in fact the case that, judged alone by how they responded to COVID-19 shocks over the short run, Democratic and Republican counties cannot be told apart.

8 Survival Analysis

My final analysis is of how long counties were in a state of reduced mobility after encountering their first wave of COVID-19 infections. This analysis is designed to test my first hypothesis **H1** that, when holding all pre-treatment variables equal, Democratic and Republican counties would hibernate for the same amount of time.

The empirical analogue for this hypothesis is a survival model. In my study context, a county enters the survival period when its people are confronted with the dangers of COVID-19. It exits the survival period the day its mobility recovers to a pre-pandemic level. Let the start day for county c be $t_{0,c}$, and let the end day be $t_{e,c}$. Then, the total "survival time" for county c is simply

$$y_c = \text{survival time} = t_{e,c} - t_{0,c}. \tag{13}$$

How do we operationalize when a county enters and exits its survival phase? Measuring when a county exits its survival phase is easy. Exit occurs when a county reaches a mobility level greater than 0. This indicates that its mobility has reached a level witnessed in the January 2020-February 2020 pre-pandemic period. To make sure the measure is robust to random instances of high mobility, I required a county to have three consecutive days of mobility levels greater than 0. This prevents a county from falsely exiting the risk set just because it had a single, unprecedented day of high mobility due to a one-off event, like a local festival or a protest.

Measuring when a county enters the survival phase is more controversial. There are a couple ways to approach the problem. For example, one could take an information approach and argue that every county was confronted with the dangers of COVID-19 when the Trump administration declared a national emergency on March 13, 2020. However, this seems unfair both to counties that were hit by COVID-19 before this date and long after this date. Counties in the geographic center of the United States, particularly in rural areas, had no reason to reduce their mobility in March; and counties with large populations on the East and West coasts were hit by COVID-19 before March 13, 2020. If we were to define survival entry using this March 13, 2020 date, then most nearly all counties in the geographic center of the United States would exit the risk set on day one. This definition is not good enough.

I chose to measure country entry based on county-specific case rates. I defined entry as the day a county first reached 100 cumulative cases per 100,000 people. This represents a prevalence of rate of $0.001 = \frac{100}{100{,}000}$, or 1 in 1,000 people. Since counties have vastly different populations, this can be confusing to interpret. For a county with 25,000 residents, it would enter the risk set when it reaches $0.001 * 25,000 = 25$ cumulative cases. For a county with 1,000,000 residents, it would enter the risk set only when it reaches $0.001 * 1,000,000 = 1000$ cumulative cases. I could have chosen alternative cumulative case rates like 150, 200, or even 500 cumulative cases per 100,000 people to make sure people in a county fully realized they were being hit by COVID-19. However, making the threshold too high is risky. We want to make it possible for relatively incautious counties to see rising numbers of COVID-19 cases, discredit the dangers, and continue to have high mobility levels. If we make the threshold too high, then we risk giving counties too much time leeway to adapt their behavior.

Using these loose concept for entry and exit into the survival phase, I formally define entry $t_{0,c}$ and exit $t_{e,c}$ as

$$\begin{aligned} \text{start time}_c &= t_{0,c} = \{\min(t) \mid \tau_{t,c} \geq 100\} \\ \text{end time}_c &= t_{e,c} = \{\min(t) \mid m_{c,t-2}, m_{c,t-1}, m_{c,t} \geq 0\}) \\ \text{survival time}_c &= y_c = t_{e,c} - t_{0,c} \end{aligned} \tag{14}$$

where $\tau_{t,c}$ is a county's cumulative case rate per 100,000 and $m_{c,t}$ is its mobility level, as in the time-series section.

The final part of setting up the hibernation model is estimation. Using the entry and exit definitions in (14), I specified and a semi-parametric Cox-Proportional Hazards (Cox-PH) model. Let $\lambda(t|x_c)$ be the hazard for county c at time t and let $\lambda_0(t)$ be the baseline hazard at time t. Then, the Cox-PH model is

$$\lambda(t|T_c) = \lambda_0(t) \exp(\delta T_c), \tag{15}$$

where $\lambda(t|\boldsymbol{x}_c)$ is the hazard for county c at time t and $\lambda_0(t)$ is the baseline hazard at time t. The expression inside the exponential term is the linear predictor, which in this case is just the Democratic treatment variable. The average treatment effect is δ. The survival times $\boldsymbol{y} = \{y_1, y_2, ..., y_C\}$ are used to iteratively adjust the risk set when estimating the partial likelihood function.

