RISK PERCEPTIONS AND POLITICS: EVIDENCE FROM THE COVID-19 PANDEMIC*

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First Version: March 27, 2020

Current Version: November 11, 2020

Politics may color interpretation of facts, and thus perceptions of risk, the formation of expectations, and choices. We find that a higher share of Trump voters in a county is associated with lower perceptions of risk during the COVID-19 pandemic. Controlling for case counts and deaths in the local area, as Trump's vote share rises, individuals search less for information on the virus and its potential economic impacts, and engage in fewer visits to non-essential businesses—suggesting less reallocation of consumer activity across categories. These patterns persist in the face of state-level guidelines to "stay home," and reverse only when conservative politicians are exposed and the White House releases federal social distancing guidelines. We find support for a media channel as an explanation for our findings, though we cannot rule out that some individuals are motivated instead by rejection of mainstream views. Our results suggest that politics and the media may play an important role in determining the formation of risk perceptions, and may therefore affect both economic and health-related reactions to unanticipated health crises.

JEL Codes: D8, I1, P16, L82

Keywords: Risk Perceptions, Expectations, COVID-19, Political Partisanship, Polarization, Pandemics

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* We thank an anonymous referee, Bill Schwert, Lauren Cohen, Francesco D'Acunto, Jonathan Dingel, Ray Fisman, Stefano Giglio, Tarek Hassan, Seema Jayachandran, Elisabeth Kempf, Christian Leuz, Charlie McLure, Paola Sapienza, Andrei Shleifer, Kelly Shue, Margarita Tsoutsoura, Michael Weber, Constantine Yannelis, Luigi Zingales for helpful conversations, comments and suggestions. Jin Deng provided excellent research assistance. Barrios gratefully acknowledges the support of the Stigler Center and the Becker Friedman Institute at the University of Chicago for data funding. All errors are our own. Corresponding Author: Yael V. Hochberg (hochberg@rice.edu), Rice University, 6100 Main St. MS-531, Houston, TX 77005.

I. INTRODUCTION

Understanding how individuals form and update their expectations—and, thus, their choices—is of critical interest to policymakers and economists alike.[1] Individuals appear to exhibit considerable heterogeneity in expectations and risk perceptions (e.g., Andre et al., 2019; D'Acunto et al., 2019a; D'Acunto et al. 2019b; D'Acunto et al. 2019c; Gennaioli et al., 2016; Coibion et al., 2019), and there is a longstanding notion that political beliefs affect individuals' perception of economic conditions (e.g., Campbell et al., 1960). An extensive literature documents an increase in political polarization over time, with political parties becoming increasingly homogeneous in the ideology of their members and exhibiting increasing hostility toward members of the opposite party (e.g., Iyengar et al., 2012; Mason, 2013; Lott and Hassett, 2014; Mason, 2015; Gentzkow, 2016; Boxell et al. 2017). This literature demonstrates that individuals have an increased tendency to view the world through a "partisan perceptual screen:" their assessment of economic conditions and policies depends on whether their party of preference is currently in power (e.g., Bartels, 2002; Gaines et al., 2007; Gerber and Huber, 2009; Curtin, 2006; Mian et al., 2018; Kempf and Tsoutsoura, 2019).[2] In this paper, we show that politics affects an individual's perception of risk and resulting choices in the face of a health-related crisis: the COVID-19 pandemic.

Unlike prior settings in the economics literature where risk perceptions or expectations are confined to the economic realm, here, the setting affects health-related behavior, which could be viewed as non-partisan (Slovic et al., 2004). Viruses are agnostic to political party affiliation, and

[1] Much of the work in this area has focused on inflation expectations, and relates cognitive ability to individuals' inflation forecasts.

[2] Evidence on how these partisan perceptions translate into differences in actual behavior and choices of economic agents, however, is mixed (see e.g., McGrath, 2017; Meeuwis, 2018; Mian et al, 2018; Makridis, 2019; Kempf and Tsoutsoura, 2019).

in a health crisis, we might assume that all seek the most objective, accurate data. Yet because individuals' perception of the virus's threat may be influenced by their news source, even a similar case or death count may be interpreted differently. Individuals may consume information from sources and authority figures that match their political leanings, either because they prefer such news because of their political dispositions (Mullainathan and Shleifer, 2005) or because they believe those sources are more credible (Gentzkow and Shapiro, 2006). At the outset of a potential crisis, while the same objective data is available to all, the individual observes a particular interpretation of that data—an interpretation shaped by political coloring associated with the media streams and authority figures he consumes from. As different populations observe the same underlying data through different political lenses (e.g., Gentzkow et al., 2018), they ultimately form different perceptions of the risk implied by an event, which then affects their decisions and behavior.

Consider an individual who consumes news through outlets that provide optimistic projections regarding how a particular potential health crisis or pandemic might play out—potentially because such optimism serves other goals of the political group that the outlet is most closely associated with. Due to their choice of a news outlet, the individual observes interpretations of data that downplay the severity of the health threat, and as a result, views that news stream as being generated by a favorable outcome scenario. They then place a higher probability weight on the favorable scenario and neglect the risk of an alternative, worse outcome.[3] Even if the individual hears alternative interpretations of the underlying data elsewhere, these do not change his mind: he views the "bad news" stories as a misinterpretation of the data and continues to under-react—particularly so if those stories are associated with news outlets or authority figures that do not align

[3] Similarly, the same predictions go through in the opposite direction, for pessimism.

with his political views, or are viewed as hostile to his views on other issues. Only when media outlets or authority figures associated with the individual's preferred political views begin to present different interpretations of the data, or when the disease hits close to home, does the individual adjust his perception of risk and change his behavior accordingly.[4]

This media exposure story suggests a mechanism based on exposure to different signals: two otherwise identical agents, one Republican and one Democrat, would form identical beliefs about the pandemic if they were exposed to the same exact signals—say, if only one media outlet existed, and no alternative narratives to interpret the same facts were allowed. Identical beliefs would then lead to similar risk perceptions and choices. Under the media exposure story, however, we observe different beliefs because agents' political views cause them to sort into different sources of information, whose slant towards the pandemic's importance or irrelevance differs. As a result, they obtain different signals and form different beliefs about COVID-19. A channel of this nature would be consistent with recent research on belief formation, such as Barone et al. (2015), D'Acunto et al. (2019), and D'Acunto, Malmendier, and Weber (2020).

An alternative mechanism for differences in risk perceptions, however, is the possibility that some individuals have an intrinsic tendency to reject mainstream views and that these individuals are more likely to prefer one political party over the other. In this case, the relevant model is one of heterogeneous agents, where some agents tend to form different beliefs irrespective of the information sources to which they are exposed. In particular, a group of agents may systematically reject mainstream views, regardless of whether they are exposed to media outlets that are slated towards or against such views. This group of agents might, for example, have selected into

[4] An alternative interpretation, with similar implications, is that rather than perceiving objective data differently, individuals may not even attempt to gather objective data because their political leaders and news sources call it a hoax.

supporting President Donald J. Trump in the 2016 Presidential elections because they viewed this as the epitome of rejection of mainstream narratives, and at the same time, they might reject a mainstream view that COVID-19 is a serious concern.

To explore the effects of political partisanship on risk perceptions in the pandemic context, we utilize several novel measures to capture risk perception and resulting choices. Our risk perception measures are based on Google Health Trends search data (e.g., Choi and Varian, 2009a; Choi and Varian, 2009b; Ginsberg et al., 2009). Google search data has been used before in analogous work to gauge individuals' attention and to predict changes in prices; here, we apply it to the pandemic setting. Our first measure utilizes Google Health Trends data to measure search share for information regarding the virus. Our intuition for this measure is as follows: internet searches are a proxy for the demand for information, which reflects an individual's level of concern about a topic. The higher the search share in a particular location and time period, the higher that population's perceived risk. Our second risk perception measure focuses on the perception of economic risk specifically. We measure search share for unemployment-related terms, capturing individuals' perceptions of the pandemic's economic and financial risk. We measure search share at the Nielsen Designated Market Areas (DMA) level at a daily frequency. Both measures follow expected patterns, rising sharply as the caseload in the U.S. increases over time. In contrast to surveys that capture perceptions at a single point in time, a significant benefit of using Google search data in this manner is that we can observe search behavior at a daily level, and track changes over the course of the pandemic's unfolding. This allows us to gain insight into how risk perceptions change in event time as cases and deaths appear, and significant events unfold.

Our second set of measures reflect the resulting choices made by individuals. We utilize proprietary data from Unacast, a company that collects and processes location data from tens of millions of U.S. cellular phones and computes various location-related measures at the county level. For each day and for each county in the U.S., we obtain the percent change in visits to non-essential retail and services from the average for the same day of the week during the pre-COVID-19 period, where essential locations include venues such as food stores, pet store and pharmacies. Goolsbee and Syverson (2020) document that COVID-19-related social distancing efforts had a significant reallocation effect, driving consumer activity from "non-essential" to "essential" businesses, and from restaurants and bars towards groceries and other food sellers. Thus, this measure allows us to capture differences across populations in the reallocation of consumption and consumer spending from one segment of the economy ("non-essential") to another ("essential"). As an additional proxy for behavior change resulting from differences in underlying perceptions of risk, we use the change in average daily distance traveled for each day and for each county in the U.S. relative to the average for the same day of the week from the beginning of the year up to March 8th (the "pre-COVID period"). Here, we use county-level observations at a daily frequency. Both measures follow expected patterns, decreasing sharply as the caseload in the U.S. increases.

