



Risk perceptions and politics: Evidence from the COVID-19 pandemic[☆]

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ARTICLE INFO

Article history:

Received 30 June 2020

Revised 30 September 2020

Accepted 26 October 2020

Available online 1 June 2021

Jel codes:

D8

I1

P16

L82

Keywords:

Risk perceptions

Expectations

COVID-19

Political partisanship

Polarization

Pandemics

Social distancing and compliance

ABSTRACT

Politics may color interpretations of facts, and thus perceptions of risk. 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 COVID-19 case counts and deaths, as Trump's vote share rises in the local area, individuals search less for information on the virus and its potential economic impacts, and engage in fewer visits to non-essential businesses. 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.

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1. Introduction

Understanding how individuals form and update their expectations—and, thus, their choices—is of critical in-

terest to policymakers and economists alike.¹ Individuals appear to exhibit considerable heterogeneity in expectations and risk perceptions (e.g., Gennaioli et al., 2015; Gennaioli et al., 2016; Andre et al., 2019; Coibion et al., 2019; D'Acunto et al., 2019a, 2019b, 2019c), 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.,

[☆] 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.

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

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.” In other words, 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; Mian et al., 2018; Kempf and Tsoutsoura, 2021).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, the COVID-19 setting affects health-related behavior, which could be viewed as non-partisan (Slovic et al., 2004). Viruses are agnostic to political party affiliation, and 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 are 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 follows. 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 if those stories are associated with news outlets or authority figures that do not align with his political views or belief system. 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 (2019), and D'Acunto et al. (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 others. 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 slanted towards or against such views. This group of agents might, for example, have selected into supporting 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, 2009b; Ginsberg et al. (2009)). Google search data have been used 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, cap-

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; Kempf and Tsoutsoura, 2021; Makridakis, 2019).

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

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.

turing 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 US 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 US cellular phones and computes various location-related measures at the county level. For each day and for each county in the US, we obtain the percentage 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 stores 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 US relative to the average for the same day of the week from the beginning of the year up to March 8 (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 US 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 for 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 COVID-19 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 relation between the number of confirmed cases and the 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 change in visits to non-essential businesses is more negative as COVID-19 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 16, 2020.

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 9 that prominent Republicans were self-quarantined due to exposure to COVID-19. Following this announcement, high

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.

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, which 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 relation 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 (i.e. the share of the population over age 60 in the county) and show that even when the share of older people 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 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 non-Trump voters “social distance” more than individual Trump voters, the alternative interpretation to our results would be that non-Trump voters in counties with higher Trump vote share react to the pandemic by *increasing* travel and visits to non-essential businesses relative to the Trump voters in that county, and relative to individuals in counties with low Trump vote share, 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 US by 40%, from 500,000 to 300,000. The authors 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 simply 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 contributions to the literature. First, there has been a revived interest among economists over the last few years in understanding how households form and update their expectations, as well as the determinants of the cross-sectional variation in economic expectations across households (Gennaioli and Shleifer, 2010; D'Acunto et al., 2019a, 2020a). While the effects of political polarization on risk preferences have been documented in a variety of economic contexts, we are 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 era, and how that may then interact with individuals' political priors, however, remains an open question.⁹

Second, our paper is related to the emerging literature on economic behavior and impacts in the COVID-19 pandemic. For example, Barro et al. (2020),

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.

⁸ Pastor and Veronesi (2020) present a model of political cycles and argue that Democrats may be more risk-averse than Republicans. Risk aversion alone, however, 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 issuance of federal social distancing guidelines. However, it may serve as a complementary explanation for the observed partisan gap in behavior changes.

⁹ Other large macroeconomic 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).

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

Barnett et al. (2020), and Eichenbaum et al. (2020) present macroeconomic frameworks for studying epidemics. Gormsen and Koijen (2020) study the stock price and future dividend reactions to the epidemic, Baker et al. (2020) study household spending and debt responses to COVID-19, Hassan et al. (2020) examine firm responses, and Barrios et al. (2021) 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 (Allcott 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 (Allcott 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 over time as the pandemic unfolds. Other work has built upon our results, including Bursztyjn et al. (2020), who show that areas with greater exposure to programs on Fox News downplaying the effects of the virus experience more significant cases and deaths, further strengthening our findings in support of a media and information channel.

