Political Affiliations, Investment in Public Health, and Effects on COVID-19

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Abstract

The COVID-19 Pandemic has had a devastating impact in the world economically, socially, and structurally. Scholars are engaging with different research threads on the economic and health effects of the virus. One of these is establishing a relationship between political polarization and behavioral responses to COVID-19. For example, Bazzi et al. (2021) show that high Total Frontier Experience (TFE) counties do not practice social distancing and are increasingly aligned with Republican ideology. Goolsbee and Syverson (2020) find that citizens' perception of risk related to the virus is significantly colored by their political lens. In this paper, I explore a different relationship between political affiliation and response to COVID-19. I examine how the pre-pandemic health expenditure at the county level affected COVID-19 health outcomes, namely the case fatality rate (CFR). I predict that given Republicans' resistance to investment in public goods, counties that vote Republican, invest less in public health. This situation may result in more deaths compared to counties that had more investment in public health. I control for population density, social distancing, ethnic, gender and age demographics, median household income, and TFE, as these variables could explain some of the correlation between political affiliation and fatalities. I find that, health expenditure is not a channel through which Republican voting affects CFR.

JEL classification: I18, H72, H75, D71

Keywords: COVID-19, Health Expenditure, Political Affiliation

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1 Introduction

The COVID-19 virus started spreading like wildfire around the world in late 2019 and has continued its relentless destructive pace and intensity into 2021. The state of the pandemic today can be attributed to many compounding factors that culminated during the early days and that resulted in its widespread and costly impact on human health and lives. These factors include lack of transparency on the part of the Chinese government during the initial outbreak; gross mismanagement of the virus by the American government throughout 2020; as well as a lack of infrastructure and general preparedness to deal with this kind of fast-spreading and deadly virus on the part of most world governments. Although each of these factors proved to be substantial obstacles in preventing the spread of COVID, only the one posed by lack of adequate infrastructure can be considered inevitable. Even though the US is the world's strongest economy and has sophisticated health infrastructure, it was still unable to effectively respond to the pandemic level health crisis brought about by COVID-19. The US's failure to traverse the rough terrain of this unprecedented crisis was only exacerbated by the political polarization of recent years.

This thesis aims to explore the effect of county level political affiliations and COVID-19 mortality working through the mechanism of pre-pandemic healthcare expenditure. Specifically, my research question is, does county level political preference, indicated by citizens' voting behavior in previous presidential elections, mainly the 2016 presidential election, causally affect deaths caused by COVID-19 by influencing local healthcare expenditure decisions before the start of the pandemic?

During the last few years leading up to the COVID-19 pandemic, the US enjoyed a robust economy and was ranked by the Global Health Security Index as number one most prepared for a pandemic in the world. Despite these clear advantages the US has fared among the worst in terms of COVID-19 human health outcomes. It surpasses most other countries in number of total cases per 1 million people as well as number of total deaths per 1 million people according to John's Hopkins University COVID tracker. While much of the blame can be justifiably placed on the Trump administration and its inability and unwillingness to face the problem head-on, the current state of the pandemic along with its course throughout the past year calls into serious question the functional capability of the American healthcare system. In a country where partisan politics has become increasingly divisive over the last many decades, it is important to understand the efficacy of the government's decisions and policies regarding healthcare. It is widely acknowledged that Republican lawmakers generally advocate for more private health coverage, i.e. less investment in more accessible public healthcare infrastructure, while Democratic lawmakers tend to advocate for higher levels of government spending toward accessible health care for all. This distinction is important because aside from the lack of adequate testing at the beginning as well as the lack of leadership from the Trump administration, one of the primary reasons for the exponential increase in COVID related deaths was the lack of capacity and resources in hospitals across the country especially in areas with high population density (Desmet and Wacziarg 2020). Therefore, if Republicans' tendency to invest less in healthcare hindered medical facilities in counties with higher concentrations of Republican voters from being able to handle the high volume of COVID patients, then healthcare expenditure could theoretically be a channel through which political affiliation affects COVID mortality. Since no one could have predicted how 2020 would unfold, local government healthcare expenditure in 2018 serves as a good exogenous measure of healthcare capacity during the pandemic.

The disbandment of the Obama-era Pandemic Response Team by the Trump administration in 2018 set the stage for the overall shortcoming in response and lack of statesmanship at the national, regional, and local leadership level. These drawbacks were most clearly visible in some of the most densely populated states of the nation – New York, New Jersey, and California. At the start of the pandemic, these three states were essentially blindsided by the effect of the virus as a result of the culmination of three factors: population density resulting in increased mobility, lack of transparency from the government, and the fast spreading yet deadly nature of the virus. The sheer number of patients in need of critical care regularly overwhelmed hospitals. Not only was there a dearth of hospital beds, there was woefully short supply of personal protective gear for frontline healthcare workers and lack of adequate equipment to treat patients. Moreover, since healthcare workers lacked access to necessary protective gear, it ultimately resulted in a higher infection and death rate for this group than the general population. These issues were all compounded by the fact that differing and confusing messages came from the Whitehouse and CDC leading to widespread mistrust of information relating to COVID-19 (Barrios and Hochberg 2020). This, in turn, resulted in a rapid increase in the number of hospitalizations since people were disinclined to follow preventative guidelines.

In the past year, several studies have demonstrated the importance of these guidelines in curbing the spread of the COVID-19 virus and consequently preventing more deaths. Greenstone and Nigam (2020) found that moderate forms of social distancing could significantly reduce fatalities and produce economic benefits. Eikenberry et al. (2020) show that even low-quality mask use is effective in significantly reducing asymptomatic transmission of the virus as well as preventing illness in healthy people. Mask use, or lack thereof, especially amongst more elderly and overweight people is found to be a significant predictor for COVID-19 related deaths (Miyazawa and Kaneko 2020). Furthermore, not only were social distancing and mask use essential to preventing the spread of the virus and reducing fatalities, but their implementation have also been found to be causally related to citizens' political ideology. Controlling for factors such as population density, public policies, and local COVID cases and deaths, Republicans engaged in less social distancing (Allcott et al. 2020) due to the fact that their perception of the risk related to virus transmission was significantly influenced by rhetoric promoted by Republican leaders throughout the pandemic (Barrios and Hochberg 2020). People in areas with high civic capital in both the US and Europe were found to be more conscientious with regard to following social distancing guidelines and wearing masks to protect their communities (Barrios et al. 2020). Finally, Bazzi, Fiszbein, and Gebresilasse (2021) suggest that rugged individualism, their measure of American frontier culture (measured in TFE: Total Frontier Experience) that encompasses the characteristics of extreme individualism and anti-statism, significantly hampered responsible individual response to COVID-19. They also discuss the fact that, especially in the two most recent decades, the characteristics of high-TFE counties have been increasingly embraced by Republican ideology.

In this thesis, I investigate whether the two relationships discussed above, between political ideology and investment in healthcare infrastructure and political ideology and COVID-19 health outcomes, can be combined to form a causal link. In particular, I argue that pre-pandemic health expenditure could be one of the channels through which Republican Voting Share (RVS), the percent of votes for a Republican candidate in a given county, affects the Case Fatality Rate (CFR) which measures the percent of confirmed cases that ended in fatalities. In the end, however I find that this conclusion is not supported by the available data. RVS in 2016 alone appears to be unrelated to CFR after including the relevant controls. It is important to note that, when I control for 2012 RVS, I find that 2016 RVS has a positive, significant effect on CFR, meaning counties with higher share of Trump voters experienced a higher CFR than others. I call this the Trump effect and discuss the probable reason behind this result. I also explore in greater detail each of the relationships between RVS, health expenditure, and CFR respectively. Finally, I suggest some reasons why health expenditure turns out not to be a channel through which RVS affects CFR.

The rest of the paper is organized as follows. Section 2 reviews the existing literature relevant to my research questions. Section 3 introduces the different data sources used and discusses some adjustments that were made to accommodate my regression analysis. Section 4 explains the methodology employed to determine causality. Section 5 examines the results and discusses robustness checks. Section 6 concludes.

2 Literature Review

Preliminary economics related research regarding the effects of policies and politics on COVID-19 outcomes focus mostly on three general categories: effects of the virus itself on the economy, effects of government efforts to mitigate shocks caused by the virus, and behavioral effects of the virus. Studies investigating effects of the virus look at effects on employment (Alon et al. 2020; Aum, Lee, and Shin 2020; Blustein, et al. 2020), the economy (Arthi and Parman 2020; Atkeson 2020; Auerbach, Gorodnichenko, and Murphy 2020), welfare and equality (Fairlie 2020; Fuchs-Schündeln et al. 2020; McLaren 2020) as well as on other forms of healthcare utilization (Ahn, Kim, and Koh 2020; Ziedan, Simon, and Wing 2020). Studies examining the impact of government mitigation policies look at the effects of government mandates to reduce the spread of the virus (Baccini and Brodeur 2020; Coibion, Gorodnichenko, and Weber 2020; Goolsbee et al. 2020; Wright et al. 2020) and of government efforts to minimize negative shocks to the economy (Elenev, Landvoigt, and Nieuwerburgh, 2020). Studies from a smaller vein of the literature observe the impact of partisan politics and government policies on citizens' behavioral response to the pandemic (Barrios et al. 2020; Barrios and Hochberg 2020; Bazzi, Fiszbein, and Gebresilasse 2021; Dave et al. 2020; Eikenberry et al. 2020; Greenstone and Nigam 2020; Karaivanov et al. 2020; Miyazawa and Kaneko 2020; Oguzhan and Gillanders 2020), but none have thus far expanded this investigation of partisan politics to its effect on COVID health outcomes. I aim to fill this gap in the literature through the exploration of my research question.