Equation (15) yields the quantity of interest $\hat{\delta}$. In terms of a survival model, $\hat{\delta}$ is the best estimate for the marginal hazard ratio, or for $\frac{\lambda(t|T_c=1)}{\lambda(t|T_c=0)}$ when averaged over the sample timeframe. But this interpretation is somewhat coarse. In terms of political theory, $\hat{\delta}$ describes how much *more likely* a Democratic county is, on average, to return to a pre-pandemic pattern of mobility than a Democratic country. A value of $\hat{\delta} = 1$ indicates that Democratic counties are just as likely as Republican counties to return to a pre-pandemic pattern of mobility; a value of $\hat{\delta} < 1$ indicates that Democratic counties are *less* likely; and a value of $\hat{\delta} > 1$ indicates that Democratic counties are more likely. If Democrats and Republican counties behave in statistically different ways, then we must reject the null hypothesis that $\hat{\delta}$ is indistinguishable from 1.

8.1 Results

Figure 11 shows the survival curves built from estimating (15). The horizontal axis describes the number of days since a county was infected while the vertical axis describes the estimate for the probability of having survived. The dark lines indicate the survival curves for the treatment and control groups while the shading indicates 95-percent confidence intervals. The points on the graph at which the curves exhibit step changes are time periods in which a county failed out of the sample.

The survival curves show that Democratic counties were more likely than Republican counties to have survived at every time point in the sample. This is demonstrated by the fact that, at each time point t, the survival curve for the Democratic group is higher on the graph (i.e., y-axis) than the survival curve for the Republican group. For example, at $t = 250$, the survival curve for the Democratic group is around 0.375 while the survival curve for the Republican group is around 0.3125. At this particular point, the ratio of their survival curves (hazard curves) is $\frac{0.375}{0.3125} \approx 1.2$. This ratio can be inverted (i.e., switching to $\frac{0.3125}{0.375} \approx 0.83$) to get the marginal hazard ratio. If this marginal hazard ratio is calculated across all $t \in 1, 2, ..., T$ and averaged, the resulting quantity if the average marginal hazard ratio $\hat{\delta}$.

Figure 12 graphs the average hazard ratio $\hat{\delta}$ across the various caliper values obtained from the propensity score model. The horizontal axis indicates the caliper value used, with higher values indicating more relaxed matching conditions. The vertical axis describes values of the average hazard ratio. The coefficients for the average hazard ratios are indicated by the small points, whereas the 95-percent confidence intervals around the estimates are indicated by the higher and lower bars. If the confidence interval crosses the 1.0 threshold (i.e., the