Third, our work provides insight 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 conclude 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, 2019b, 2019c). The fact that voluntary requests for social distancing may be viewed at differing levels of seriousness by people with 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 which he comes in contact with, willingly or unwillingly. While an individual whose perceptions of the risk of the pandemic are high may choose to be as cautious as possible, if her neighbors do not have the same risk perceptions, she may face a higher chance of being exposed to the disease. Our results suggest that relying on voluntary compliance may be inadequate to stop the spread of disease and that strict enforcement of guidelines may be required to flatten the curve.

2. 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 spread of the virus 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 the end of September 2020, over 2 million cases of COVID-19 had been reported in the US 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 US was in Washington State on January 21, 2020, involving a male patient who had returned from Wuhan, China. Several other cases followed. The US government established the White House Coronavirus Task Force on January 29. On February 26, the first case in the US 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 US 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.

3. Data sources

We use 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 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.¹⁰ Below, we describe our key variables of interest.

3.1. 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

¹⁰ Detailed information about each dataset is provided in the online Appendix, with a summary of the variables used additionally provided in Online Appendix Table 1.

the virus's presence in the US. We rely on an API from the COVID Tracking Project to obtain these data.¹¹ The data includes the location and date of each case and death, allowing us to geo-assign them to a county-day.

3.2. 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.¹² We track trends for searches for these terms using the Google Health Trends API for all Nielsen DMAs at daily frequency from November 1, 2019 to March 31, 2020.

3.3. 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 from February 24, 2020 to March 31, 2020. The data include 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 8, 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.¹³

¹¹ <https://coronavirus.1point3acres.com/en>.

¹² 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.

¹³ In the Online Appendix, Fig. 1, Panel D plots the geospatial 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.

3.4. Partisanship measure

To proxy for political partisanship at the DMA or county level, we utilize data from the 2016 US presidential election, obtained from the MIT Election Data Science and Lab (MEDSL) (MIT Election Data and Science Lab 2018).¹⁴ For each county, we calculate the share of voters that voted for Trump in the 2016 election (*Trump VS*).¹⁵ 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 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.

3.5. 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 over the sample period 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 pre-pandemic, defined as the year 2019. Nielsen tracks cable television audience size 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 obtain 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.

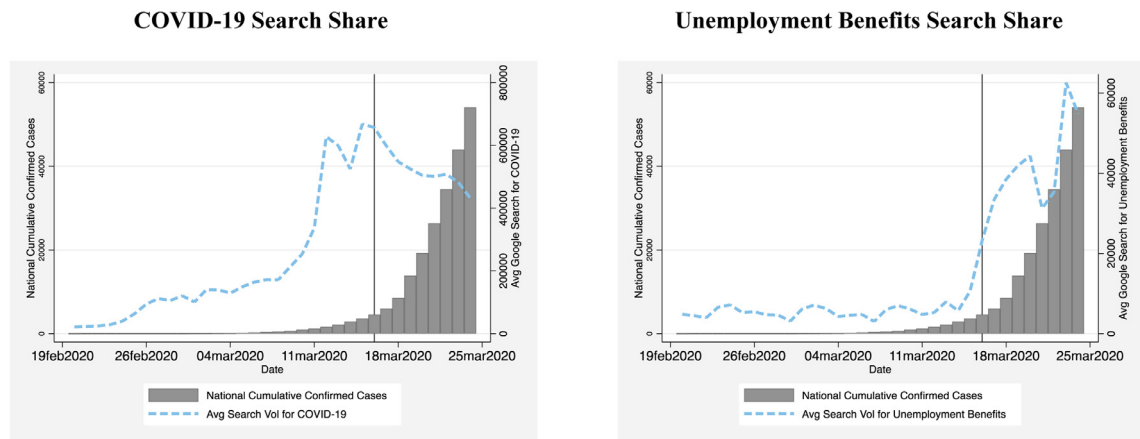
4. Empirical analysis and results

We begin our analysis by examining the relationship between our risk perception measures and the increasing spread of the Covid-19 pandemic in the US. In Panel A of Fig. 1, we plot 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 US. In Panel B, we plot 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 the search shares for COVID-19 as initial cases appear in the US. This search behavior levels off towards the end of March 2020, once much of the population has presumably educated themselves about the virus. Search for unemployment terms rises sharply beginning mid-March, 2020, as cases begin to increase rapidly and state-level closures of

¹⁴ <https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/LYWX3D>.