I will first discuss several papers that examine what factors have an effect on COVID-19 mortality. Greenstone and Nigam (2020) use a COVID-19 simulation model to estimate the effects of various levels of social distancing. They verify the result that has been promoted by the CDC since the beginning of the pandemic – that social distancing does save lives by reducing the pressure on hospital capacity. Similarly, Eikenberry et al. (2020) demonstrate the importance of wearing masks in reducing asymptomatic COVID-19 transmission. Miyazawa and Kaneko (2020) go further and find that, just like social distancing, wearing masks reduces the potential death rate by flattening the curve. These results provide some initial support to motivate my research question. Social distancing seems to be reducing COVID mortality through its effect on healthcare capacity. It then follows that pre-pandemic health expenditure, which determines the healthcare capacity of any given location, could be a channel through which COVID mortality is affected. Desmet and Wacziarg (2020) explore some other alternative factors that are related to higher COVID mortality. Population density is discovered to be highly significantly and positively correlated with COVID mortality. Areas where there are greater populations of Black and Hispanic[1] people are also found to have higher death rates (Benitez et al. 2020; McLaren 2020), although Benitez et al. (2020) suggests that this is due to a higher rate of incidence among these populations rather than a higher case fatality rate. Counties with a higher share of Trump voters have also fared worse in terms of COVID mortality after controlling for demographic factors (Desmet and Wacziarg, 2020). I confirm this result in Section 5.

My research question is based on the assumption that partisan politics affects individual behavior in a meaningful way that can then have an effect on various economic and, in this case, health outcomes. Gerber and Huber (2009) explore this very relationship. They find that individuals believe the economy will fare better when their party holds the presidency and adjust their economic behavior accordingly. By similar logic, this argument can be extended to include behavioral response to COVID-19. Barrios and Hochberg (2020) and Goolsbee and Syverson (2020)'s research provide support for this extension. Barrios and Hochberg (2020) study the role of risk perception colored by political lens in modulating individuals' COVID response. They argue that, due to the increased polarization of American politics in recent years, political preferences have significantly affected people's perceived risk of the COVID-19 virus. The authors track social distancing and measure the volume of internet searches regarding economic and health risks associated with COVID-19. This serves as a proxy for individuals' perceived risk about the issue. Counties with high Trump Voting Share (TVS) tend to be less concerned with the health risks of the virus, more

[1] Although Benitez et al. (2020) finds that Hispanic populations face higher COVID deaths, McLaren (2020) finds that Hispanic population do not face a significantly different death rate. The information released by the CDC supports Benitez et al. (2020)'s conclusion. I also control for both Black population share as well as Hispanic population share regardless.

concerned with economic outcomes, and less likely to practice social distancing and wear masks (Barrios and Hochberg 2020). Similarly, Goolsbee and Syverson (2020) show that fear, rather than government mandated policy was a key determinant of social distancing. They combine cell phone location data at the business level with comprehensive state and county level data regarding legal restrictions on businesses. They use shelter-in-place (SIP) orders as their main treatment variable and track daily visits to local businesses to measure social distancing. Goolsbee and Syverson (2020) use week and county fixed effects among other relevant controls and find that the effect of SIP orders is insignificant. They conclude that fear, rather than movement-restricting policies, was the main driver of social distancing practices. Gerber and Huber (2009)'s work suggests that fear likely affected people's behavior differently depending on their partisan views. Taking into account the general rhetoric of the two political parties throughout the pandemic, Democrats were likely more afraid of health outcomes thus practicing more social distancing while Republicans were likely more afraid of economic outcomes, thus refusing to practice social distancing. This explanation is also supported by Barrios and Hochberg (2020). Clearly, personal beliefs, risk perception, and political affiliations were more central determinants of individual behavior in response to COVID-19 than government policies.

Bazzi, Fiszbein, and Gebresilasse (2021) employ an event-study specification in order to draw a causal link between Total Frontier Experience (TFE) and individuals' COVID-19 response. They define TFE as the total amount of time a county has spent within 100 miles of the frontier between the years 1790 and 1890[2] (Bazzi, Fiszbein, and Gebresilasse 2020). They hypothesize that the frontier experience of a community results in the development of

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[2] These are considered to be the start and end years of the "Frontier Era" as defined by Bazzi, Fiszbein, and Gebresilasse (2020).

individualistic norms, that are in direct conflict with the type of collective action necessary to prevent the proliferation of a pandemic. The authors demonstrate that this American tradition of rugged individualism, what they define as a combination of extreme individualism and opposition to government intervention, greatly obstructed the function of collective action during the pandemic (Bazzi, Fiszbein, and Gebresilasse 2021). The authors estimate the level of social distancing in a county using TFE as their main regressor. They also use data from Unacast and the Google Mobility Report. These sources of data both document movement through cellphone location tracking, with the former capturing the number of non-essential visits outside the home and the latter measuring the percent change in visits since the beginning of the pandemic to six types of locations such as workplaces, grocery stores, etc. In general, Bazzi, Fiszbein, and Gebresilasse (2021) find that high-TFE counties tend to practice less social distancing than low-TFE counties. Their results are robust to the inclusion of potential confounders such as population density, temperature, income, and demographic factors. Through this analysis, Bazzi, Fiszbein and Gebresilasse (2021) establish an important relationship between cultural traditions and individual COVID response that is closely linked to the causal mechanisms used by Barrios et al. (2020) and Barrios and Hochberg (2020) in their respective analyses.

Several papers explore the correlation between trust and COVID-19 responses. Dincer and Gillanders (2020) use a Corruption Convictions Index (CCI) at the state level to measure corruption in a given state and find that corruption is negatively and significantly correlated with SIPs. They argue that citizens living in states where corruption proliferates do not trust the government or each other, leading to a lower incentive to practice social distancing. Bargain and Aminjonov (2020) also measure trust, using results from the

European Social Survey (ESS) to show that regions that demonstrate higher levels of trust in Europe also have much greater participation in social distancing. Barrios et al. (2020) similarly draw a causal link between civic capital and individuals' COVID response in the US. The authors hypothesize that civic capital, or the willingness of individuals to consider the welfare of collective society when taking their own actions, has a direct impact on social distancing behaviors. They create a trust index by conducting phone interviews and measure electoral participation as an indicator for civic capital. Voting does not necessarily provide direct gains to every voter but requires a consideration of the society as well and thus can be considered a proxy for civic capital. The authors find that counties with higher levels of civic capital tend to practice social distancing and mask wearing more than counties with lower levels of civic capital, echoing the findings from Bargain and Aminjonov (2020). This result reflects essentially the inverse of the relationship with social distancing that is captured by Bazzi, Fiszbein, and Gebresilasse (2021)'s measure of TFE, i.e., counties with high civic capital have low TFE and vice versa. Barrios et al. (2020) expand their analysis to Europe to explore whether or not their results are externally valid outside the US. They find that even in Europe, areas with higher levels of electoral participation tend to practice greater levels of social distancing than those with lower electoral participation, again confirming the results from Bargain and Aminjonov (2020).

Combining these various measures of trust and inclination toward collective action we have that counties with high TFE, high TVS, and low civic capital tend to practice less social distancing than their low TFE, low TVS and high civic capital counterparts. Each of these variables is related in some way to Republican voting. Since social distancing and mask-wearing have both been shown to be determinants of infection and death rates related to COVID, this sets the stage for me to investigate the relationship between Republican voting and COVID-19 mortality.

The papers discussed previously reach insightful conclusions about social distancing measures during the pandemic, however they are still only telling half of the story. While social distancing was indeed crucial to flattening the curve, it is important to investigate the very need to flatten the curve. Flattening the curve through significantly decreasing social interactions, especially crowded ones, and wearing masks has been acknowledged by disease and medical experts in the US and around the world as the single most important preventative non-pharmaceutical measure that could be effective against the COVID-19 virus. It was especially critical due to the fact that existing health care infrastructure lacked the capacity to manage and treat the exponentially increasing influx of patients infected with COVID-19. Reducing the speed at which the virus permeated through the society would help alleviate the pressure on hospitals and medical centers to treat more patients than they could handle. Therefore, just as it is important to understand the political and social factors that contributed to social distancing behaviors, it is equally important to consider the effect of varying health care infrastructure on health outcomes during the pandemic.