Using a variety of fixed effects difference-in-differences specifications run in event time (versus first COVID case in the local area) that control for various time-varying and invariant characteristics at the local level that could be related to fundamental risk as well as local economic activity, and controlling for DMA-level COVID-19 case counts and deaths, we show that search share for both COVID-19 information (our proxy for the perception of risk related to health impacts) and unemployment information (our proxy for the perception of risk related to economic impacts) decreases strongly in the share of voters in the county who voted from Donald J. Trump in the 2016 presidential election.[5] By estimating our models in event time, we alleviate concerns regarding the fact that cases first appeared in Democrat-leaning counties, arriving only later in the sample period in Republican counties. Overall, search share for both types of terms is increasing in the number of confirmed cases announced, but this increase is muted in counties with higher Trump vote share (VS). To illustrate the magnitude of the effect, for every doubling of the number of confirmed COVID-19 cases, search share for terms related to COVID-19 increases by 40%, holding all else constant. For the same doubling of cases, a one standard deviation increase in the Trump vote share (0.12) mutes this effect by 7.8%. Consistent with differences in risk perceptions for the same underlying data, search share for COVID-19 terms increases sharply in low Trump vote share counties surrounding the first case of COVID-19 in the county, relative to high Trump vote share counties, and reverses pattern only surrounding the first confirmed death from COVID-19 in the county, with high Trump vote share counties playing catch up once deaths are imminent.

While the search share results reflect perceptions of risk, whether and how this is reflected in choices is unclear. We next conduct a similar analysis at the county level using the measures of change in visits to non-essential businesses, and daily distance traveled. Consistent with our search share findings, and holding constant the number of cases and deaths at the county level daily, we observe an overall negative relationship between the number of confirmed cases and the percent change in visits to non-essential businesses and average daily distance traveled, suggesting important differences between Trump and non-Trump leaning counties in consumer behavior and reallocation of spending. Once again, this effect is muted in higher Trump vote share counties. To give a sense of magnitudes, while the percent change in visits to non-essential businesses is more

[5] For example, given that the spread of the COVID-19 is accelerated in highly dense locations, we control for population and population density. Our strictest specifications utilize Nielsen DMAs or county fixed effects.

negative as COVID case counts increase, the effect is muted by 40% in counties in the top quartile of Trump vote share in the 2016 election. Similar patterns are exhibited when we employ the change in daily distance and traveled as the outcome variable.

We then proceed to demonstrate that this effect persists even in the face of local government guidelines on social distancing behavior. Over the course of the pandemic, state governments issued various directives regarding the closure of non-essential businesses and schools and "stay home-work safe" (shelter-in-place). We use the variation in Trump vote share across counties within the same state and show that choices in the face of such directives still varies substantially by political leaning: in high Trump vote share counties, there is a significantly lower reduction in visits to non-essential businesses given the same directive in the same state, and holding county characteristics fixed, suggesting that reallocation across economic categories is lower in Republican-leaning counties even in the face of social distancing guidelines. The same results obtain when using the average daily distance traveled as the outcome measure. In contrast, this pattern reverses when President Trump announced federal guidelines for social distancing for a 15-day period on March 16th.

Further consistent with the hypothesis that political priors may color interpretation of objective data, we show that these patterns shifted considerably once Republican politicians began to be affected by the pandemic. We exploit the emergence of COVID-19 in participants at the CPAC meetings that led to the announcement on March 9th that prominent Republicans were self-quarantined due to exposure to COVID-19. Following this announcement, high Trump vote share counties shift their behavior, reducing visits to non-essential businesses and daily distance traveled more in response to confirmed cases. In essence, they begin to play catchup: low Trump share counties, who already had reduced daily distance and non-essential visits considerably, continue to increase their level of reallocation as cases rise; high Trump vote share counties do so at an even greater rate—roughly twice the magnitude. Moreover, when we map risk perceptions and responses before and after the CPAC announcement to the 2019 ratio of Google search share for Fox News to search share for MSNBC in the DMA, we observe that responses across the media ratio are much higher after the CPAC announcement, and the slope of the relationship between search share for COVID-19 terms and the FOX-to-MSNBC search ratio flips from downward sloping to upward sloping in the media search share.

Presumably, when—objectively speaking—death is on the line, we may expect individuals of all political stripes to react similarly, and for politics to have less influence in the face of the same objective case and death counts. We exploit the varying levels of a high-risk population—the share of the population over age 60 in the county—and show that even when the share of older population is high, we continue to observe divergence in responses between high and low Trump vote share counties, holding all else equal. This further suggests that politics may trump objective facts in the formation of risk perceptions and, as a result, in choices made.

Finally, we show that the ability to work from home similarly does not erase this divergence. In areas where the share of employment that can be done via telework (Dingel and Neiman, 2020) is higher, we continue to observe divergence in response between high and low Trump vote share counties, holding all else equal.

We acknowledge that it is difficult to extrapolate individual behavior from patterns of behavior at the aggregate level (here, county or DMA). Changes in behavior at the aggregate level, however, are still informative about the potential for change in (or reallocation of) economic behavior, and thus are policy-relevant.[6] While we cannot specifically assume that individual Democrats "social

[6] Often referred to as issues with ecological inference (inferring individual behavior from group level data).

distance" more than individual Republicans, the alternative interpretation to our results would be that Democrats in Republican counties react to the pandemic by *increasing* travel and visits to non-essential businesses relative to the Republicans in that county, and relative to individuals in high Democrat counties, which seems less plausible.

The implications of the differences in responses that we document could be quite significant. Pei and Shaman (2020), in simulations of a transmission model for SARS-CoV2, show that a 25% reduction in contact rate is enough to reduce the peak number of daily confirmed cases in the U.S. by 40%, from 500,000 to 300,000. Pei and Shaman (2020) note that high reductions in both commuting and cross-county travel across the entire country are needed to reduce the spread and rapid increase in infections.

Importantly, however, we take no stance on whether one political group is more correct than the other. We note that if one group misinterprets the underlying data and mistakenly underestimates the severity of the virus, it may have significant health outcome externalities; on the other hand, if a group overestimates the virus's severity, it may lead to extensive economic shutdowns with severe economic externalities. Additionally, we are agnostic as to how particular political preferences arise—we simply take as given that some agents in the population hold differing political views. Moreover, we do not explicitly model why a certain political group may choose to prefer a particular interpretation of the data surrounding a health event, beyond the fact that political priors may affect which viewpoint is chosen.[7]

Our findings make a number of distinct contributions to the literature. First, there has been a revived interest among economists over the last few years in understanding how households form

[7] For example, while it is possible that a party in power during a crisis will try to downplay the extent of the crisis for reelection purposes, it is also possible that the opposition party may exaggerate it to galvanize the population to seek change or to argue that the party in power mismanages crises.

and update their expectations, as well as the determinants of the cross-sectional variation in economic expectations across households (Gennaioli and Shleifer, 2018; D'Acunto et al., 2019a; D'Acunto et al., 2020). While the effects of political polarization on risk preferences have been documented in a variety of economic contexts, our paper is among the first to explore its impact in a health crisis-related setting, documenting significant effects on both risk perceptions and choices. While we know that individuals have a more optimistic view on future economic conditions when they are more closely affiliated with the ruling party (e.g., Bartels, 2002), there has been no clear evidence of these shifts in perceptions being reflected in actual household spending (Mian et al., 2018). In contrast, our findings demonstrate that the effects of political beliefs on risk perceptions in the COVID-19 pandemic led to a significant divergence in the reaction of households associated with different political party affiliations, suggesting differences in the reallocation of economic activity from non-essential to essential businesses in Republican and Democrat-leaning counties.[8] How the current pandemic will affect the expectations of households going forward in the post-pandemic period, and how that may then interact with individuals' political priors, however, remains an open question.[9]

Second, our paper speaks to the emerging literature on economic behavior and impacts in the COVID-19 pandemic. For example, Eichenbaum et al. (2020), Barro et al. (2020), Barnett et al. (2020), and Jones et al. (2020) present macroeconomic frameworks for studying epidemics. Gormsen and Koijen (2020) study the stock price and future dividend reactions to the epidemic,

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[8] Pastor and Veronesi (2019) in their model of political cycles argue that Democrats may be more risk averse than Republicans, however risk aversion alone cannot explain the differences that we document in our analyses, specifically the catch up by Republicans after conservative politicians are exposed and the White House issues Federal social distancing guidelines. However, it may serve as a complementary explanation for the observed partisan gap in behavior changes.

[9] Other large macro-economic shocks, such as the Great Depression and the Black Death, have been shown to have long-lasting effects on people's attitudes towards risk (Malmendier and Nagel, 2009; D'Acunto et al. 2019a).

Baker et al. (2020) study household spending and debt responses to COVID-19, Hassan et al. (2020) examine firm responses, and Barrios et al. (2020) examine the role of civic capital for social distancing compliance. Among this emerging literature, our paper is at the forefront of a new stream of research exploring the effects of political partisanship on risk perceptions and choices by individuals and households. The most related contemporaneous work in this area is Alcott et al. (2020), who show differences in survey responses regarding perceived risk (using a Facebook survey) and social distancing (using cellphone pings). In contrast to the survey data used in Alcott et al. (2020) to assess risk perceptions at a single point in time, we utilize population-level Google search data, which allows us to capture risk perceptions at a broader scale and overtime as the pandemic unfolds. Other work has since built upon our results, including Bursztyn et al. (2020), who show that areas with greater exposure to shows on Fox News downplaying the effects of the virus experienced more significant cases and deaths, further strengthening our findings in support of a media and information channel.