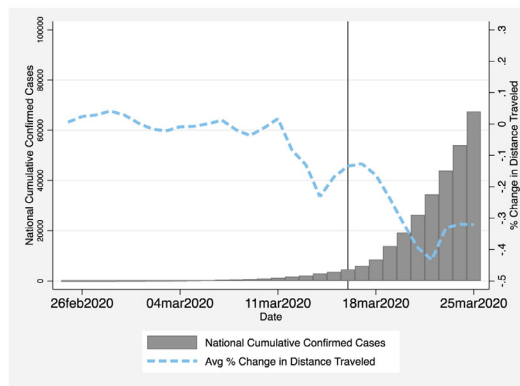
¹⁵ In Online Appendix Fig. 1 Panel A, we plot *Trump VS* by county.

Panel A: Trends in search shares and COVID-19 cases



Panel B: Trends in behaviors and COVID-19 cases

Percentage Change In Avg. Distance Traveled



Percentage Change in Visits to Non-essential Business

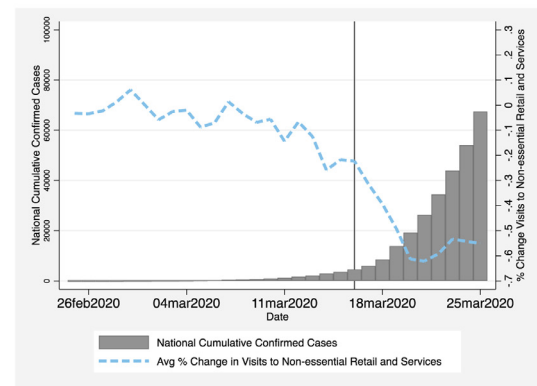


Fig. 1. Trends in search shares, behaviors and COVID-19 cases. We plot the national average trends for each of our outcomes of interest over the first few months of 2020 against the cumulative number of confirmed COVID-19 cases in the US. In Panel A, we plot the average search share for COVID-19 on Google (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 businesses in the county (relative to the pre-COVID-period). A vertical line marks March 16, the day that the federal guidelines for social distancing were announced.

non-essential businesses start to come under consideration and continue to grow with the increasing economic uncertainty of the pandemic spread in the US. Both daily distance traveled and visits to non-essential businesses fall sharply as search shares for the virus rise.¹⁶

¹⁶ In Online Appendix Fig. 1, Panel C, we plot when areas researched their peak search level for COVID-19. In Panel D, we plot when the percentage change in our two measures of social distancing first fell by 30% for each county. Data are through March 28, 2020.

4.1. Risk perceptions

Fig. 2 presents bin scatters relating search shares for COVID-19 (left panel) and unemployment benefits (right panel) to the *Trump VS* in US DMAs. In each of the plots, we 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 COVID-19 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.

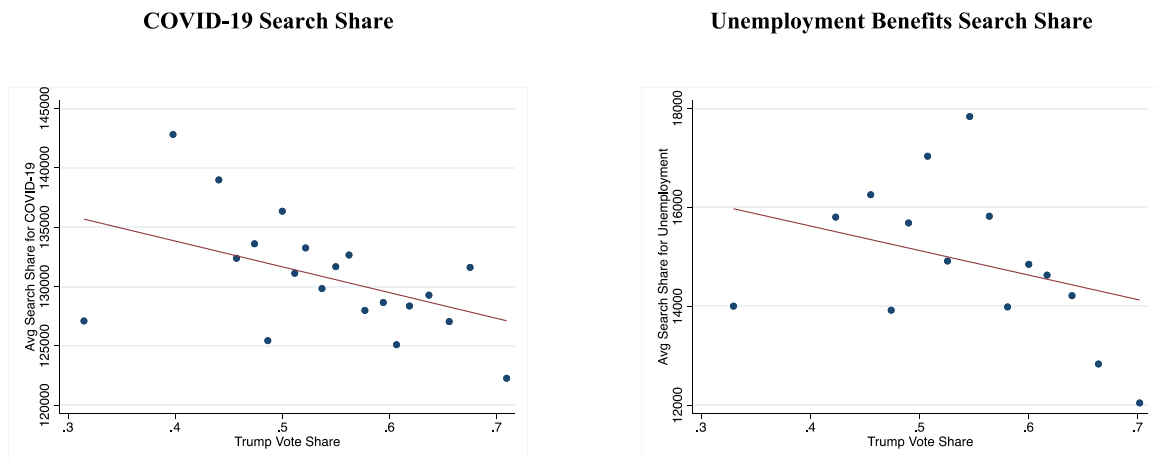


Fig. 2. Search share and political polarization – Trump vote share. We plot our two measures of search share on the *Trump VS* in the 2016 election in each of the Nielsen DMAs. In the left panel we use COVID-19 search shares while we use the search share for unemployment in the right. In each of the panels we 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 COVID-19 case in the DMA.