Khan et al. (2020) conduct a global study of health care capacity and its effect on CFR, or the percent of confirmed cases that ended in fatalities. They account for the following variables in their regression analysis: health expenditure as a percentage of GDP, population density, the share of population over 65, and variables that capture the health vulnerability of the country before the pandemic among other factors that could affect a country's CFR. Due to the large scale of their project, they use data from a wide variety of sources, only sampling those countries with more than 1000 confirmed COVID cases. The authors index these countries into three categories based on their healthcare capacity as a percentage of GDP: low, medium, and high. They find that healthcare capacity is negatively correlated with CFR with a 1% increase in capacity relating to a 42% decrease in CFR. While this finding certainly contributes to a holistic understanding of the relationship between health infrastructure and COVID, the paper does not delve into a discussion of a *causal* relationship. Most of the literature surrounding this topic is similarly approached from a public health perspective rather than an economic perspective, and therefore lacks the important discussion of the causal mechanism that is integral to economics research. Moreover, economics papers have yet to explore the relationship between politics and CFR at the county level in the US. This results in a unique opportunity for further research relating to this specific issue.

3 Data

All of my analysis is conducted using observational open-source data at the county level. I have used voting data for the past three presidential elections, before 2020, from the MIT Election Data and Science Lab; COVID-19 data from Johns Hopkins University (JHU) gathered by the Center for Systems Science and Engineering (CSSE) throughout the duration of the pandemic; pre-pandemic health expenditure data from 2018 as well as demographic data from 2019 accessed from the US Census Bureau; frontier data from Bazzi, Fiszbein, and Gebresilasse (2020); and mobility data from the Google Mobility Report that uses cell-phone location data to track people's movement after the start of the pandemic. This is used as a measure of people's adherence to social distancing guidelines by comparing the frequency of visits to different types of locations on certain days of the week with a baseline frequency of the same day of the week established in pre-pandemic January of 2020.

Google tracks cell phone location data in order to assemble this dataset. Thus, it does not include all US counties depending on privacy preferences in different regions. Since the social distancing variable is used in several of my regressions as a control variable, to avoid running regressions with differing number of observations I restrict the sample size of all of my regressions to the observations for which the Google Mobility data is available. Table 1 shows the average RVS across counties for which the social distancing data is available versus those for which the data is not. On average, counties that do not have social distancing data report an RVS that is 11 percentage points higher than counties that do have social distancing data. Keeping in mind that numerous papers have shown that Republicans practice less social distancing (Barrios and Hochberg 2020; Bazzi, Fiszbein, and Gebresilasse 2021; Goolsbee and Syverson 2020), this means that including these counties in my analysis would reveal an even more negative relationship between RVS and social distancing than I find. I address this more in-depth in Section 5.

Table 1: Summary of 2016 RVS - Social Distancing Data

	Mean (%)	Std. Dev.	Freq.
Social Distancing Data Reported	61.433	15.318	2,570
No Social Distancing Data Reported	72.039	14.220	540
Total	63.274	15.655	3,110

Note: Republican voting share in counties that do not report social distancing data 11 percentage points higher on average, meaning they are disproportionately Republican.

Due to the fact that voting districts in Alaska are not the same as its counties as identified by FIPS codes, it was not possible to match Alaskan counties across datasets. As a result, for the purpose of this paper, Alaska is not included in my analysis. I do not expect that excluding Alaska will affect my results as the reason for the mismatched counties and voting difference is unlikely to be correlated with CFR in any way. I also exclude Hawaii from my regression analysis to maintain the same sample size because it is not included in the frontier data which is used in several of my regressions. The finance data is also missing numerous observations that are likely due to non-response. The 44 counties in Virginia, 28 counties in Tennessee, and 22 counties in North Carolina that are not represented in the data could possibly cause a bias. Each of these three states, that are missing nearly half of their total possible observations, are heavily Republican and conservative. Therefore, if there is some underlying factor that is related to why there is no data as well as CFR, then my results could be affected. The data in my final collated dataset is structured so that each observation reports the following variables of interest as well as numerous control variables at the county level: Republican Voting Share (RVS) from 2016 measured as a percent, the mean daily Case Fatality Rate (CFR) through the course of the pandemic, also measured as a percent, and Health Expenditure per Capita (HEPC) in 2018, measured in thousands of dollars.

4 Methodology

In this section, I discuss the methods I employ in order to establish a causal link between Republican voting and COVID-19 mortality through pre-pandemic healthcare expenditure. Due to the fact that many factors affect people's voting behavior and randomization is not possible, the results of a simple bivariate regression do not provide sufficient evidence to support conclusions about the causal effect of RVS on CFR. As such, I have constructed a four-tiered regression model designed to account for the confounding factors that are likely to bias the results.

The purpose of the four-tiered regression model is to establish causality between each of the links in my hypothesis, namely RVS, CFR, and health expenditure per capita (HEPC).

In each of these regressions I include state level fixed effects and control for a combination of the following county level factors depending on their applicability to the regression: population density, median household income (MHI) as a percent of state mean, Black population share, Hispanic population share, elderly population share (above the age of 65), female share, total frontier experience (TFE), and the percent change in visits to retail and recreation locations as compared with the baseline established in January of 2020 (hereafter referred to as Retail), which serves as a measure of social distancing.

Table 2: Descriptive Statistics at the County Level

Variable	Obs.	Mean	Std. Dev.	Min	Max
CFR	2560	1.99	1.378	0	12.031
Deaths per 100,000	2560	46.401	42.209	0	707.104
2016 RVS	2560	61.464	15.283	8.405	90.503
2012 RVS	2560	58.089	14.167	7.193	93.29
HEPC	2560	.774	1.88	0	25.384
% Women	2560	50.112	1.961	34.982	57.008
% Black	2560	10.964	14.488	.489	87.227
% Hispanic	2560	10.018	13.995	.648	96.353
% Above 65	2560	26.131	5.466	7.087	66.627
Population Density	2560	.327	1.961	.001	71.341
2019 Population	2560	125,952.83	365,192.06	2171	10,039,107
TFE	2560	1.447	1.284	0	6.3
MHI as % of State Mean	2560	91.173	20.605	44.275	263.573
MHI	2560	53,752.044	14,281.828	25,385	140,382
% Change in Visits to Retail	2560	-10.509	12.472	-66	57.213

Note: CFR and Deaths per 100,000 are the daily average for the duration of the pandemic. TFE is measured in decades. Population Density is measured in 1000 people per square mile. MHI stands for Median Household Income. HEPC is measured in 1000s of $.

Table 2 displays some summary statistics regarding these variables. CFR and Deaths per 100,000 are interpreted as the daily average throughout the pandemic. For example, approximately 47 people per 100,000 people died per day between March of 2020 and January of 2021. Similarly, percent change in Retail is also averaged over the course of the pandemic. There has been a 10.5% decrease in visits to retail and recreation locations between March of 2020 and February of 2021. One particularly interesting observation is that the average RVS in the US is 61%, demonstrating that the US leans distinctly toward the conservative side of the political spectrum[3]. Finally, the average county in the US spends $774 on healthcare per person.

Population density is arguably the most important control variable since it potentially affects each of the three variables of interest individually as well as in concert with each other: CFR, RVS, and HEPC. Due to the fast-spreading nature of the COVID-19 virus, more densely populated areas were impacted far more heavily than their less densely populated counterparts, especially towards the beginning of the pandemic when there was little relevant information in circulation. The systems of public transportation that under normal circumstances enhance mobility in metropolitan areas, contributed greatly to helping the virus spread pervasively. It is a well-known fact that areas that are more densely populated are generally more liberally skewed political sphere[4]. In the US, this means larger cities tend to have larger concentrations of Democrats than Republicans. I discuss this further in Section 5. Medical resources are also more readily available and easily accessible in metropolitan

[3] Mean RVS is 61% when the sample is restricted as I have described above, but 63% when considering data from all the counties in the US.

[4] I revisit this in Section 5, but it's worth mentioning here that this statement is supported by my data as well. The counties with population density within the 66-100th percentile average less than 55% RVS.

areas that tend to be more focused on public service and public welfare due to the large clusters of population that they serve.

Median Household Income (MHI) demonstrates the average income of citizens in a county. I choose to use MHI as a percent of state mean in my specifications instead because it represents the average income in a county relative to the rest of the counties in the same state. This is an important distinction. Consider two people in two counties with the same average income such that one county is located in California while the other is located in Mississippi. The person in the Mississippi county will have a higher buying power as compared with the person from the California county because the standard of living is significantly higher in California. The Mississippi person will then theoretically will have greater access to medical resources, from a monetary perspective, relative to the California person. Using MHI as a percent of state mean allows me to account for this phenomenon in my regression analysis. With regard to COVID-19, a county's wealth level has two implications. First, people who are less wealthy are also generally unable to afford equally comprehensive healthcare which could result in a higher prevalence of pre-existing conditions. Second, with lower income on average, less wealthy neighborhoods have limited access to resources. COVID is more deadly for those who suffer from underlying conditions. Resources such as access to testing and ventilators were essential to slowing the spread of the virus and preventing unnecessary deaths. Since both of these factors are influenced by the relative wealth of a county as compared with others in the state, wealth could be a potential confounder for CFR.