Third, our work sheds light on the efficacy of certain types of policy interventions during a health pandemic. Our findings suggest that requests for voluntary compliance with recommended behaviors may not be effective when different populations assess the riskiness of the situation differently. This conclusion has a number of parallels to the extensive literature exploring the effects of risk perception on economic choice in the context of inflation expectations, which concludes that policies aimed to stimulate consumption expenditure may be less effective than theory implies given, for example, differing levels of cognitive ability among households (D'Acunto et al., 2019a; D'Acunto et al. 2019b; D'Acunto et al. 2019c). The fact that voluntary requests for social distancing may be viewed at differing levels of seriousness by groups of different political leanings suggests that such approaches may lead to significant negative externalities for society as a whole. Suppose a particular group chooses to ignore voluntary directives due to lower perceived risk. In that case, this affects more than just that group: an individual's actual risk in a pandemic is a function not only of that individual's own actions but also those of the individuals into which he comes in contact, willingly or unwillingly. While an individual whose perceptions of the risk of the pandemic are high may choose to be as precautious as possible, if her neighbors do not have the same perceptions of the risk, she may face a higher chance of being exposed to the disease. Our results suggest that relying on voluntary compliance may be inadequate and that strict enforcement of guidelines may be required to flatten the curve.

II. THE COVID-19 PANDEMIC

A pneumonia of unknown cause was first detected in the Wuhan province of China in early November 2019. The first cases were linked to a virus that was thought to be of animal origin. By December 2019, however, the infection's spread was almost entirely driven by human-to-human transmission in the province. The virus, which was identified as a novel coronavirus, was labeled the Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV2), and the disease it inflicts in humans was labeled Novel Coronavirus Disease-2019 (COVID-19). The World Health Organization (WHO) declared the outbreak to be a Public Health Emergency of International Concern on January 30, 2020, and by March 11, upgraded the outbreak to a Pandemic status. As of September 28, 2020, over 2 million cases of COVID-19 had been reported in the U.S. alone, and 33.5 million worldwide, resulting in over 1 million deaths (for real-time case numbers, please see https://www.worldometers.info/coronavirus/).

The first reported case in the U.S. was in Washington State on January 21, 2020, involving a male patient who had returned from Wuhan, China. Several other cases followed. The U.S. federal government established the White House Coronavirus Task Force on January 29. On February 26, the first case in the U.S. in a person with "no known exposure to the virus through travel or close contact with a known infected individual" was confirmed by the Centers for Disease Control and Prevention (CDC) in northern California, marking the beginning of community spread of the disease. In the days that followed, most major airlines suspended flights between the U.S. and China, and the Trump administration declared a public health emergency and announced restrictions on travelers arriving from China.

Because the major transmission vector for COVID-19 is through respiratory droplets and fomite (i.e., through close contact and by respiratory droplets produced when people cough or sneeze), efforts to prevent the virus primarily focus on preventing exposure. These include travel restrictions, quarantines, curfews, workplace hazard controls, event postponements and cancellations, facility closures, work-from-home, and voluntary or mandatory social distancing efforts.

III. DATA SOURCES

Our study uses a diverse set of novel datasets to explore the relation between risk perceptions and political polarization. We obtain the COVID-19 case counts and deaths from the Centers for Disease Control and Prevention (CDC), search trends data at the Nielsen DMA-level from Google Health Trends, and the measures of average change in daily travel distance and average change in visits to non-essential businesses and services for residents in a county by county-day from a large location data products company. We integrate political, social, and demographics data from numerous other standard datasets. Detailed information about each dataset is provided in the online Appendix, with a summary of the variables used displayed in online Appendix Table 1. Below, we describe our key variables of interest.

A. COVID-19 Cases and Deaths

We compute both the number of confirmed COVID-19 cases and deaths in a DMA (county) each day to capture the virus's presence in the U.S. We rely on an API from the COVID Tracking Project to obtain this data.[10] The data includes the location and date of each case and death, allowing us to geo-assign them to a county-day.

B. Google Health Trends Search Share

We utilize the Google Health Trends interface to extract data on two types of searches which inform our knowledge of risk perceptions during the pandemic: searches for COVID-19 related terms (COVID-19, SARS-CoV2, coronavirus, Wuhan virus, Wuhan pneumonia, Chinese virus) and searches for unemployment-related terms (using the corresponding Google freebase identifier). The standard Google Trends index, which scales results from 0 to 100 based on the most popular term entered, does not easily allow comparisons across geographic areas and time periods. Instead, we use data from the Google Health Trends API, which describes how often a specific search term is entered relative to the total search volume on Google's search engine within a geographic region and time range and returns the probability of a search session that includes the corresponding term for that region and time period. This makes comparisons across locations and time feasible.[11] We track trends for searches for these terms using the Google Health Trends API for all Nielsen DMAs at daily frequency beginning in November 2019 to March 31st.

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[10] https://coronavirus.1point3acres.com/en.

[11] These probabilities are calculated on a uniformly distributed random sample of 10%-15% of Google web searches. Mathematically, the numbers returned from the Google Trend API can be officially written as:

$Value[time, term\ restriction] = P term{-}restriction time\ and\ geo{-}restriction * 10M$

This probability is multiplied by 10 million in order to be readable.

C. Economic Reallocation Proxies

We obtain two measures that proxy for potential economic reallocation from Unacast, a large location data products company. The company combines granular location data from tens of millions of anonymous mobile phones and their interactions with each other each day and then extrapolates the results to the population level. The data spans the period of February 24th to March 31st, 2020. The data provided to us includes the change in visits to non-essential retail and services from baseline (avg. visits for the same day of the week during the non-COVID-19 time period for a specific county) and the change of average daily distance traveled from baseline (avg. distance traveled for the same day of the week during the pre-COVID-19 period for a specific county), with the pre-COVID period defined as January 1, 2020, to March 8th, 2020. The company uses the guidelines issued by various state governments and policymakers to categorize venues into essential vs. non-essential, with essential locations including venues such as food stores, pet stores, and pharmacies.[12]

D. Partisanship Measure

To proxy for political partisanship at the DMA or county level, we utilize data from the U.S. Presidential Election of 2016, obtained from the MIT Election Data Science and Lab (MEDSL).[13] For each county, we calculate the share of voters that voted for Donald J. Trump in the 2016 election (*Trump VS*).[14] We define *High Trump VS* ("high Trump areas") as an indicator taking the value of one if the county is in the top quartile for voter share for Donald J. Trump in the 2016

[12] In Appendix Figure 1, Panel D we geospatially plot the timeline of when the percentage change in our two measures of county social distancing first fell by 30% in each of the counties. There is significant variation in the timing across counties.
[13] https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/LYWX3D.
[14] Appendix Figure 1 Panel A plots the Trump VS by county.

election. Similarly, we define *Low Trump VS* ("low Trump areas") as an indicator variable taking the value one if the county is in the top quartile for voter share for Donald J. Trump in the 2016 election.

E. Exposure to Media Sources

We use two measures of exposure to media sources. First, we use the Google Health Trends search share for Fox News and MSNBC on a daily basis to construct a time-varying ratio of exposure to "right" versus "left" wing media. Second, we use Nielsen's monthly NLTV data to measure the viewership of Fox News in the pre-pandemic period. Nielsen tracks cable television audience sizes using a rotating panel of households with meters and diaries recording their television viewing behavior. While we do not have access to the individual-level viewership behavior, the NLTV data we obtained measures Fox News primetime viewership as the percentage of panelists who tune in to the channel for at least five successive minutes during the prime time line up each day (this includes viewers of Tucker Carlson, Shawn Hannity, and the Laura Ingram show). The monthly viewership rating consists of the average cable viewership for each channel within a market across days. We then take the yearly average in 2019 and generate quintiles based on the viewership intensity of Fox News.

IV. EMPIRICAL ANALYSIS AND RESULTS

We begin our analysis in Figure 1 by examining the relationship between our risk perception measures and the increasing spread of the Covid-19 pandemic in the U.S. Panel A of Figure 1 plots the average search shares for COVID-19 (left panel) and unemployment terms (right panel) by calendar time against the cumulative share of confirmed COVID-19 cases in the U.S. Figure 1 Panel B plots the percentage change versus baseline in average daily distance traveled and visits to non-essential businesses. Consistent with search shares reflecting perceptions of risk, we see a drastic increase in search for COVID-19 as initial cases appear in the U.S. This search behavior levels off towards the end of March, once much of the population has presumably educated themselves about the virus. Search for unemployment terms rises sharply beginning mid-March, as cases begin to increase rapidly and state-level closures of non-essential businesses start to come under consideration and continue to grow with the increasing economic uncertainty of the pandemic spread in the U.S. Both daily distance traveled and visits to non-essential businesses fall sharply as search shares for the virus rise.[15]

A. *Risk Perceptions*

Figure 2 presents bin scatters relating search shares for COVID-19 (left panel) and Unemployment Benefits (right panel) to the Trump VSs in U.S. DMAs. Each of the plots controls for the log number of confirmed cases, population density, income per capita, population, the day of the week, and the number of days since the first case in the DMA. Increases in Trump VS are associated with decreases in both search share measures. This negative association provides preliminary evidence on the variation of risk perceptions across political leanings.