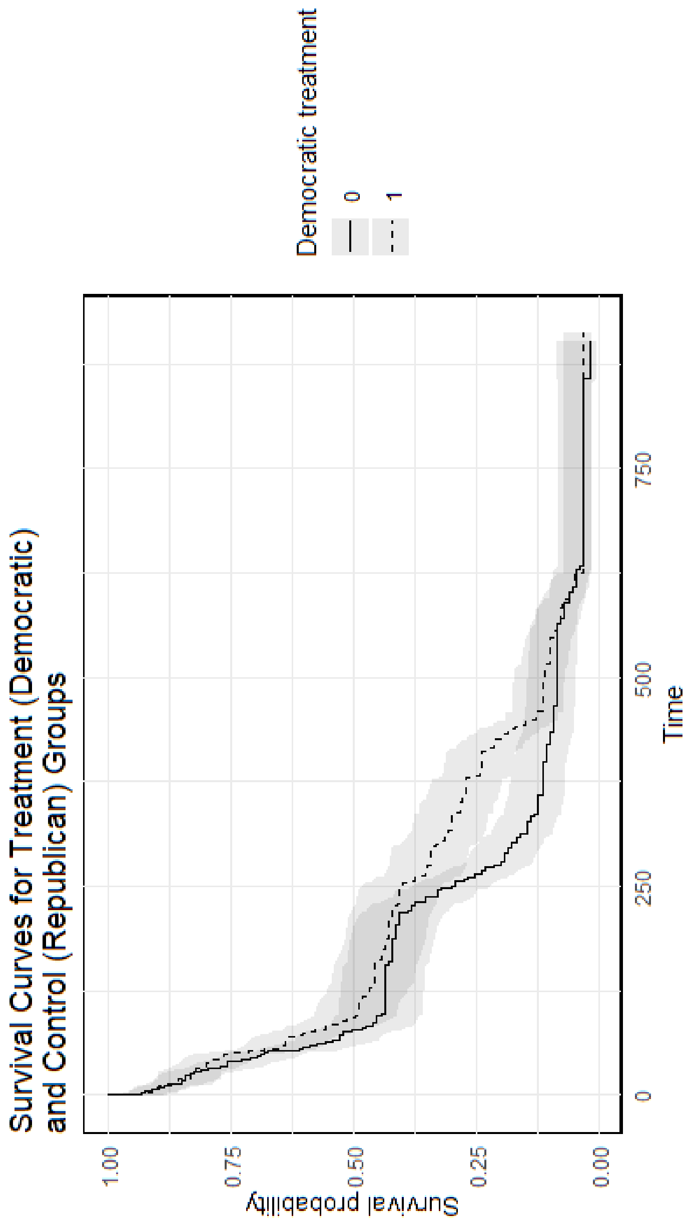

Figure 11: Kaplan-Meier curves for the survival probabilities of Democratic and Republican counties over the sample timeframe.

null hypothesis condition), then given that particular matching model, the effect of the Democratic treatment variable on survival time is not significant.

Figure 12 should be interpreted as failing to reject the null hypothesis that Democratic and Republican counties behaved similarly during the pandemic. In other words, my models find that the average effect of "Democratic status" on how long a county hibernated after being infected by COVID-19 is indistinguishable from zero. This result is consistent across each of the unique samples obtained from the propensity score models.

The results from the Cox-proportional Hazard models defy public wisdom about politics and mobility. Is it possible my choice of empirical model was bad? To test whether the proportionality assumption made by the Cox-PH model is valid, I computed the Schoenfeld residuals and ran a diagnostic test. Figure 13 displays a visual representation of the test. The test is designed to calculate how the marginal hazard ratio, $\hat{\beta}$, changes over time. The Cox-PH model assumes that $\hat{\beta}$ is constant over time, while other hazard models let $\hat{\beta}$ vary over time such that $\hat{\beta}$ depends on t, or $\beta(t)$. As the plot shows, however, the estimate for $\beta(t)$ is largely constant over time. There are very minor deviations from its constant value near the end of the sample period, but the null hypothesis $H_0 : \beta = \beta(t)$ of a constant beta cannot be rejected. The p-value for the test is 0.7163. This implies that the Cox-PH model is a valid model specification given the data.

9 Discussion

In this paper, I set out to test the assumption in the public that Democrats did a better job than Republicans in decreasing their mobility during the COVID-19 pandemic. In such polarized times, testing whether this assumption is true or hyperbole is important. If Republicans really were more mobile than Democrats, and if mobility really was a reliable explanatory variable for explaining morbidity, then public health experts and political scientists should get to work together on understanding what exactly it was that made Republicans behave differently - news sources, ideological beliefs that serve to discredit information from political authorities, or something else strongly correlated or directly caused by political beliefs. But if Republicans behaved no differently than Democrats, then we should question how much the news media and politicians should be trusted to report fairly and honestly about politics and public behavior.

I found strong evidence for my hypotheses that Republican and Democratic counties largely behaved the same during the pandemic. I tested three types of mobility: preempting the disease by quickly reducing mobility after the Trump administration declared a national emergency on March 13, 2020; hibernating for long periods of time after being infected by