The percent of county population that is made up of Black and Hispanic individuals can also potentially affect both CFR and RVS, albeit in slightly different ways. Both of these demographic groups have lower income on average as compared to their white counterparts. As such, the concerns discussed previously regarding relative wealth also apply to these demographic groups. In fact, these factors played a rather large role in determining the extent of the impact of the virus on specific populations. Their combined effect suggest that the Black and Hispanic populations of the US faced a higher COVID death rate, which is confirmed by data released from the CDC and by Benitez et al. (2020). When it comes to voting patterns, however, Black and Hispanic voters may not behave the same way. It is a well-known fact that Black voters have historically voted democratic and have also been subject to discriminatory voter suppression tactics. Hispanic voters' behavior is more difficult to generalize. Aside from personal preference and individual upbringing, Hispanic political preference seems to be influenced by their urban versus rural location in the states as well as their Hispanic culture of origin in most cases. Clearly, a person's racial identity in the US is correlated with numerous other factors that could possibly affect COVID mortality as well as voting patterns.

One of the most shocking and devastating aspects of the COVID-19 virus was its disproportionately severe effect on elderly people. Elderly populations have weaker immune systems, more prevalent chronic conditions, and are many times clustered together in senior care facilities. These conditions made the older demographic far more susceptible to the effects of COVID than any other demographic population. By far the highest volume of deaths by age category have occurred in the 65+ age category according to the CDC. Meanwhile, older populations are also associated with much more conservative ideology and thus tend to vote Republican by a large margin. Women have longer lifespans as compared with men. This means that women constitute a higher percent of the 65+ age group than men.

Women also tend to vote democratic, albeit by a small margin. These factors make it necessary to include the percent of women and the percent of people older than 65 in a given county as control variables.

Including Total Frontier Experience (TFE) and percent change Retail as controls allows me to capture two sides of the same coin – individuals' behavioral response to COVID-19. In their paper, Bazzi et al. (2020) demonstrate the causal effect of frontier experience on individualism and opposition to government intervention, naming the combination of these characteristics "rugged individualism". Specifically, they show that counties that have high TFE also express higher levels of "rugged individualism". Subsequently in another paper, they find that the tendency toward "rugged individualism" served as an obstacle to collective action within these communities which consequently resulted in less social distancing and higher incidence of COVID-19 cases (Bazzi, Fiszbein, and Gebresilasse 2021). I use percent change in visits to Retail collated by the Google Mobility Report as an indicator for social distancing. Participation in social distancing was a key factor in flattening the curve and preventing the rapid spread of the virus (Greenstone and Nigam 2020). As a result of the rhetoric publicized by the Republican-controlled White House during the majority of the pandemic, Republicans were less likely to practice social distancing (Barrios and Hochberg 2020). By including TFE and percent change in Retail, I hope to account for some of these less easily observable factors that could otherwise bias my results. The regression equations are modeled as follows:

(1) $CFR_c = \propto + \beta_1 RVS_c + \delta StateFE + \varphi Controls_c + \epsilon$

(2) $CFR_c = \propto + \beta_1 RVS_c + \beta_2 HEPC_c + \delta StateFE + \varphi Controls_c + \epsilon$

(3) $HEPC_c = \propto + \beta_1 RVS_c + \delta StateFE + \varphi Controls_c + \epsilon$

(4) $CFR_c = \propto + \beta_1 HEPC_c + \delta StateFE + \varphi Controls_c + \epsilon$

Equation (1) addresses the question of whether or not local political affiliation has any effect on COVID mortality. In this equation, I include each of the previously discussed control variables. It is not realistically possible to consistently measure RVS in local elections across the country in a way that would allow it to be a true representation of local political affiliations that directly affect local policies. For this reason, I use RVS with regard to voting in presidential elections as an indicator for local political affiliation. Someone voting Republican in a presidential election is also likely to vote Republican in local elections; thus, presidential voting behavior serves as an adequate proxy for local political affiliation. Moreover, local political affiliation is also an indicator for collective preferences at the county level. I include state fixed effects in order to account for unobservable differences between states that could bias the results one way or another.

There is likely a distinct difference in personal beliefs held by voters who voted Republican in 2016 because they were lifelong Republican voters and those who voted for the first time as Republican because they wished to jump on the Trump train. Such a difference in beliefs could potentially obscure the true relationship between RVS in 2016 and COVID-19 mortality. Observing the results from the three presidential elections between 2008 and 2016, it is immediately evident that there has been an increase in RVS during that time. One way to address the issue of separating the effect of lifelong Republican voters versus those who were drawn to Trump's brand of Republicanism is to calculate the percent increase in RVS in a given county between the years of 2008 and 2016 and regress CFR on this value instead. These years saw an increase in conservative voting due in part to the election of the first black president as well as the popularization of Trump and his rhetoric. Alternatively, I include 2012 RVS in my regression along with 2016 RVS. This enables me to isolate the Trump effect. I effectively separate the new Trump voters in 2016 from the lifelong Republican voters who voted in 2012. Given that Trump's rhetoric shaped many people's behavior during the pandemic and consequently health outcomes, this seems like an important distinction to make.

Equation (2) explores whether or not any part of the relationship between COVID mortality and RVS can be attributed to Health Expenditure per Capita (HEPC). I use HEPC since my hypothesis states that counties with higher RVS will spend less on healthcare per person because they spend less on public goods in general, not because they spend less on healthcare than other types of public goods. Here, I include the same controls as in Equation (1) since the dependent variable and the independent variable of interest are the same. Equation (3) explores the effect of RVS on HEPC in order to determine the nature of the direct relationship between these two variables. Similar to Equation (1), 2016 RVS in the presidential election here is a proxy for local policy preferences. I include the same controls as Equation (1) minus the social distancing indicator since both RVS and HEPC are static and pre-pandemic variables. Equation (4) determines whether or not and to what degree pre-pandemic healthcare expenditure actually affected COVID mortality. I include the same controls and fixed effects in Equation (4) as I do in the first two regressions.

5 Results

This section details the results of the four-tiered regression analysis. After executing different permutations and combinations of the four regressions, I find that higher RVS in 2016 does not have a significant effect on CFR until I include RVS 12 as a control. This implies that Republican ideology in general is not associated with a higher COVID mortality, but specifically Trumpian ideology could be the key factor. Health expenditure does not appear to be a channel through which RVS in either year affects CFR.

5.1 Main Regression

I start my analysis by observing the base level relationship between CFR and RVS in 2016. Table 3 shows that initially, counties with higher 2016 RVS experienced a lower CFR, meaning fewer people died in areas with more Republicans. Specifically, a one percentage point increase in 2016 RVS results in a 0.014 percentage point decrease in the CFR. This result contradicts the findings confirmed by Bazzi, Fiszbein, and Gebresilasse (2021) and Allcott et al. (2020) that Republicans are less likely to participate in collective action and practiced social distancing less than non-Republicans (Barrios and Hochberg 2020). We can see in Columns (2) and (3) that the coefficient on 2016 RVS remains significant and negative even after accounting for state fixed effects and HEPC but decreases in magnitude. The coefficient on HEPC is both statistically and economically insignificant but positive, meaning a $1,000 increase in HEPC results in a 0.008 increase in CFR, all else equal.

Columns (4), (5), and (6) show that the results in the first three columns can be attributed to omitted variable bias. Including the controls mentioned in the previous section results in a change in the sign of the coefficient on 2016 RVS as well as its significance. The control coefficients are interpreted as follows. A 1,000 person increase in population per square mile is expected to increase CFR by 0.1 percentage points; a one percentage point increase in female share, Black share, Hispanic share, and share of population above the age of 65, results in a 0.077, 0.02, 0.007, and 0.047 percentage point increase in CFR respectively; a one percentage point increase in the median household income as a percent of the state mean is expected to decrease the CFR by 0.003 percentage points; a 10-year increase in frontier exposure results in a 0.001 percentage point increase in the CFR, all else equal; and finally, a one percentage point increase in the percent change in visits to retail locations since January of 2020 is expected to produce a 0.003 percentage point decrease in the CFR, all else equal, but it is not significant.

This result, although not the focus of my thesis, also directly contradicts findings confirmed by Greenstone and Nigam (2020). This could be due to reverse causality between social distancing and the CFR. Even though social distancing probably does reduce the CFR, it is likely also the case that counties facing high CFRs begin to practice more social distancing due to fear as well as government mandates. The duration of the illness is about 10 days on average, and the most serious cases that end up in fatalities usually spend some time in the hospital before passing. Little social distancing could lead to widespread transmission of the disease which would only be reflected in the CFR approximately two weeks later. Similarly, once people notice the increase in CFR and start practicing social distancing, the effect of this decrease in exposure will not become apparent in the CFR for another two to three weeks. Thus, according to such a timeline, low levels of social distancing correspond to low CFRs while high levels of social distancing correspond to high CFRs at the surface. A more in-depth analysis would show the nuance between cause and effect. One way to address this issue would be to use time lags as done by Philip et al. (2020) in order to account for the delay between the date of infection and the date of death, however, this is beyond the scope of my paper.