We formally investigate this relationship in the following regression, estimated at the DMA level in event time vis a via the first case in a county. We include the six days before and the six days after the day the first case appears in the DMA (in some DMAs, there are not a full six days following the first case, so the number of observations for those DMAs will be lower than 13). Since we estimate in event time, this alleviates concerns regarding the fact that cases first appeared

[15] Appendix Figure 1 Panel C plots when areas researched their peak search level for COVID-19. Panel D plots when the percentage change in our two measures of social distancing first fell by 30% for each county. Data is through March 28, 2020.

in Democrat-leaning counties, arriving only later in the sample period in Republican counties. We estimate the model:

$$\log(Search\ Share_{d,t} + 1) = \beta_1 \log(COVID\ Cases_{d,t} + 1) + \beta_2 \log(COVID\ Cases_{d,t} + 1) * Trump\ VS_d + DMA\_FE + DMA\_FE * day + \varepsilon_{d,t}$$

We use the COVID-19 search share in the first set of specifications, and unemployment terms in the second set. We regress our search share measures on the log number of confirmed COVID-19 cases. We include DMA fixed effects to capture various time-invariant (given that we are looking in total at a period of a single month) risk factors in the areas, such as population level and density, per capita income, education, industries and so forth. We also allow for a DMA-specific linear trend, which allows for different patterns of search over the time period for each DMA.[16] To examine differential responses, we interact the log number of cases with the DMA Trump vote share. In some specifications, we replace Trump vote share with an indicator variable for the DMA is in the highest quartile of DMAs with respect to Trump vote share (High Trump). Standard errors are clustered at the DMA level.

Table 1 displays the estimates. Columns (1) and (4) include the confirmed case count and the DMA FE; columns (2) and (5) add an interaction with Trump vote share and the DMA specific linear trends; columns (3) and (6) replace the vote share with the indicator for High Trump DMA.

In all specifications, we observe a positive relationship between the case count and the search shares. Importantly, however, the interaction models indicate that this positive relationship is muted in areas with higher Trump vote share. Consider column (3). A 10% increase in the number

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[16] We also run the models without DMA fixed effects to examine the relation of search to various observable risk factors. Results remain unchanged.

of confirmed cases increases the search share by 7%. For the High Trump DMAs, however, this increase is essentially canceled out by the interaction term. We observe similar patterns of coefficient signs for the search for unemployment in columns (3)-(5).

In Appendix Table 1, we demonstrate robustness to alternative functional forms to $\log(Search\, Share_{d,t} + 1)$, and in Appendix Figure 2, Panel A plots the estimate of the coefficient on the interaction between log cases and Trump vote share for several alternative specifications in which we add components one by one (controls for national cases, Day and DMA FE). Inferences remain unchanged. Appendix Table 2 demonstrates robustness to clustering standard errors at the state level, rather than DMA, as spatial correlation across DMAs close to each other might lead to downward-biased estimated standard errors.[17]

Suppose high Trump vote share counties perceive the risk to be lower, as suggested by the results in Table 1. In that case, it likely requires a more salient data point—either a higher number of cases or a COVID-19 related death—to change their perceptions than merely the arrival of a case of COVID-19 in the region. Figure 3[18] presents an event study for changes in search shares surrounding two inflection points: the first confirmed case in a DMA and the first confirmed death for Low and High Trump VS DMAs. The estimates are obtained by estimating an OLS where the daily log search share is regressed on event time dummies. Each specification controls for DMA time-invariant characteristics such as population, per-capita income, and density. We control for calendar time trends via day fixed effects, and in the first death event study, we also control for time since the first confirmed case. When we look at search shares around the first confirmed case

[17] For example, Trump vote share might vary systematically across space at coarser levels than DMA. Also beliefs and choices might be similar across inhabitants of neighboring areas.
[18] Throughout the paper, we often present the coefficients of interest from our formal models in graphical form, for ease of interpretation. Table versions of the estimations are provided in the Online Appendix (available upon request).

in a DMA, we observe that Low Trump vote share DMAs search almost 40% more than high Trump DMAs in reaction to the DMA's first reported case. Consistent with the High Trump DMAs exhibiting lower perceived risk, it is only following the first death that these counties begin to increase search for information about the virus, essentially playing catchup.

B. Economic Reallocation Proxies

Next, we examine how these different perceptions manifest in individuals' choices, as reflected in their change in visits to non-essential businesses and daily distance traveled. Figure 4 presents bin scatter plots relating percentage changes in daily travel distance (left panel) and percentage changes in the number of visits to non-essential businesses (right panel) to Trump vote share in the counties, once again controlling for observables related to the risk of COVID-19, as in Figure 2. The plots show that increased Trump vote share is negatively (positively) associated with decreases (increases) in daily distances and non-essential trips.

We formalize this analysis in Table 2. We replace the dependent variable in the search share regressions with the two economic reallocation proxies: change in visits to non-essential business and average daily distance traveled. We estimate a county level regression with county and day fixed effects, and cluster standard errors at the county level. Once again, we include the six days before and the six days after the day the first case appears in the DMA (censored on March 31st). Since we estimate in event time, concerns about Democrat counties having been among the earliest and hardest hit are ameliorated.[19] The estimates suggest that changes in behavior increase in confirmed cases (as cases go up, the change in visits to non-essential businesses and daily distance

[19] As in the search share models, the N in each column is slightly different given the variations of the fixed effects structures (in some counties, when we add the linear trend, there is insufficient variation in the outcome to estimate, and observations for that county are automatically dropped).

traveled goes down, becoming more negative), and this effect is again muted as Trump vote share increases. Consider columns (3) and (6). In (3), the coefficient on log cases is -0.04, and the coefficient on the interaction of log cases with the *HighTrumpVS* indicator is 0.02; in other words, the effect of an increase in confirmed cases is muted by 50%. In (6), the respective coefficients are -0.05 and 0.02, a muting of 40%.[20]

Figure 5 demonstrates further robustness with variations on an alternative specification. We regress our behavior change measures on the interaction of *HighTrumpVS* and day indicators, using a variety of specifications, including county and day F.E., state-day F.E., and controls for cases and death counts. More specifically, we estimate variations on the following model:

$$\begin{aligned} Behavior\ Change_{ct} \\ &= \beta_t High\ Trump\ VS_c * Day_t + \alpha'\ Health\ Controls_{c,t} + County_{FE} \\ &+ StateXDay_{FE} + \varepsilon_{c,t} \end{aligned}$$

Figure 5 graphs these estimates in calendar time for high vs. low Trump vote share counties for each specification. The figures show a similar clear difference between *High TrumpVS* counties and other (lower three quartiles of Trump vote share) counties as March began, for all specifications, with less behavior change in high Trump voter share counties as compared to the lower three quartiles, for both the change in visits to non-essential businesses and the change in daily distance traveled. This difference holds even in the strictest specification, where we also control for State x Day fixed effects which capture any differences in state-level stay-at-home mandates in effect. The results remain robust when we omit the county fixed effects and instead control directly for (time-invariant in our sample) education, population, population density, and

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[20] Appendix Figure 2 Panel B examines the sensitivity of our estimates to sample composition.

per-capita income, flexibly interacted with day fixed effects. The gap is mildly attenuated but remains statistically and economically significant.

C. Compliance around State Stay-at-Home Guidelines

Our results in the previous subsections suggest a strong relationship between the county's political leanings and the perceived risk of COVID-19. This perceived risk also appears to translate into differences in choices. Some behavior changes may be driven by state-level orders to close school and businesses or "stay home–work safe."[21] Our analysis next turns to examine directly whether the differences in behavior that we perceive at large survive even in the presence of stay-at-home orders.

To examine this, Table 3 presents estimates from the following difference-in-differences regression:

$$
\begin{aligned}
&Behavior\ Change_{d.t} \\
&\qquad = \beta_1 Post\ Fed\ 15\ Days\ to\ Slow + \beta_2 Post\ State\ Mandating\ Stay\ Home \\
&\qquad + \beta_3 Post\ State\ Mandating\ Bus\&School\ Close + \beta_4 Post\ Fed\ 15\ Days\ to\ Slow \\
&\qquad * High\ Trump\ VS + \beta_5 Post\ State\ Mandating\ Stay\ Home * High\ Trump\ VS \\
&\qquad + \beta_6 Post\ State\ Mandating\ Bus\&School\ Close * High\ Trump\ VS + CountyFE \\
&\qquad + \ \varepsilon_{d,t}
\end{aligned}
$$

As can be seen from the table, even in the presence of stay-at-home guidelines, within a state, and holding all else constant at the county level, *High Trump VS* counties exhibit less change in

[21] Appendix Figure 1 Panel B provides a map of the U.S. which depicts the states adopting mandatory stay at home orders.

behavior from the pre-pandemic period, reducing non-essential business visits less. We observe similar patterns for changes in distance traveled. Only when the Federal order to "slow the spread" arrives from the White House do *High Trump VS* counties begin to catch up. To put this in perspective, consider the estimates presented graphically in Figure 6, which presents the estimates for High and Low Trump vote share counties for each mandate. When states mandate the closure of non-essential businesses and schools, *Low Trump VS* areas reduce average daily travel distance by 9.3%, whereas *High Trump VS* areas reduce by only 6.7%. The difference in behavior for stay-at-home orders is even larger.

The fact that the differences between Democrat-leaning counties and Republican-leaning counties persist even in the face of state-level guidelines to stay at home has important policy implications: issuing guidelines or orders may be insufficient to induce desired social distancing behavior. Put differently, these results suggest that risk perception matters even in the face of local government orders, as those who do not perceive the risk to be that high will not necessarily comply. In the face of a health crisis such as a pandemic, where compliance with such guidelines can be the difference between life or death for many, strict enforcement may be necessary to induce compliance.

D. COVID-19 at the CPAC meeting and Self-Quarantine of Republican Politicians

Is the difference in behavior for different politically-leaning groups driven by media streams from which they consume news or the authority figures conveying interpretation of that news? The increasing political divide in the U.S. and its reflection in how individuals consume news—and, correspondingly, interpret facts—is of particular interest in this context. The viewpoints presented by news sources with different political leanings may lead to different interpretations of factual data, instilling different perceptions of risk in their viewers—who may, in turn, respond differently to social distancing guidelines.