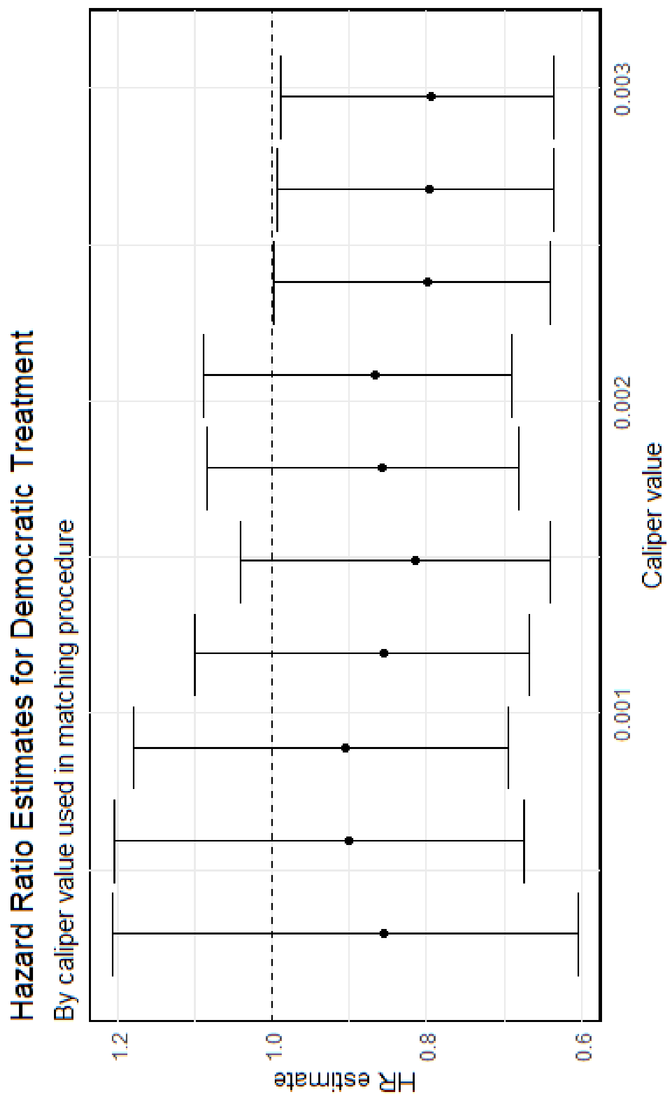

Figure 12: Estimates of the marginal hazard ratio (HRs) from the effect of Democratic county status with 95-percent confidence intervals. The horizontal axis measures the caliper values used in the matching procedure, with higher levels indicating less restrictive matching requirements. All caliper values represent valid and highly balanced treatment and control groups (see paper for details). The vertical axis represents the estimate for the marginal hazard ratio. Estimates with confidence intervals crossing the 1.0 threshold imply that the effect of Democratic status is not significant.