In the last two columns, I introduce 2012 RVS as a control. Doing so produces a statistically significant effect of 2016 RVS on CFR. This essentially isolates what I will label the Trump effect. The Trump effect, on the government side, refers to the polar shift in attitude amongst Republican lawmakers that gained in popularity and influence towards the end of and even after Obama's presidency, with Republican legislators attempting to dismantle as many Obama era policies as possible, the most important one being Obamacare (Rice et al 2018). On the citizen side, the Trump effect refers to his wide range of influence amongst his fans. Trump era rhetoric has consistently been characterized by fiery language. Through this kind of bombastic behavior, hosting concert-like rallies and providing endless fodder for conspiracy theories through Twitter, he garnered attention and support from a fanbase that regarded him more like a celebrity than as the president of the United States. Barrios and Hochberg (2020) find that Trump voters' perception of the risk of the pandemic was dramatically different from that of non-Trump voters due to Trump's own rhetoric as well as the nature of the cult-like following described above. Trump voters engaged in less social distancing which has been promoted by the CDC and confirmed by Greenstone and Nigam (2020) as being essential to reducing the spread of the virus and the overall death toll. Trump voters also generally avoided wearing masks which was similarly highly suggested by the CDC in order to reduce transmissions and flatten the curve. By including 2012 RVS in the specifications for the last two columns, I ensure that the coefficient on 2016 RVS represents the effect of the voters who likely did not vote in 2012 but came out to vote for Trump in 2016 as a result of their cult-like support. Given the general behavior of Trump voters during the pandemic, it comes as no surprise that the coefficient on 2016 RVS is positive and highly significant when controlling for 2012 RVS. Since this coefficient remains significant despite the fact that I control for social distancing, it is likely that 2016 RVS is also working through the channel of mask-use to have an effect on CFR. I will address this concern Section 5.3.

Finally, in Column (3) I include health expenditure per capita as a single control and in Column (8) I include it as a control amongst the other covariates. In both instances, including health expenditure per capita in the specification does not change the results of the regression. In other words, based on this analysis, health expenditure per capita is not an omitted variable when considering the relationship between CFR and RVS. This is the first indicator that health expenditure is not a channel through which voting Republican affects COVID-19 mortality.

Table 3: Equations (1) and (2) Results - Determinants of CFR

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				CFR				
2016 RVS	-0.014***	-0.007**	-0.007***	0.003	0.003	0.004	0.028***	**0.028*** **
	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.007)	(0.007)
Population Density				0.104***	0.104***	0.101***	0.104***	0.104***
				(0.010)	(0.010)	(0.011)	(0.010)	(0.011)
% Women				0.075***	0.075***	0.077***	0.084***	0.084***
				(0.014)	(0.014)	(0.014)	(0.015)	(0.015)
% Black				0.020***	0.020***	0.020***	0.020***	0.020***
				(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
% Hispanic				0.008	0.008	0.007	0.007	0.007
				(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
% Above 65				0.047***	0.047***	0.046***	0.042***	0.042***
				(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Median Household Income				-0.003	-0.003	-0.003	-0.001	-0.001
As a % of State Mean				(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
HEPC			0.008					0.001
			(0.010)					(0.011)
TFE					0	0.001	-0.003	-0.003
					(0.025)	(0.025)	(0.025)	(0.025)
% Change in Visits to						-0.003	-0.003	-0.003
Retail and Rec Locations						(0.002)	(0.002)	(0.002)
2012 RVS							-0.026***	-0.026***
							(0.007)	(0.007)
Constant	2.861***	2.445***	2.439***	-3.253***	-3.253***	-3.395***	-3.782***	-3.782***
	(0.146)	(0.170)	(0.168)	(0.809)	(0.836)	(0.835)	(0.873)	(0.873)
Observations	2,560	2,560	2,560	2,560	2,560	2,560	2,560	2,560
R-squared	0.025	0.007	0.007	0.116	0.116	0.117	0.123	0.123
State Fixed Effects	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Robust standard errors are included in parentheses. *, **, *** denote significance at the 10%, 5%, and 1% levels.

I next analyze the relationship between RVS and health expenditure per capita directly. The primary regression in Table 4 again shows that voting Republican is related to increased spending on healthcare per person. A one percentage point increase in 2016 RVS is expected to produce an insignificant $1 decrease in HEPC. Here, it is important to note that approximately 600 of the over 2500 counties included in the sample report zero health expenditure, i.e. no health expenditure at all for the year of 2018. If we consider counties that are small enough in scale to rely solely on federal and state spending or located in close enough proximity to neighboring counties that do provide access to healthcare infrastructure for their citizens, then this data seems plausible. For example, Loving County in Texas has a population of just 169 and does not have a single medical facility located within the county. In fact, the nearest medical facility is located an hour's drive away in the next county over.

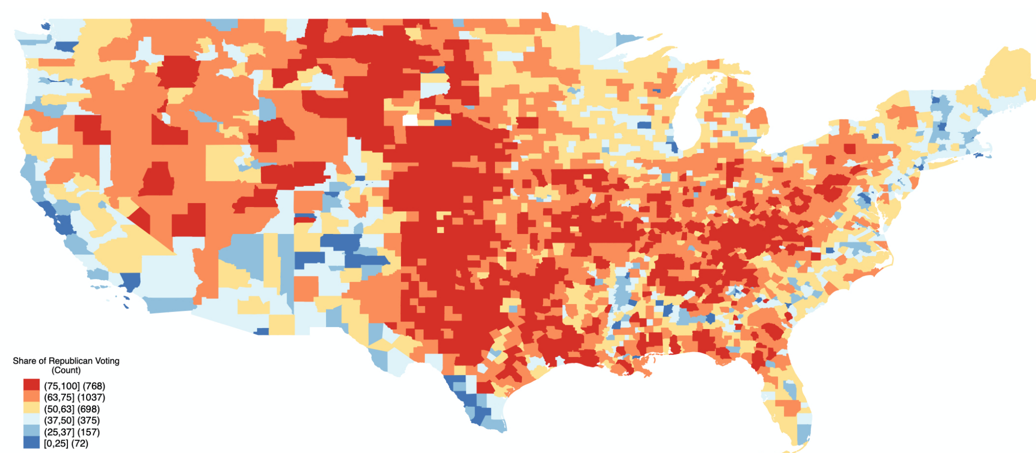
Table 4: Equation (3) - Determinants of HEPC

	(1)	(2)	(3)	(4)
			HEPC	
2016 RVS	-0.001	-0.002	0.005	-0.028**
	(0.002)	(0.003)	(0.006)	(0.012)
Population Density			0.074***	0.070***
			(0.007)	(0.008)
% Women			0.006	-0.003
			(0.021)	(0.020)
% Black			0.004	0.004
			(0.005)	(0.005)
% Hispanic			0.009**	0.009**
			(0.004)	(0.004)
% Above 65			-0.001	0.005
			(0.012)	(0.012)
Median Household Income			0	-0.004
As a % of State Mean			(0.002)	(0.002)
2012 RVS				0.037***
				(0.013)
Constant	0.862***	0.896***	0.042	0.604
	(0.151)	(0.189)	(1.104)	(1.075)
Observations	2,560	2,560	2,560	2,560
R-squared	0	0	0.008	0.012
State Fixed Effects	No	Yes	Yes	Yes

Note: Robust standard errors are included in parentheses. *, **, *** denote significance at the 10%, 5%, and 1% levels.

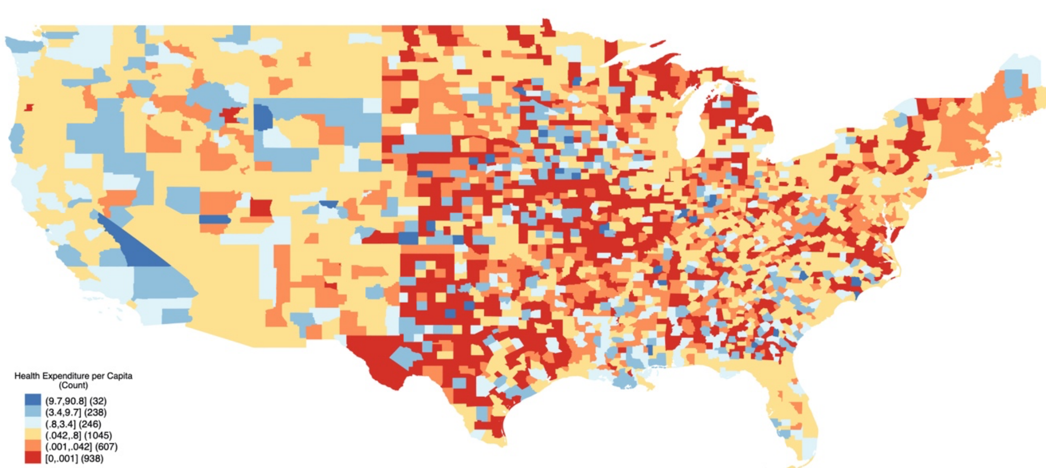
In order to investigate further, I create a dummy variable that equals one when a county reports zero healthcare expenditure and zero when a county reports healthcare expenditure and take the mean of 2016 RVS across this dummy variable. I find that counties that report zero health expenditure per capita have a 10-percentage point higher RVS than counties that report a greater than zero health expenditure per capita. This result is also supported by Figures 1 and 2 that map RVS and health expenditure respectively. The areas of the country that appear to be most Republican in Figure 1 are the same areas that report zero health expenditure in Figure (2). In Column (3) of Table 4 we can observe that including all the control variables results in a change in both sign and significance. This unexpected result can also be supported by Figures 1 and 2.