Figure 7 examines behavior changes surrounding the March 9th announcement that Republican politicians were exposed to COVID-19 at the annual CPAC meetings the previous week and had entered self-quarantine. Importantly, the announcement was a change in information only, not a change in county fundamental risk. The figure presents the estimates for High and Low Trump vote share counties from a difference-in-difference specification similar to that presented in Table 2, augmented by a Post-CPAC indicator which we also interact with the base variables from the models in Table 2. The estimation includes the period beginning in February and running until March 31st, 2020. As in prior models, behavior changes are measured in percentage change versus the COVID pre-period. The specification controls for the log number of confirmed cases, population density, income per capita, population, the day of the week, the number of days since the first case in the DMA. We observe that *HighTrumpVS* areas change their behavior significantly following the announcement, reducing daily distance traveled and visits to non-essential businesses by a factor of almost two relative to non-*HighTrumpVS* areas—essentially, catching up—now that the risk is made salient by the fact that political figures on "their side" have been affected. This is not to say that lower Trump vote share counties are not also changing behavior during this period as a result of these and other related events, but rather that High Trump vote share counties react *more* than Low Trump vote share counties.

E. Distinguishing Mechanisms for the Effect

So far, our results do not allow us to directly distinguish whether the mechanism for our documented effects comes through the media channel or rejection of mainstream ideas. Distinguishing the two are important because they imply different belief formation models and have very different policy implications. In particular, the first channel suggests that if Trump voters were exposed to information through news sources that they trust but that argue for a more cautious approach to behavior during the pandemic, they would change their beliefs. The second channel suggests that irrespective of what information they are exposed to, they would not change their beliefs or behavior. Of course, both channels may be at play.

While the results in Figures 6 and 7 indicate that high Trump counties begin to “catch up” once the White House issues social distancing guidelines and conservative politicians are exposed at CPAC are consistent with the media channel, they do not fully allow us to disentangle the two mechanisms. We thus turn next to direct tests of the media channel. First, we examine risk perception in the form of search shares for COVID-19 pre- and post-CPAC as a function of the average ratio of Fox News searches to MSNBC News searches on google in the DMAs during 2019. Figure 8 Panel A presents bin scatter plots relating the search share for COVID-19 on the average ratio of Fox News searches to MSNBC News searches on google in the DMAs during 2019. Each of the plots controls for the log number of confirmed cases, population density, income per capita, population, the day of the week, and the number of days since the first case in the DMA.

To examine the CPAC event's impact on the relation between our measures and the Fox News to MSNBC search ratio, we partition between pre-CPAC event searches and post-CPAC searches. The figure shows that in the pre-CPAC period, the relationship between the Fox News to MSNBC search share ratio and searches for COVID-19 is negative; this reverses and becomes a positive relationship post-CPAC, consistent with Fox News viewers playing catchup once their “own” are affected.

Second, in Figure 8, Panel B, we present estimates from a model similar to that in Figure 7, but where we add an interaction of High Trump vote share with high Fox news viewership from the

Nielsen NLTV data. The figure examines differential changes between High and Low Trump vote share counties in behavior based on Fox news viewership. Specifically, it plots the cumulative change in the percentage change in distance traveled (left panel) and the percentage change in non-essential visits given a 20% increase in the number of confirmed cases after the CPAC announcement in High and Low Trump vote share counties, with the addition of the interaction between High Trump vote share counties and high Fox News Viewership counties (top quintile). We obtain these estimates by estimating models like those in columns (1) and (2) in Table 2. Specifically, we augment the models by using a Post-CPAC indicator and interacting them with the base variables used in the models in Table 2 as well as indicator variables for high Fox News viewership in the county (defined as counties in the top quintile of fox news viewership in 2019 based on Nielsen data). Each plotted estimate includes the 95% confident intervals, and standard errors are clustered at the county level.

The figure shows that the behavior reversal effect is stronger in high Trump counties with high Fox News viewership, suggesting that the media channel is indeed at play in this setting. In high Trump vote share counties, high Fox News viewership is associated with a 21% larger reduction in the distance traveled than in high Trump vote share counties with low Fox News viewership. The media source hypothesis is further bolstered in subsequent work by Bursztyn et al. (2020), who demonstrate using a quasi-natural experiment that within the Fox News viewership, DMAs that watched Sean Hannity more than Tucker Carlson (who acknowledged the dangers of COVID-19 earlier on) had higher caseloads and deaths, and Simonov et al. (2020) who show that higher Fox News viewership leads to lower compliance with social distancing guidelines over the pandemic period.

Thus, overall, we find strong evidence consistent with the existence of a media channel. We cannot rule out that the rejection of mainstream beliefs channel is also contemporaneously at play, however. We note that, to the extent that high Trump vote share counties do not completely "catch up" to low Trump vote share counties in terms of behavior and consumption change, this suggests that some portion of the population is not changing its behavior, irrespective of the news sources they are watching or the viewpoints of party-aligned politicians and authority figures. Thus, it suggests that some portion of the population is likely engaging in similar behavior to pre-COVID periods—likely due to the rejection of mainstream views channel suggested above.

That said, as can be seen from Figure 5 in the paper, high Trump vote share counties begin to catch up to low Trump vote share counties only at the end of March, and only in the most conservative specification. While the estimated coefficient indicates a difference in % change in visits to non-essential businesses that is still ten percentage points lower from high Trump counties, the confidence interval for the estimates does contain zero, at least in the most conservative specification that includes county, and state-x-day fixed effects and COVID cases and deaths, indicating that we cannot reject the null that high Trump vote share counties completely caught up to low Trump vote share counties in terms of behavior changes. This would suggest that the effect is driven primarily by the media source channel rather than the rejection of mainstream views channel. That said, in other specifications we can and do reject the null of complete catchup, suggesting that the rejection of mainstream views channel may be active. Thus, we do not feel it is appropriate to rule out this channel fully.

F. Partisanship and Risk Factors

Presumably, when—objectively speaking—death is on the line, we may expect individuals of all political stripes to react similarly, and for politics to have less influence in the face of the same objective case and death counts. We next conduct similar analyses for varying levels of the elderly population (over age 60) and the ability to work from home in a county. Figure 9 graphically examines the relationship between the population's share over 60 and search share (Panel A) and changes in the daily distance traveled (Panel B). We examine both the fundamental relationship (left column) and the differential effect based on high Trump vote share (right column) for each measure. Each of the plots control for the log number of confirmed cases, population density, income per capita, population, the day of the week, and the number of days since the first case in the DMA or county. In Panel A, as expected, we observe that search for COVID-19 is higher when a higher percentage of the population is at high risk (older than 60). Consistent with the previous findings, this effect is muted in High Trump vote share areas. The reverse patterns hold for average daily distance traveled: distance traveled is lower when a higher percentage of the population is at high risk (older than 60); this effect is muted (if not erased) in High Trump vote share areas.

G. Telework Ability

Figure 10 graphs the estimates from a similar analysis examining the relationship between behavior change and the share of the workforce that can easily conduct work from home ("Telework," Dingel and Neiman, 2020).[22] In the left graph, we examine the fundamental relation, while in the right graph, we examine the differential effect based on high versus low Trump vote share counties. In areas where the share of employment that can be done via telework is higher, visits to non-essential businesses and daily distance traveled is lower. Even so, we continue to observe the divergence in response between high and low Trump vote share counties, holding all else equal: the change is smaller in high Trump vote share counties.

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[22] Dingel and Neiman (2020) classify the feasibility of working at home for all occupations, and merge this classification with occupational employment counts for the United States.

V. CONCLUSION

The contention that partisanship is an active force, resulting in meaningful differences in beliefs and expectations, is a striking claim made in a nascent literature in economics. In this paper, we provide an indication of the possible broad scope of political influence on perceptions of risk and choices by examining politically-related variation in risk perceptions during the current COVID-19 pandemic. Using novel data on individuals' search behavior on Google and geospatial mapping data capturing changes in individuals' daily travel distance and trips to non-essential businesses and service locations, we document a significant divergence in the reactions of areas with high and low Trump vote share areas in the 2016 election to local COVID-19 cases. We document a muted response to preliminary cases in high Trump vote share areas—even as state governments imposed a variety of school and business closures and stay-at-home recommendations—with a catchup in attention only after the disease became salient in Republican political circles and the White House announced Federal restrictions.

As countries across the world struggle to flatten the pandemic curve and lessen the possibility of significant deaths and prolonged economic contraction, understanding how individuals and households react to information treatments and voluntary compliance measures becomes ever more important for the ultimate resolution of the current crisis. Our findings suggest that risk perceptions and—consequently—choices may be shaped through a political screen, rendering certain types of interventions that rely on a uniform interpretation of the risk associated with the outbreak less effective. While many questions remain for future research, the findings provide initial insights that may guide the path of future theoretical and empirical work.