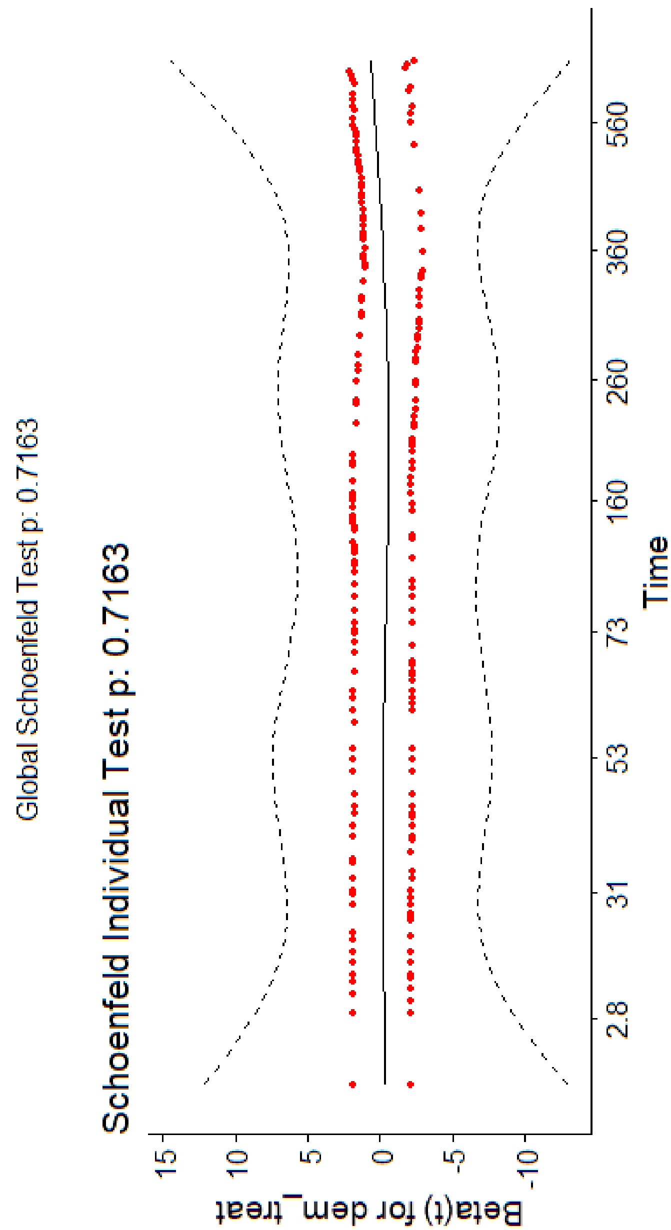

Figure 13: Schofeld residual test for proportionality assumption underlying Cox model. The x-axis is time and the y-axis is estimates of the treatment effect across time.

the first wave of COVID-19; and reacting to the disease by quickly reducing mobility after the number of local COVID-19 cases rose. In only one model did I find that Democratic counties were less mobile than Republican counties - the preemption model, which analyze the early days of the pandemic. Here, Democratic counties were roughly 11 percent more procative in reducing their mobility than Republican counties. However, this early period of the pandemic was when medical information about the virus was scarce and unreliable. I find that, in my models of hibernation and reaction, Republican and Democratic counties were indistinguishable in their behavior. The treatment of "Democratic status" has no effect on how many days a county survived in a state of reduced mobility after being introduced to COVID-19; neither did it have an effect on simulation results for how much a county reduced its mobility after being shocked by a sudden increase in COVID-19 cases. These results suggest a clear conclusion - Democratic and Republican counties only behaved differently during the early days of the pandemic, when medical information about the virus SARS-CoV-2 and its disease COVID-19 was admittedly not reliable.

There is good reason to believe in the results of this study. Unlike other scholars, I made sure to account for county self-selection into being Democratic or Republican. It is no secret that Democratic counties tend to be more densely populated, higher in total population, younger, more educated, and more racially diverse than Republican counties. If any of these variables happen to explain how mobile a person would be during the pandemic, or even how a person selects into a a media outlet for information, then an empirical model which does not account for self-selection would be biased. To combat this potential issue, I used a propensity score model (PSM) before conducting any of my hypothesis tests. I modeled selection into county Democratic status as depending on a variety of social, economic, and demographic characteristics, and I obtained sample adjustment weights to prune my original sample down to an adjusted sample of Democratic and Republican counties with similar characteristics. The statistical balance between the subsamples passed conventional tests, like standardized mean difference and variance ratios. I only used this adjusted sample when conducting my empirical tests.

The results of my study are somewhat consistent with those of other scholars. BISBEE and HONIG (2022) finds that exposure to COVID-19 cases made local populations more supportive of moderate political candidates, rather than right or left extremists. I take this to be an indication of how anxiety, measured as exposure to a deadly virus, pushes counties to behave similarly. My results are similar in that I found Republican and Democratic counties to behave the same way after being exposed to COVID-19. Before exposure, or at least during the preemptive phase, they behaved differently.

Most other studies, however, reach different conclusions. They find that politics is a statistically significant variable in explaining how people responded to political elements of the pandemic. For example, Grossman et al. (2020) finds that a person's partisanship influenced how they responded to their governor's recommendation to stay at home. Similarly, Ye (2023) finds that Republican counties had much lower vaccination rates than Democratic counties, and the gap between them increased over time. Both these studies seem to contradict the broader picture of my conclusion.

I argue that these results are actually consistent with each other. Per TERNULLO (2022), a key factor in explaining pandemic behavior was media, trust, and information. When people hear proclamations by politicians and government institutions to behave a certain way, that behavior gets politicized and covered extensively by the media. Reliable information is suddenly scarce, and people are forced to resort to mental heuristics to choose how to behave. Given this environment, the following propositions seem reasonable: (1) in the early days of the pandemic, when little information was reliable, people behaved in ways consistent with their trust in scientific and government institutions; (2) when some behavior $x \in X$ in the pandemic is endorsed by a politician, a person only follows x if their political views are in line with the politician; and (3) when push comes to show, and when the cost of adaptation is minimal, exposure to COVID-19 will cause people to adapt in similar ways independent of their political beliefs - but when the cost of adaptation is large or requires actions that core beliefs (e.g., getting a vaccine), then even exposure to COVID-19 will not cause adaptation. Although these propositions (1)-(3) are nuanced, they are logical and consistently represented in research results.

10 References

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