Figure 1: Republican Voting Share in 2016



Note: I include the mean value of RVS, 63, as a color break to demonstrate the true political character of the country. I then select 37 as a break since it is symmetrical to 63 about 50.

Figure 2: HEPC in 2018 (1000s of $)



In some regions such as the Midwest[5], Texas, and the Southeast[6], my hypothesis that more Republican areas spend less on healthcare appears to be supported. However, in the West[7], Southwest[8], and Northeastern[9] most regions, the relationship is more obscured. There are several possible explanations for this result. Regardless of urban or rural location, hospitals and other medical facilities require a significant minimum level of constant upkeep expenditure in order to remain functional. Under normal circumstances, the healthcare infrastructure of a given location does not need to be equipped to serve every single person residing in that area because the likelihood that even a small majority of the population will need to access hospitals and medical facilities at the same time is extremely low. According to the CDC, generally less than 10% of people spend the night in a hospital. Even if we greatly increase the margin here and include all public and private hospitals as well as medical facilities, we could reasonably claim that less than 30% of people use the given healthcare infrastructure at any given point in time. As such, although there are indeed more medical facilities located in areas with higher population density, the difference in number of medical facilities compared with the difference in number of people in urban versus rural areas is not by any means proportional.

To demonstrate this, I compare Los Angeles County in California which is the most populous county in the US and Aurora County in South Dakota which is within 5% of the least populated counties in the US. On the one hand, Los Angeles County operates four hospitals and 19 health centers for a total of 23 medical facilities serving a population of

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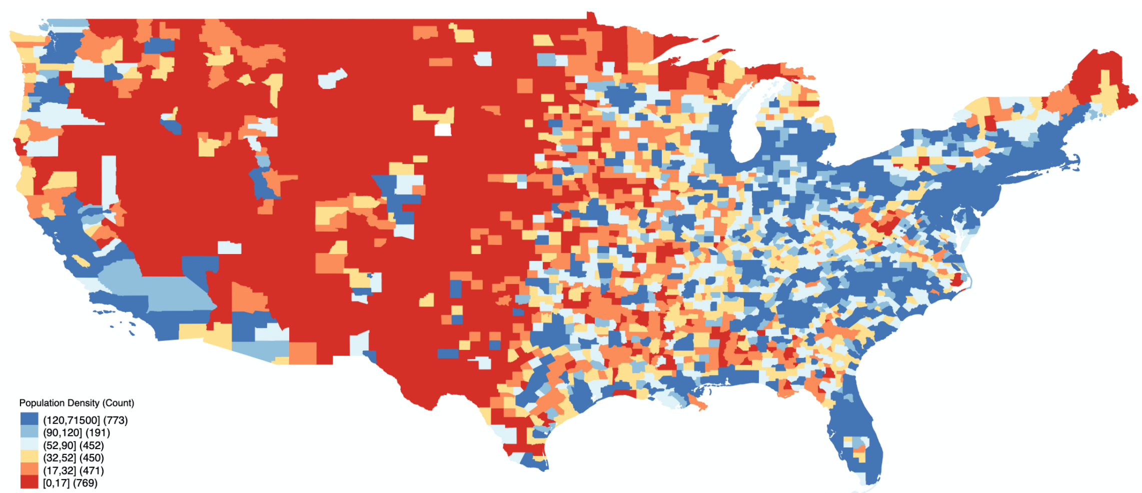
[5] Midwest here refers to the states between the Dakotas and Ohio.
[6] Southeast refers to the region spanning from Louisiana to Florida and the Virginias.
[7] West refers to Montana, Wyoming, Colorado, Idaho, Nevada, Utah, Washington, Oregon, and California.
[8] Southwest refers to Arizona and New Mexico.
[9] Northeast refers to every state beyond Pennsylvania and Maryland.

approximately 10 million residents. This means each facility is theoretically expected to be able to serve about 434,000 people. Aurora County, on the other hand, contains one medical center that serves a population of 2,751 people. Los Angeles County has a population density of 2,473 people per square mile while Aurora County has a population density of 4 people per square mile. Clearly, the more densely populated area does have more medical facilities than the less densely populated area, and thus likely spends more in total on healthcare. However, the difference between the number of medical facilities and the number of people is highly disproportional. Moreover, among the 33 most densely populated counties, the average share of Republican voters in 2016 is 33% with a standard deviation of 12.7%. The mean of RVS in 2016 is 61%. This means that these most densely populated counties are also within the threshold of 25% of the most deeply Democratic areas in the nation.

Figure 3: Population Density



Note: For the purpose of interpreting this map, population density is measured in people per square mile, not 1,000 people per square mile.

In summary, due to the disproportionality of population density distribution across rural and urban areas, at the surface level, it appears to be the case that more densely populated counties spend less on healthcare per person than their less densely populated counterparts. This relationship seems to be supported by Figures 2 and 3. The more densely populated areas are also the areas where counties are generally spending less per capita on healthcare. Upon further inspection, we can see from Table 3 that population density is positively related to HEPC. I revisit this topic in Section 5.3 to confirm. Finally, just like the results from Table 3, when I include 2012 RVS, the Trump effect shows that a one percentage point increase in 2016 RVS produces a significant $28 decrease in HEPC.

Having inspected the relationship between RVS and health expenditure per capita, I now move on to examine the relationship between health expenditure per capita and CFR. Based on the results in Table 5, it is evident that while a $1,000 increase in HEPC does seem to result in a lower CFR by 0.002 percentage points, this result is insignificant across the board and robust to the inclusion and exclusion of relevant controls.

Table 5: Equation (4) - Determinants of CFR

	(1)	(2)	(3)	(4)
		CFR		
HEPC	-0.012	0.008	0	-0.002
	(0.015)	(0.011)	(0.010)	(0.010)
Population Density			0.104***	0.099***
			-0.015	-0.011
TFE				0.002
				(0.025)
% Women				0.073***
				(0.014)
% Black				0.017***
				-0.005
% Hispanic				0.006
				(0.004)
% Above 65				0.047***
				(0.009)
Median Household Income				(0.004)
As % of State Mean				-0.002
% Change in Visits to				(0.003)
Retail and Rec Locations				(0.002)
Constant	1.999***	1.983***	1.956***	-2.896***
	(0.030)	(0.008)	(0.008)	(0.685)
Observations	2,560	2,560	2,560	2,560
R-squared	0.000	0.000	0.030	0.117
State Fixed Effects	No	Yes	Yes	Yes

Note: Robust standard errors are included in parentheses. *, **, *** denote significance at the 10%, 5%, and 1% levels.

5.2 Secondary Regression: Average Daily Deaths per 100,000

In my original research question, I was most interested in exploring the effect of local political affiliation on COVID related deaths. I employed CFR to measure COVID fatalities because CFR documents the death rate of people who were actually infected by the virus. Although this is the main variable of interest, there is a potential for the analysis to be biased considering the fact that places that were more efficient at testing would naturally record a higher number of cases. This could bias the results in one of two ways. First, areas that experienced higher rates of testing likely did a better job of documenting both mild and serious illnesses. Assuming only the serious cases ended in fatalities, the CFR could be lower in these counties as compared with those that failed to test as effectively. Counties that were inefficient or ineffective in testing would likely tend towards documenting only the more serious cases, resulting in a higher overall CFR. Alternatively, counties where testing rates were low are also likely to be Republican leaning counties. Since the inception of the pandemic, Republican leaders have publicly and repeatedly dismissed the importance of mask-wearing, social distancing, and testing. Therefore, counties with low rates of testing are probably locations where COVID is not taken as seriously implying that there could be more cases and deaths than is revealed by the data since the virus is able to spread more easily. Given these two different possible biases related to CFR as a measure of COVID mortality, I run a second set of regression specifications with mean COVID deaths per capita as the dependent variable instead.