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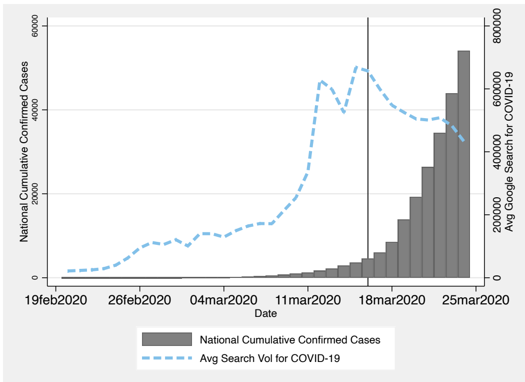
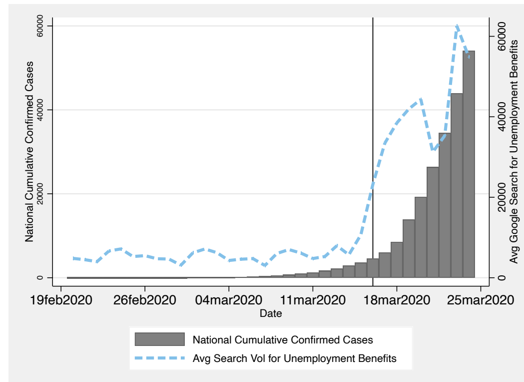
FIGURE 1

PANEL A: TRENDS IN SEARCH SHARES AND COVID-19 CASES

COVID-19 Search Share

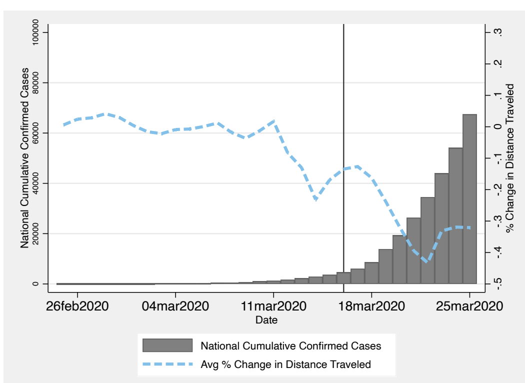


Unemployment Benefits Search Share



PANEL B: TRENDS IN BEHAVIORS AND COVID-19 CASES

Percentage Change In Avg. Distance Traveled



Percentage Change in Visits to Non-essential Business

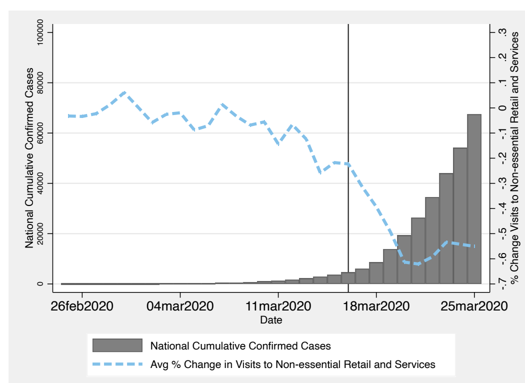
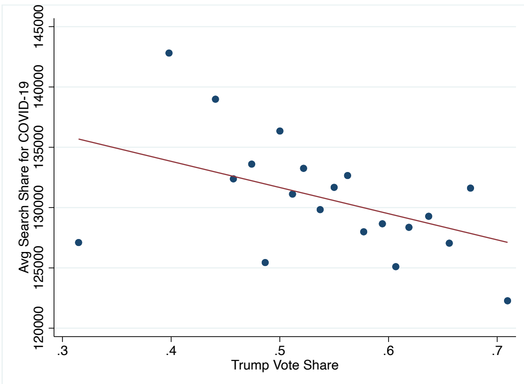


Figure 1 plots the national average trends for each of our outcomes of interest over the first few months of 2020 against the cumulative number of confirmed COVID-19 cases in the United States. In Panel A, we plot the average search share for COVID-19 on google (left panel) as well as search share for unemployment benefits related terms (right panel). In Panel B, we plot the average daily level of our two behavior change variables. In the left panel, we plot the daily average of the percentage change in distance traveled in the county (relative to the pre-COVID period), while in the right panel, we plot the daily average of the percentage change in visits to non-essential business in the county (relative to the pre-COVID-period). A red vertical line marks March 16, the day that the federal guidelines for social distancing where announced.

FIGURE 2

SEARCH SHARE AND POLITICAL POLARIZATION – TRUMP VOTE SHARE

COVID-19 Search Share



Unemployment Benefits Search Share

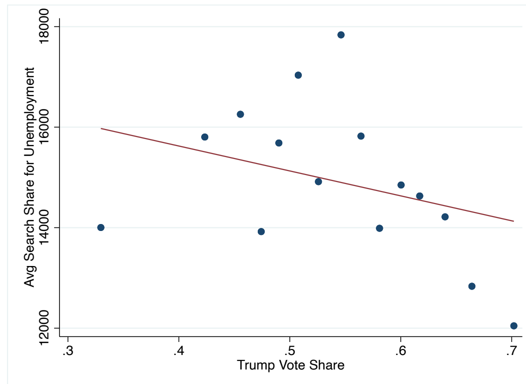


Figure 2 plots our two measures of search share on the Trump VS in the 2016 election in each of the Nielsen DMAs. The left panel uses COVID-19 search shares while we use the search share for unemployment on the right. Each of the plots controls for the log number of confirmed cases, population density, income per capita, population, the day of the week, the number of days since the first case in the DMA.

FIGURE 3

EVENT STUDIES: CHANGES IN SEARCH SHARES AROUND CONFIRMED CASES AND DEATHS FOR HIGH AND LOW TRUMP VOTE SHARE AREAS

First Confirmed COVID-19 Case **First COVID-19 Death**

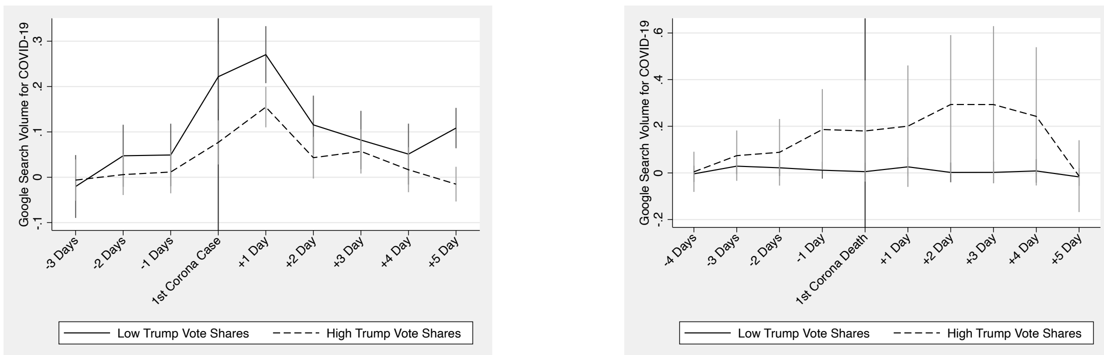


Figure 3 plots abnormal search share for COVID-19 relative to 5 days before the first confirmed case of COVID-19 in a DMA (left panel) and the first COVID-19 death (right panel). These estimates are done for high (red) and low (blue) Trump vote share DMAs. The estimates are obtained by estimating an OLS where the daily log search share is regressed on event time dummies. Each specification controls for DMA time-invariant characteristics like population, per-capita income, and density. We also control for calendar time trends via day fixed effects. Moreover, in the first death event study, we also control for time since the first confirmed case.

FIGURE 4

BEHAVIOR CHANGE AND POLITICAL POLARIZATION – TRUMP VOTE SHARE

Percentage Change in Avg. Distance Traveled **Percentage Change in Visits to Non-Essential Business**

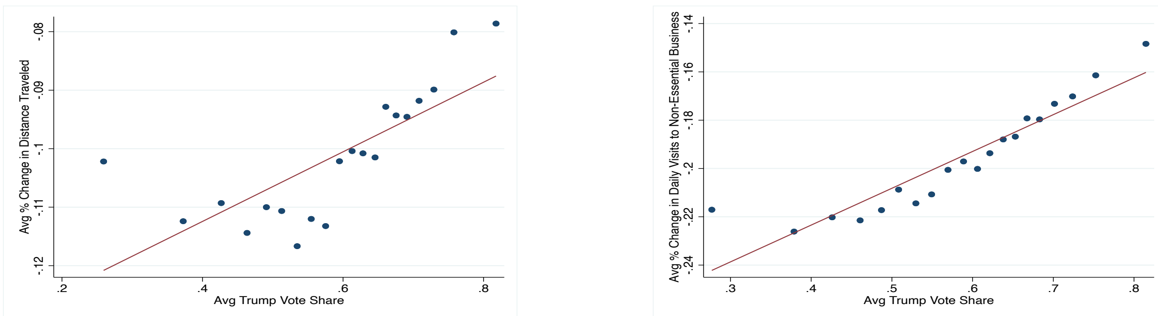


Figure 4 plots our two county social distancing measures on the Trump VS in the 2016 election in each of the counties. The left panel uses the percentage change in the average distance traveled in the county while on the right panel, we examine the percentage change in visits to non-essential businesses in the county. Each of the plots controls the log number of confirmed cases, population density, income per capita, population the day of the week, and the number of days since the first case in the county.

FIGURE 5

TRUMP VOTE SHARE AND BEHAVIOR CHANGE - ROBUSTNESS

Percentage Change in Travel Distance **Percentage Change in Visits to Non-Essential Businesses**

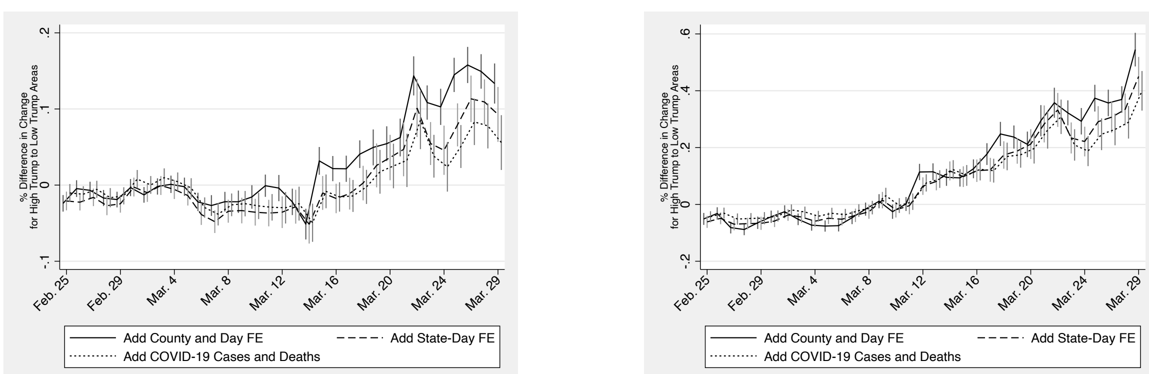


Figure 5 plots the differential changes in the percentage change in travel distancing (right panel) and visits to non-essential businesses for High Trump VS counties to Low Trump by calendar time. The plotted estimates are obtained by regressing the behavior change measures on the interaction between High Trump VS county and the day indicator. In each figure, we plot three specifications – including county and day fixed effects (blue), adding state by day fixed effects, and finally adding controls for COVID-19 cases and Deaths. The higher the coefficient, the lower the behavior change in high trump counties as compared to low trump share counties. Each of the estimates includes 95 percent confidence intervals. The standard errors to estimate these intervals are clustered at the county level.