We formally investigate this relationship in the following regression, estimated at the DMA level in event time via the first COVID-19 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 in Democrat-leaning counties, arriving only later in the sample period in Republican counties. We estimate the following model:

$$\log(\text{Search Share}_{d,t} + 1) = \beta_1 \log(\text{COVID Cases}_{d,t} + 1) + \beta_2 \log(\text{COVID Cases}_{d,t} + 1) * \text{Trump VS}_d + \text{DMA_FE} + \text{DMA_FE} * \text{day} + \varepsilon_{d,t}. \quad (1)$$

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 (*COVID Cases*). We include DMA fixed effects (*DMA_FE*) 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 (*DMA_FE*day*), which allows for different patterns of search over the time period for each DMA.¹⁷ 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 whether or not 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. In the regressions for columns (1) and (4), we include the confirmed case count and the DMA FE; in the regressions for columns (2) and

(5), we add an interaction with Trump vote share and the DMA specific linear trends; and in the regressions for columns (3) and (6), we replace the vote share with the indicator variable for *High Trump DMA*.

In all specifications, we observe a positive relation between the case count and the search shares. Importantly, however, the interaction models indicate that this positive relationship is muted in areas with a higher Trump vote share. For example, in column (3), a 10% increase in the number 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 in columns (3) to (5) for the search for unemployment.

In the Online Appendix, Table 1, we demonstrate robustness to alternative functional forms to $\log(\text{Search Share}_{d,t} + 1)$, and in Online Appendix Fig. 2, Panel A, we plot 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). Our inferences remain unchanged. In Online Appendix Table 2, we demonstrate robustness to clustering standard errors at the state level, rather than DMA level, as spatial correlation across DMAs close to each other might lead to downward-biased estimated standard errors.¹⁸

Suppose people in high Trump vote share counties perceive the COVID-19 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. Fig. 3¹⁹ presents the results of an event study for changes

¹⁷ We also run the models without DMA fixed effects to examine the relation of search to various observable risk factors. The results remain unchanged.

¹⁸ 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.

¹⁹ 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.

Table 1

Changes in search shares around confirmed cases and political polarization.

Table 1 provides the results of 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). For 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. +, *, and ** represent coefficients that are statistically significant at the 0.10, 0.05, and 0.01 levels, respectively.

	Log Search Share COVID-19			Log Search Share Unemployment		
	(1)	(2)	(3)	(4)	(5)	(6)
Log Num of Confirmed COVID Cases	0.29** (0.02)	0.42** (0.14)	0.08** (0.03)	0.68** (0.07)	1.40** (0.53)	0.18+ (0.10)
Log Num COVID Cases X Trump Vote Share		−0.67** (0.24)			−2.69** (1.01)	
Log Num COVID Cases X High Trump Vote Share			−0.10* (0.04)			−1.04** (0.35)
Observations	2203	2203	2203	2203	2203	2203
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 2

Changes in social distancing behavior around confirmed COVID-19 cases and political polarization – Trump vote share.

Table 2 provides the results of 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. +, *, and ** represent coefficients that are statistically significant at the 0.10, 0.05, and 0.01 levels, respectively.

	Perc Change in Distance Traveled			Perc Change in Non-Essential Visits		
	(1)	(2)	(3)	(4)	(5)	(6)
Log Num of Confirmed COVID Cases	−0.04** (0.00)	−0.06** (0.00)	−0.04** (0.00)	−0.04** (0.00)	−0.06** (0.00)	−0.05** (0.00)
Log Num COVID Cases X Trump Vote Share		0.04** (0.01)			0.04** (0.01)	
Log Num COVID Cases X High Trump Vote Share			0.02** (0.01)			0.02** (0.01)
Observations	77,517	77,517	74,587	46,254	46,254	46,254
Adjusted R-squared	0.541	0.678	0.657	0.730	0.821	0.821
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	−0.14	−0.14	−0.13	−0.25	−0.25	−0.25