In Table 6, we can see that the result is rather similar to the results from my main regression specification. For the most part RVS in 2016 has a rather small, economically insignificant effect on mean deaths per capita. Even the direction of the effect changes from negative to positive once I include most of the control variables. One main difference is that these coefficients, although economically insignificant, are statistically significant, unlike the previous results. In the first three columns, as I add fixed effects and HEPC the coefficient on 2016 RVS remains negative implying that counties with a higher share of Republicans generally fared better. Similar to the main regression, once I include the rest of the control variables, the sign changes to positive and increases marginally in magnitude. This secondary regression specification therefore confirms my findings from the primary regression that 2016 RVS has a very small statistically significant effect on mortality controlling for factors such as population density, demographic makeup, income, and social distancing, but this effect does not seem to be working through the channel of pre-pandemic health expenditure.

Table 6: Secondary Regression - Determinants of Mean Deaths per 100,000

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Average Daily Deaths per 100,000							
2016 RVS	-0.435***	-0.534***	-0.533***	0.363**	0.364**	0.381***	1.008***	1.008***
	(0.090)	(0.155)	(0.153)	(0.138)	(0.137)	(0.138)	(0.197)	(0.196)
Population Density				7.896***	7.897***	7.836***	7.911***	7.910***
				(0.917)	(0.918)	(0.931)	(0.923)	(0.923)
% Women				1.331***	1.328***	1.384***	1.558***	1.558***
				(0.475)	(0.476)	(0.477)	(0.486)	(0.486)
% Black				1.025***	1.020***	1.021***	1.024***	1.024***
				(0.197)	(0.205)	(0.206)	(0.202)	(0.201)
% Hispanic				0.836***	0.833***	0.826***	0.825***	0.825***
				(0.240)	(0.242)	(0.240)	(0.236)	(0.236)
% Above 65				0.577*	0.575*	0.567*	0.458	0.458
				(0.304)	(0.306)	(0.307)	(0.314)	(0.314)
Median Household Income				-0.249***	-0.252***	-0.260***	-0.193**	-0.193**
As a % of State Mean				(0.085)	(0.086)	(0.087)	(0.089)	(0.089)
HEPC			0.787					0.012
			(0.697)					(0.345)
TFE					-0.238	-0.209	-0.325	-0.325
					(0.722)	(0.720)	(0.756)	(0.754)
% Change in Visits to						-0.090	-0.090	-0.090
Retail and Rec Locations						(0.063)	(0.063)	(0.063)
2012 RVS							-0.691***	-0.692***
							(0.175)	(0.173)
Constant	73.110***	79.250***	78.545***	-57.120*	-56.346	-60.219*	-70.375**	-70.377**
	(5.972)	(9.498)	(9.009)	(33.104)	(34.254)	(34.464)	(34.575)	(34.583)
Observations	2,560	2,560	2,560	2,560	2,560	2,560	2,560	2,560
R-squared	0.025	0.036	0.038	0.310	0.310	0.311	0.315	0.315
State Fixed Effects	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Robust standard errors are included in parentheses. *, **, *** denote significance at the 10%, 5%, and 1% levels.

5.3 Robustness Checks

In this section, I run several robustness checks to confirm that RVS in 2016 has an insignificant effect on CFR and does not work through the channel of pre-pandemic health expenditure. I first use TFE as an instrumental variable for RVS in order to address the concern of omitted variable bias in my original regression. Several papers confirm that using masks greatly reduces transmission of the COVID virus. As previously mentioned, reducing transmission rates is essential to limiting the pressure on hospitals to accept patients with severe cases beyond their capacity. In short, using masks could affect the CFR independent of other factors including social distancing. Moreover, similar to their attitude toward social distancing, Republican leaders have also dismissed the importance of wearing masks. Thus, mask-use could be an omitted channel through which 2016 RVS affects CFR. Since I have no measure of mask-use in my data, I use TFE to estimate RVS in 2016 and run my regression specification (2), using the estimated 2016 RVS.

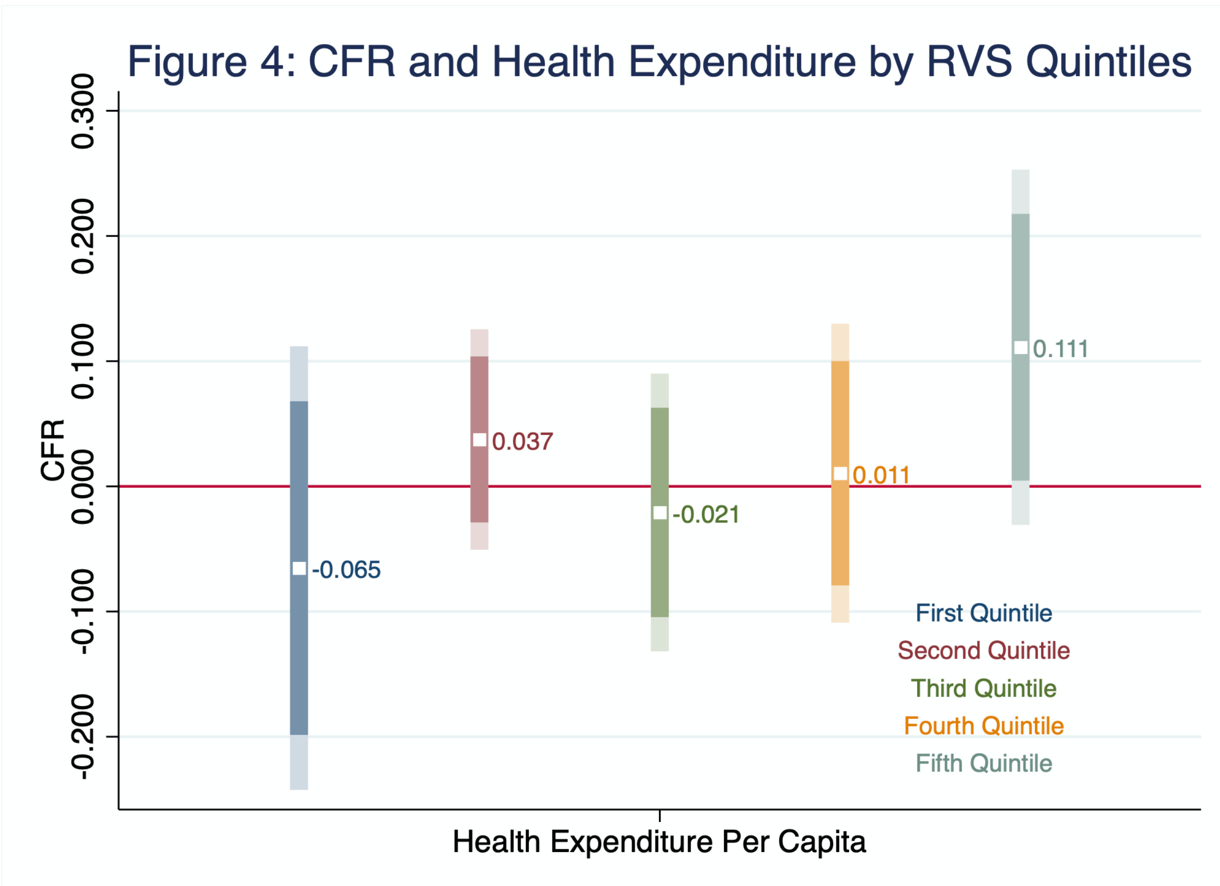
Bazzi et al. (2021) state that over the past two decades, TFE has been increasingly able to accurately estimate RVS as the Republican Party has gradually embraced more extreme individualistic and anti-statist views. As constructed by Bazzi et al. (2020), TFE measures the individualistic values and beliefs present in counties that have experience on the American frontier during past two centuries. Bazzi et al. (2021) also show that counties that have more frontier experience exhibit less mask use. If mask-use is an omitted variable and my instrument is TFE, this would mean that TFE highly correlated with the error term, making it an unsuitable instrument. In Figure (4) I plot TFE against the residuals to find that there is no relationship. Since TFE is correlated with 2016 RVS and not correlated with the error term it serves as an adequate instrument. However, mask-use is likely not the omitted variable affecting the exogeneity of 2016 RVS. I find that the results of the instrumental variable regression, shown in Table 7, are consistent with my original results: 2016 RVS does not have a significant effect on CFR.