FIGURE 6

CHANGE IN DISTANCE TRAVELED FOR HIGH AND LOW TRUMP COUNTIES

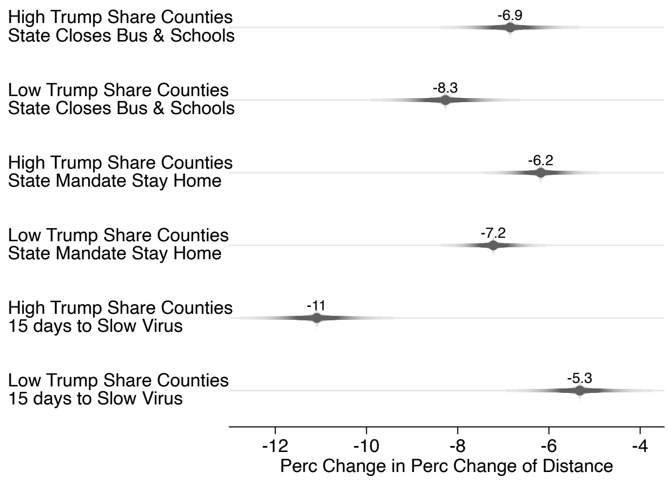


Figure 6 plots the cumulative reaction concerning changes in distance traveled for high and low trump counties around each of the orders along with .95 confidence intervals. These are estimated from the specification in column 1 of Table 3 but using only the high and low trump counties for variation.

FIGURE 7

COVID-19 SCARE AT CPAC AND CHANGES IN SOCIAL DISTANCING BEHAVIOR

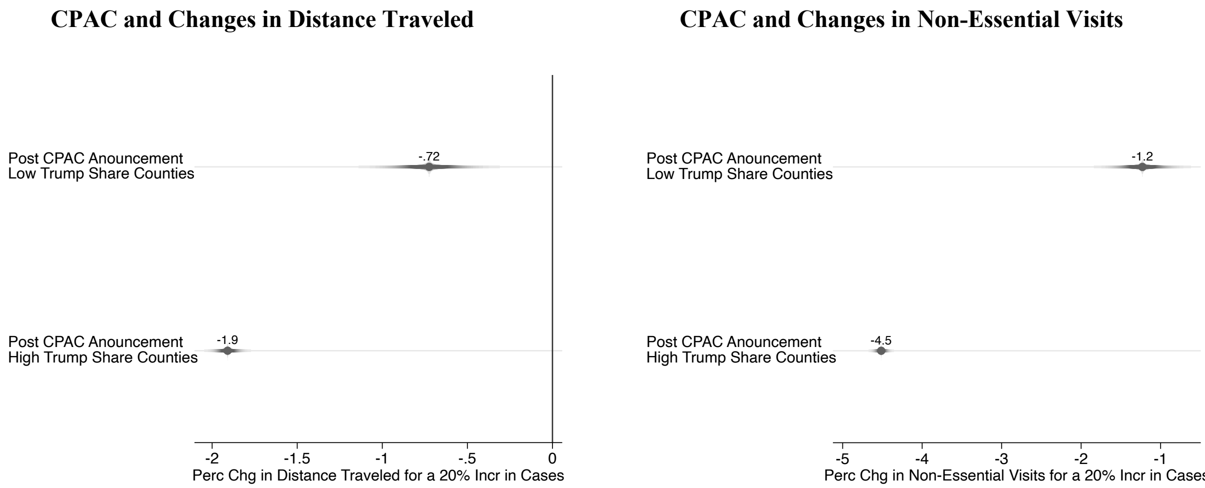
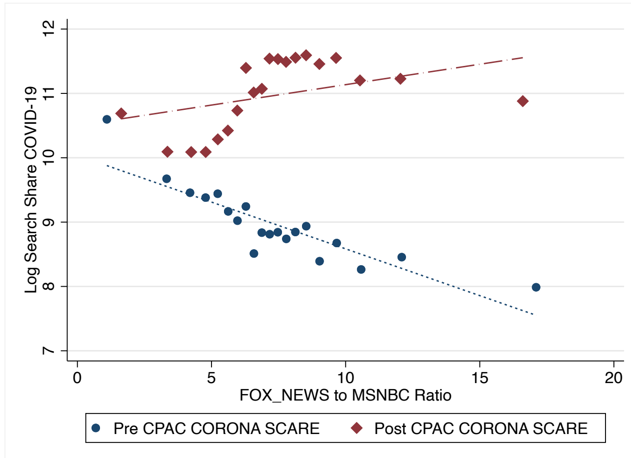


Figure 7 plots the cumulative change in the percentage change in distance traveled (left panel) and the percentage change in non-essential visits given a 20% increase in the number of confirmed after the CPAC announcement in high and low trump vote share counties. We obtain these estimates by estimating models like those in columns (1) and (2) in Table 2. Specifically, we augment the models by using a Post-CPAC indicator and interacting them with the base variables used in the models in Table 2. Each plotted estimate includes 95% confident intervals, and standard errors are clustered at the county level.

FIGURE 8

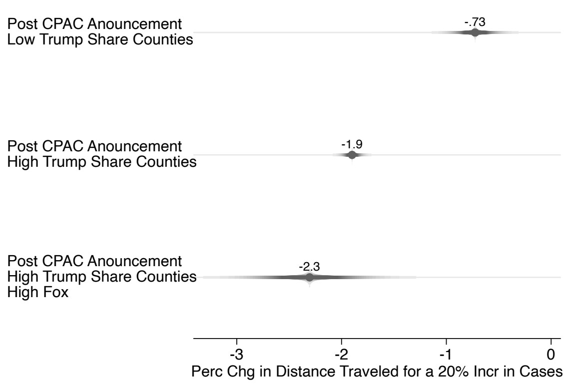
Panel A: COVID-19 SCARE AT CPAC AND RISK PERCEPTIONS BASED ON NEWS VIEWERSHIP

CPAC and Changes in Search Shares



PANEL B: COVID-19 SCARE AT CPAC AND CHANGES IN SOCIAL DISTANCING BEHAVIOR HIGH TRUMP & HIGH FOX NEWS VIEWERSHIP

CPAC and Changes in Distance Traveled



CPAC and Changes in Non-Essential Visits

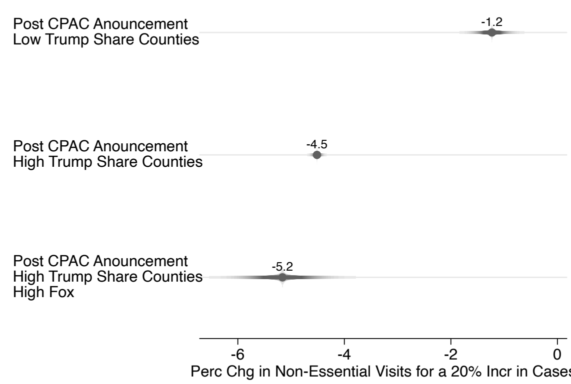


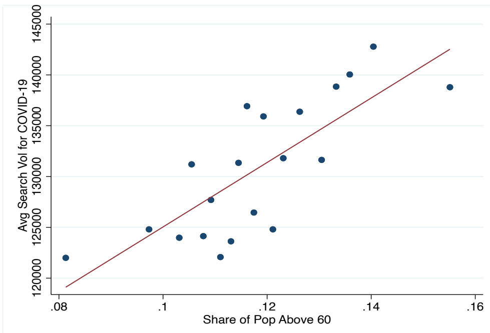
Figure 8 provides two sets of analyses to examine the media's role in affecting risk perceptions using the CPAC scare. Panel A provides bin scatter plots relating the search share for COVID-19 on the average ratio of Fox News searches to MSNBC News searches on google in the DMAs during 2019. Each of the plots control for the log number of confirmed cases, population density, income per capita, population, the day of the week, the number of days since the first case in the DMA. To examine the CPAC event's impact on the relation between our measures and the Fox News ratio, we partition between pre-CPAC event searches and post-CPAC searches. Panel B examines differential changes between high and low trump counties in social distancing behavior and risk perceptions based on news viewership. Specifically, it plots the cumulative change in the percentage change in distance traveled (left panel) and the percentage change in non-essential visits given a 20% increase in the number of confirmed after the CPAC announcement in high and low trump vote share counties as in Figure 7 with the addition of the cumulative change in High trump areas that have high Fox News Viewership. We obtain these estimates by estimating models like those in columns (1) and (2) in Table 2. Specifically, we augment the models by using a Post-CPAC indicator and interacting them with the base variables used in the models in Table 2 as well as Indicator variables for high Fox News viewership in the county (defined as counties in the top quintile of fox news viewership in 2019 based on Nielsen data). Each plotted estimate includes 95% confident intervals, and standard errors are clustered at the county level.