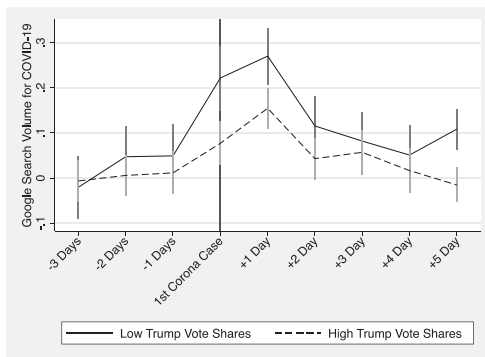
in search shares surrounding two inflection points: the first confirmed COVID-19 case in a DMA and the first confirmed death for low and high Trump VS DMAs. The estimates are obtained using an OLS where the daily log search share is regressed on event time dummies. In each specification, we control for 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 in a DMA, we observe that people in low Trump vote share DMAs search almost 40% more than

people in high Trump DMAs in reaction to the DMA's first reported COVID-19 case. Consistent with people in high Trump vote share DMAs exhibiting lower perceived risk, it is only following the first death from COVID-19 that people in these counties begin to increase search for information about the virus.

4.2. 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 trav-

First Confirmed COVID-19 Case



First COVID-19 Death

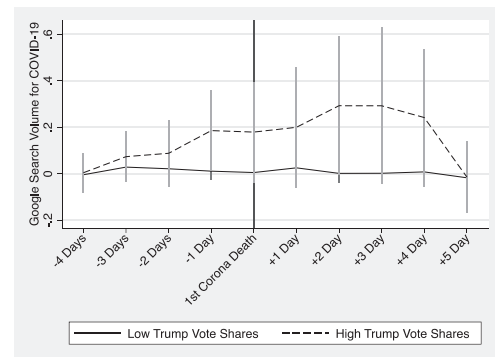
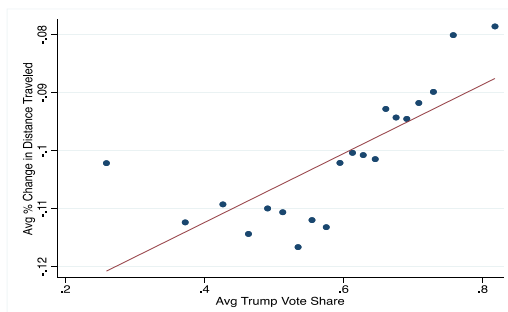


Fig. 3. Event studies for changes in search shares around confirmed cases and deaths for high and low Trump vote share areas. We plot abnormal search share for COVID-19 relative to five days before the first confirmed case of COVID-19 in a DMA (left panel) and the first COVID-19 death (right panel). These estimates are done for high (dotted) and low (solid) Trump vote share DMAs. The estimates are obtained by estimating an OLS where the daily log search share is regressed on event time dummies. In each specification, we include controls for DMA time-invariant characteristics like population, per capita income, and population 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 of COVID-19.

Percentage change in avg. distance traveled



Percentage change in visits to non-essential business

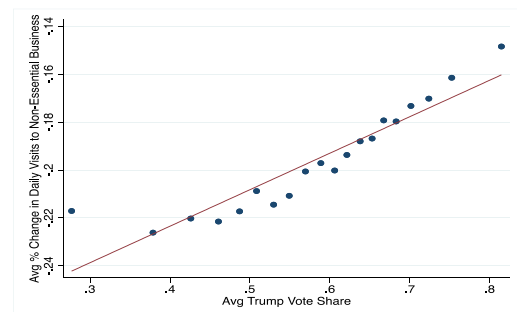


Fig. 4. Behavior change and political polarization. We plot our two county social distancing measures on the *Trump VS* in the 2016 presidential election in each of the counties. The left panel uses the percentage change in the average distance traveled in the county while on the right panel, we examine the percentage change in visits to non-essential businesses in the county. In each of the plots, we control for the log number of confirmed COVID-19 cases, population density, income per capita, population the day of the week, and the number of days since the first case of COVID-19 in the county.