Table 7: Robustness Check - Instrumental Variable Regression

	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
	First Stage: 2016 RVS					**Second Stage: CFR**				
TFE	3.384***	2.432***	2.245***	0.185	0.187***					
	(0.231)	(0.252)	(0.249)	(0.185)	(0.061)					
2016 RVS						-0.015**	-0.007	-0.002	0.01	0.01
						(0.006)	(0.008)	(0.008)	(0.102)	(0.101)
2012 RVS					0.943***					-0.01
					(0.010)					(0.095)
Population Density			-1.676***	-0.515***	-0.170***			0.101***	0.105*	0.101***
			(0.581)	(0.199)	(0.047)			(0.019)	(0.054)	(0.021)
% Black				-0.753***	-0.112***				0.025	0.018
				(0.017)	(0.010)				(0.077)	(0.012)
% Hispanic				-0.369***	-0.051***				0.01	0.006
				(0.038)	(0.009)				(0.038)	(0.006)
% Women				-1.057***	-0.389***				0.084	0.077*
				(0.110)	(0.035)				(0.108)	(0.041)
% Above 65				0.149***	0.171***				0.045***	0.045**
				(0.054)	(0.023)				(0.016)	(0.018)
Median Household Income				-0.105***	-0.106***				-0.003	-0.003
As % of State Mean				(0.013)	(0.005)				(0.011)	(0.011)
HEPC				0.15	-0.086***				-0.003	-0.001
				(0.101)	(0.032)				(0.019)	(0.014)
% Change in Visits to				0.110***	0.016**				-0.004	-0.003
Retail and Rec Locations				(0.019)	(0.006)				(0.011)	(0.002)
Constant	56.567***	60.688***	61.137***	147.956***	34.831***	2.895***	2.303***	1.995***	-4.818	-3.658
	(0.464)	(2.373)	(2.381)	(5.853)	(2.339)	(0.390)	(0.516)	(0.557)	(15.113)	(3.668)
Observations	2,560	2,560	2,560	2,560	2,560	2,560	2,560	2,560	2,560	2,560
R-squared	0.081	0.331	0.374	0.698	0.956	0.025	0.331	0.348	0.404	0.407
State Fixed Effects	No	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes

Note: Robust standard errors are included in parentheses. *, **, *** denote significance at the 10%, 5%, and 1% levels. I use TFE as an instrument for 2016 RVS.

Second, I consider how 2016 RVS can be factored into the relationship between HEPC and CFR. It is clear that social distancing and mask wearing play a crucial role in reducing the spread of COVID as well as COVID fatalities. Several papers have also confirmed that areas where Republican or conservative ideologies proliferate, social distancing and mask wearing guidelines were not followed strictly. As such, the effect of these behavioral factors could have far outweighed the effect of health care expenditure on CFR in the counties where the ideology driving this behavior was particularly deeply rooted. In other words, the effect of pre-pandemic health expenditure could be overshadowed in counties where people were blatantly disregarding COVID safety guidelines. In contrast, counties where people did follow safety protocols, we might be able to see the effect of health expenditure more clearly.



Note: Each quintile represents a 20 percentile 'bin' of RVS, i.e. the 'First Quintile' refers to all the counties with RVS falling between the 0-20th percentile (essentially the most Democratic counties).

With this in mind, I run specification (4) regressing CFR on HEPC with fixed effects and controls depending on the value of 2016 RVS. I essentially run five regressions. First with only the observations that have 2016 RVS in the bottom quintile (within the 20th percentile), second with only the observations that have 2016 RVS in the second quintile (in between the 20th and 40th percentile), so on and so forth. The plot of coefficients in Figure 4 helps explicate the relationship between HEPC and CFR allowing for variation in the degree of *Republican-ness* by displaying the coefficients and confidence intervals on HEPC that result from these regressions. While once again none of these results are significant since each of the confidence intervals intersect with zero, there is clearly a nominally positive relationship. When the share of Republican voters is the lowest, investment in healthcare reduced the CFR. As the share of Republican voters in an area increases, the relationship between health expenditure and CFR becomes obscure. I find a similar trend when I run the same regressions using deciles instead i.e., splitting the data into 10 bins of 2016 RVS rather than five. These results by no means change my initial finding from the main regression that HEPC has essentially no effect on CFR since none of them are significant, but they do provide some more context to the nuances in the relationship.

The results from Table 3 can also be used to examine whether or not population density is causally linked to HEPC. Initially the coefficient is insignificant, however once I introduce fixed effects and controls the effect does become significant. Every increase in 1,000 people per square mile is expected to produce a $70 increase in health expenditure per capita. I will also note that the R-squared is rather low for each of these regressions implying that they only explain 1.2% of the variance in the data. Therefore, even though this result directly contradicts my earlier supposition that there is naturally less spending on healthcare per capita in more densely populated areas, more in-depth analysis is required to ascertain the true link between these variables. This is beyond the scope of my paper, but the ambiguity in the relationship between population density and health expenditure per capita that is revealed through this process suggests that controlling for population density in my original regression specification is sufficient to prevent population density-related prevent omitted variable bias from affecting my results.

As my final robustness check, I once again run regression specification (2), weighting county observations by population. Since my main variable of interest is the *average* daily case fatality rate, estimates from counties with higher populations that, represent the outcomes for more people, would likely more closely represent reality. I find that the results are consistent with those from my original regression. In Table 8, we can see that the coefficient on 2016 RVS starts out negative and significant, becomes positive and insignificant when I introduce most controls, and finally remains positive and significant when I introduce 2012 RVS. As before, even though the final result is significant and positive, the actual effect of 2016 RVS is very small in magnitude

Table 8: Robustness Check - Population Weighted Regression

	(1)	(2)	(3)	(4)	(5)	(6)
				CFR		
2016 RVS	-0.030***	-0.020***	-0.001	-0.001	-0.001	0.027**
	(0.008)	(0.004)	(0.004)	(0.004)	(0.004)	(0.012)
HEPC				-0.046**	-0.045**	-0.046**
				(0.018)	(0.018)	(0.019)
Population Density			0.091***	0.095***	0.094***	0.095***
			(0.011)	(0.010)	(0.010)	(0.010)
% Women			0.111***	0.108***	0.110***	0.126***
			(0.024)	(0.023)	(0.023)	(0.024)
% Black			0.015**	0.013**	0.014**	0.014**
			(0.007)	(0.006)	(0.007)	(0.006)
% Hispanic			0.014***	0.013***	0.015***	0.015***
			(0.004)	(0.004)	(0.004)	(0.004)
% Above 65			0.071***	0.070***	0.071***	0.065***
			(0.007)	(0.007)	(0.007)	(0.008)
Median Household Income			0.001	0.001	0.001	0.004**
As a % of State Mean			(0.002)	(0.002)	(0.002)	(0.002)
% Change in Visits to			-0.001	-0.001	-0.003	-0.004
Retail and Rec Locations			(0.005)	(0.005)	(0.005)	(0.005)
TFE				-0.076***		
				(0.025)		
2012 RVS						-0.029**
						(0.012)
Constant	3.772***	2.896***	-5.443***	-5.223***	-5.434***	-6.270***
	(0.447)	(0.536)	(1.343)	(1.322)	(1.324)	(1.341)
State Fixed Effects	No	Yes	Yes	Yes	Yes	Yes

Note: Robust standard errors are included in parentheses. *, **, *** denote significance at the 10%, 5%, and 1% levels. This set of regressions is weighted by population at the county level.

6 Conclusion

It is debatable which of the several factors that exacerbated the COVID-19 pandemic turned out to be the deadliest. Each of the following factors played a significant role in increasing the number of COVID related deaths faced by the US between 2020 and 2021: highly contagious and deadly virus, initial lethargic governmental response, lack of testing, lack of social distancing, lack of mask wearing, lack of uniform message from leading figures, and the resulting healthcare capacity crisis. Each of these elements contributed to increasing the pressure on hospitals to attempt to treat a greater number of serious cases than they had the capability to treat, leading to hundreds of thousands of unnecessary deaths. As such, in my thesis I attempt to exploit the links between conservative ideology and distaste for investment in public goods and conservative ideology and refusal to follow COVID protocols to make the claim that there is a causal relationship between political affiliation and COIVD mortality that works through the channel of pre-pandemic healthcare expenditure.

I use a four-tiered regression model that attempts to individually establish each of these links while control for all possible confounding factors. I find that controlling for 2012 RVS, 2016 RVS is indeed related to lower healthcare expenditure but does not affect CFR through this channel. In fact, I find that the only effect that RVS has on CFR is through what I term the Trump effect. The Trump effect essentially captures the effect of the people who were energized by Trump in the 2016 election as a result of his ostentatious approach to politics. These were likely the same people who, due to Trump's inflammatory rhetoric throughout the course of the pandemic, refused to wear masks or practice social distancing, thereby increasing the CFR in their counties. Although I find that the Trump effect is statistically significant, it is still rather small in magnitude and most likely economically insignificant.

I run several robustness checks to ensure the validity of my conclusion. Among these, I use TFE as an instrument to predict 2016 RVS which I then use to estimate CFR. This instrumental variable regression supports the previous result showing that RVS has a minimal and insignificant effect on CFR. I also delve deeper into the relationship between pre-pandemic health expenditure and CFR. My results are again insignificant, but I do find that there is a positive correlation between effect of HEPC on CFR and the degree to which a county is Republican. Specifically, in more Democratic areas, investment in HEPC results in a decrease in CFR while in more Republican places, the relationship between HEPC and CFR is more obscure.

Although at this point, the data does not support the conclusion that there is a causal link between RVS and CFR through HEPC, there is still room for this topic to be explored. Political affiliation, policy preferences, and policy implementation are not only difficult to measure by themselves, but also shift subtly over time. I suspect that a more in-depth study of the trajectory of healthcare expenditure over the last several years or decades leading up to the pandemic, rather than in just one year, could reveal some aspect of this relationship that has yet to be discussed and explored.

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