FIGURE 9

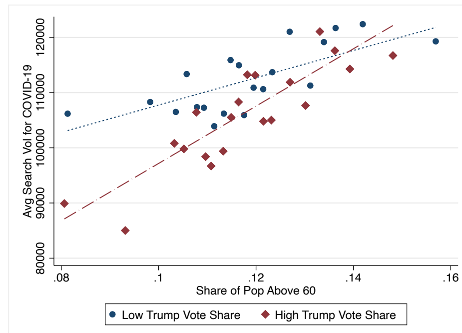
RISK PERCEPTIONS AND SHARE OF THE POPULATION OVER 60

PANEL A: SEARCH SHARE COVID-19

Search Share COVID-19

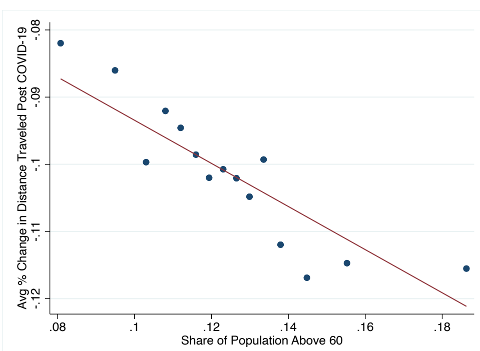


Political Polarization Interaction – Search Vol



PANEL B: PERCENT CHANGE IN DISTANCE TRAVELED

Percentage Change In Avg. Distance Traveled



Political Polarization Interactions – Distance

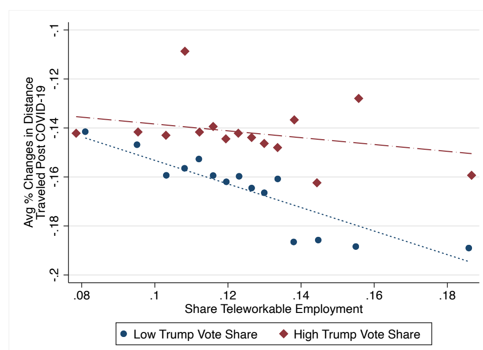
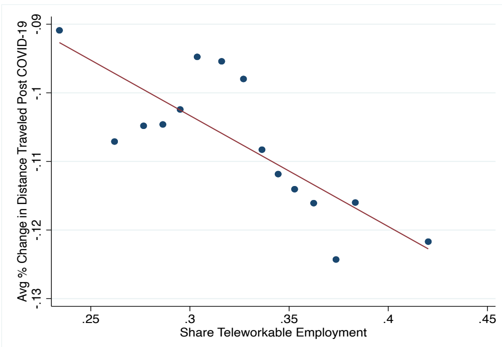


Figure 9 examines the relation between the population's share over 60 and search share (Panel A) and changes in the daily distance traveled (Panel B). For each measure, we examine both the fundamental relation (left column) and the differential effect based on high Trump VS. The search share panels are measured at the Nielsen DMA level while the daily travel distance change is measure at the county level. Each of the plots control for the log number of confirmed cases, population density, income per capita, population, the day of the week, and the number of days since the first case in the DMA or county.

FIGURE 10

SOCIAL DISTANCING BEHAVIOR AND TELEWORKING

Percentage Change In Avg. Distance Traveled



Political Polarization Interactions

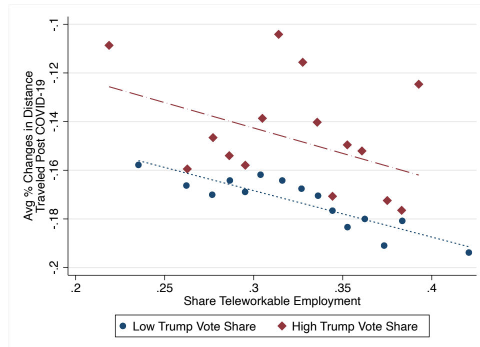


Figure 10 examines the relation between social distancing behavior and the share of the workforce that is easily done at home (Telework). The Telework measure is obtained from Dingel and Neiman (2020). They classify the feasibility of working at home for all occupations and merge this classification with occupational employment counts for the United States. In the left column, we examine the fundamental relation while in the right column, we examine the differential effect based on high Trump VS counties. Each of the figures control for the log number of confirmed cases, population density, income per capita, population, the day of the week, and the number of days since the first case in the DMA or county.

TABLE 1

CHANGES IN SEARCH SHARES AROUND CONFIRMED CASES AND POLITICAL POLARIZATION

	Log Search Share COVID-19			Log Search Share Unemployment		
VARIABLES	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Log Num of Confirmed COVID Cases	0.29**	0.42**	0.08**	0.68**	1.40**	0.18+
	(0.02)	(0.14)	(0.03)	(0.07)	(0.53)	(0.10)
Log Num COVID Cases X Trump Vote Share		-0.67**			-2.69**	
		(0.24)			(1.01)	
Log Num COVID Cases X High Trump Vote Share			-0.10*			-1.04**
			(0.04)			(0.35)
Observations	2,203	2,203	2,203	2,203	2,203	2,203
Adjusted R-squared	0.685	0.849	0.848	0.303	0.390	0.382
Sample	DMA	DMA	DMA	DMA	DMA	DMA
DMA FE	Yes	Yes	Yes	Yes	Yes	Yes
DMA Linear Trend	No	Yes	Yes	Yes	Yes	Yes
Mean Search Share	12.69	12.68	12.69	8.51	8.52	8.51

Table 1 provides a multivariate analysis of changes in search share with respect to COVID cases. The dependent variable is the log search share for COVID-19 (column 1-3) and Unemployment terms (column 4-6). In columns (1) and (4), we regress the search shares on the Log Number of confirmed COVID cases, including DMA fixed effects. In columns (2) and (5), we interact the number of cases with the Trump Vote Share in each of the DMAs and include DMA specific linear trends. Finally, in columns (3) and (6), we replace the vote share with an indicator for High Trump Vote share DMAs (DMA is in the upper quartile of DMAs in trump vote share). Standard errors are clustered by DMA and are reported in parenthesis.

TABLE 2

CHANGES IN SOCIAL DISTANCING BEHAVIOR AROUND CONFIRMED CASES AND POLITICAL POLARIZATION – TRUMP VOTE SHARE

	Perc Change in Distance Traveled			Perc Change in Non-Essential Visits		
VARIABLES	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Log Num of Confirmed COVID Cases	-0.04**	-0.05**	-0.04**	-0.04**	-0.05**	-0.05**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Log Num COVID Cases X Trump Vote Share		0.04**			0.03**	
		(0.01)			(0.01)	
			0.02**			0.02**
Log Num COVID Cases X High Trump Vote Share			(0.01)			(0.00)
Observations	74,587	77,028	77,495	46,254	48,280	62,056
Adjusted R-squared	0.515	0.652	0.638	0.725	0.820	0.808
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Sample	County	County	County	County	County	County
Day FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	No	Yes	Yes	No	Yes	Yes
Mean of Dependent Variable	-0.13	-0.13	-0.13	-0.14	-0.14	-0.11

Table 2 provides a multivariate analysis of our measures of changes in behavior with respect to COVID cases. The dependent variable is the percentage change in distance traveled in the county (column 1-3) and non-essential visits (column 4-6). In columns (1) and (4), we regress the S.D. behavior on the Log Number of confirmed COVID cases, including day fixed effects as well as controls for county population, density, per-capita income, and time since the first case. In columns (2) and (5), we interact the number of cases with the Trump Vote Share in each of the counties while in columns (3) and (6), we replace the vote share with an indicator for High Trump Vote share counties (counties is in the upper quartile of counties in trump vote share). Columns (2), (3), (5), and (6) include county fixed effects. Standard errors are clustered by county and are reported in parenthesis.

TABLE 3

DIFFERENTIAL CHANGES IN S.D. BEHAVIOR AROUND STATE MANDATES

	(1)	(2)
VARIABLES	**Per Chg Dist**	**Per Chg Visit**
Post Fed 15 Days to Slow	-0.08**	-0.18**
	(0.00)	(0.01)
Post State Mandating Stay Home	-0.08**	-0.07**
	(0.00)	(0.00)
Post State Mandating Bus & School Closure	-0.08**	-0.15**
	(0.00)	(0.01)
High Trump Vote Share X Post Fed 15 Days to Slow	-0.03**	-0.00
	(0.01)	(0.01)
High Trump Vote Share X Post State Mandating Bus & School Closure	0.01	0.02
	(0.01)	(0.01)
High Trump Vote Share X Post State Mandating Stay Home	0.02**	0.05**
	(0.01)	(0.01)
Observations	77,495	48,352
Adjusted R-squared	0.459	0.718
Control for Number of Cases	Yes	Yes
Sample	County	County
County FE	Yes	Yes
Mean of Dependent Variable	-0.13	-0.14

Table 3 provides a multivariate analysis of changes in social distancing behavior around the adoption of various measures at the state and federal level to motivate the citizenry to engage in social distancing. Specifically, we focus on the federal regulations to slow the virus, state regulations that closed schools and businesses, and states adopting mandatory stay at home orders. On the right panel, we run a multi-variable regression where we regress our two measures of social distancing on various indicators for the federal and state orders. To examine the differential social distancing behavior by trump areas, we interact with the indicators an indicator for High Trump Vote share counties. Each specification includes controls for the log number of confirmed cases and county fixed effects. Standard errors are clustered by county.