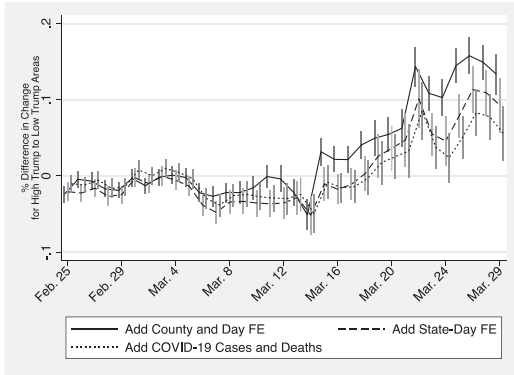
eled. Fig. 4 presents binned scatterplots relating percentage changes in daily travel distance (left panel) and percentage changes in the number of visits to non-essential businesses (right panel) to Trump vote share in the counties, once again controlling for observables related to the risk of COVID-19, as in Fig. 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 businesses 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 COVID-19 case ap-

pears in the DMA (right censored on March 31st). Since we estimate in event time, concerns about Democrat-leaning counties having been among the earliest and hardest hit are ameliorated.²⁰ 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 traveled goes down, becoming more negative), and this effect is again muted as Trump vote share increases. For example, in column (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

²⁰ 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).

Percentage change in travel distance



Percentage change in visits to non-essential businesses

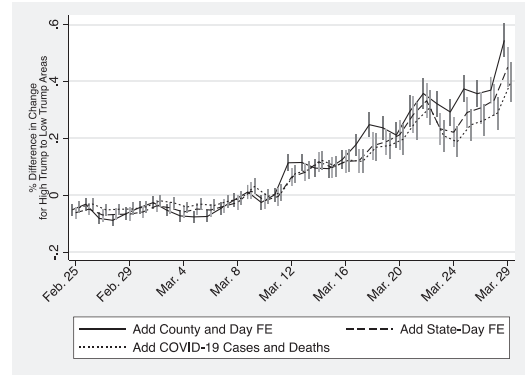


Fig. 5. Trump vote share and behavior change – robustness. We plot the differential changes in the percentage change in travel distancing (right panel) and visits to non-essential businesses for high Trump VS counties to low Trump VS counties by calendar time. The estimates are obtained by regressing 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, 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 share counties as compared to low Trump share counties. Each of the estimates includes 95% confidence intervals. The standard errors to estimate these intervals are clustered at the county level.

effect of an increase in confirmed cases is muted by 50%. In column (6), the respective coefficients are -0.05 and 0.02 , a muting of 40%.²¹

Fig. 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 fixed effects, state-day fixed effects, and controls for cases and death counts. More specifically, we estimate variations on the following model:

$$\text{Behavior Change}_{ct} = \beta_t \text{High Trump VS}_c * \text{Day}_t + \alpha' \text{Health Controls}_{c,t} + \text{CountyFE} + \text{StateXDayFE} + \varepsilon_{c,t} \quad (2)$$

Fig. 5 shows these estimates in calendar time for high versus 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 than in 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 $\times$ Day fixed effects which capture any differences in state-level stay-at-home mandates. 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 per-capita income, flexibly interacted with day fixed effects. The gap is mildly attenuated but remains statistically and economically significant.

4.3. Compliance around state stay-at-home guidelines

Our results in the previous sections 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 mandates to close school and businesses or “stay home–work safe.”²²

Next, we examine directly whether the differences in behavior survive even in the presence of stay-at-home orders. Table 3 presents estimates from the following difference-in-differences regression:

$$\begin{aligned} \text{Behavior Change}_{d,t} = & \beta_1 \text{Post Fed 15 Days to Slow} \\ & + \beta_2 \text{Post State Mandated Stay Home} \\ & + \beta_3 \text{Post State Mandated Bus\&School Close} \\ & + \beta_4 \text{Post Fed 15 Days to Slow} * \text{High Trump VS} \\ & + \beta_5 \text{Post State Mandated Bus\&School Close} \\ & + \beta_6 \text{Post Fed 15 Days to Slow} * \\ & \text{High Trump VS} + \beta_7 \text{Post State Mandated Bus\&School Close} \\ & * \text{High Trump VS} + \text{CountyFE} + \varepsilon_{d,t} \end{aligned} \quad (3)$$

As can be seen in Table 3, 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 behavior from the pre-pandemic period, reducing non-essential business visits less. We observe similar patterns for changes in distance traveled. Only when the 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 in Fig. 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*

²¹ In the Online Appendix, Fig. 2, Panel B, we examine the sensitivity of our estimates to sample composition.

²² In the Online Appendix, Fig. 1, Panel B, provides a map of the US that depicts the states mandating stay at home orders.

Table 3

Differential changes in social distancing behavior around state mandates.

Table 3 provides the results of 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. In each specification, we include controls for the log number of confirmed cases and county fixed effects. Standard errors are clustered by county. +, *, and ** represent coefficients that are statistically significant at the 0.10, 0.05, and 0.01 levels, respectively.

	(1) Per Chg Dist	(2) Per Chg Visits
<i>Post Fed 15 Days to Slow</i>	−0.11** (0.00)	−0.22** (0.01)
<i>Post State Mandating Stay Home</i>	−0.07** (0.00)	−0.05** (0.00)
<i>Post State Mandating Bus & School Closure</i>	−0.05** (0.00)	−0.11** (0.01)
<i>High Trump Vote Share Area X Post Fed 15 Days to Slow</i>	−0.02** (0.01)	−0.00 −0.01
<i>High Trump Vote Share Area X Post State Mandating Stay Home</i>	0.02** (0.01)	0.03** (0.01)
<i>High Trump Vote Share Area X Post State Mandating Bus & School Closure</i>	−0.00 (0.01)	0.01 (0.01)
Observations	80,549	50,425
Adjusted R-squared	0.578	0.756
Control for Number of COVID Cases	Yes	Yes
Sample	County	County
Weekday FE	Yes	Yes
County FE	Yes	Yes
Mean of Dependent Variable	−0.14	−0.26

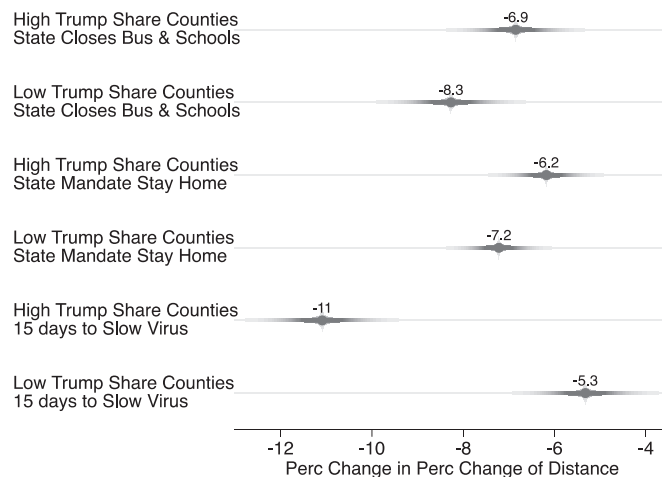


Fig. 6. Change in distance traveled for high and low Trump vote share counties. We plot the cumulative reaction concerning changes in distance traveled for high and low Trump share counties around each of the orders along with 0.95% confidence intervals. These are estimated from the specification for column 1 of Table 3 but using only the high and low Trump share counties for variation.

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 im-

portant policy implications: issuing guidelines or unenforced mandates 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

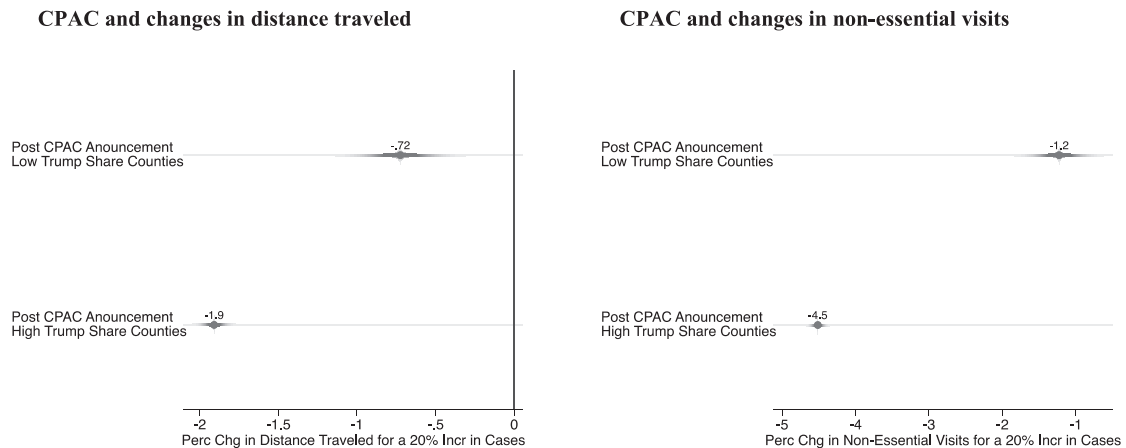


Fig. 7. COVID-19 scare at CPAC and changes in social distancing behavior. We plot the cumulative change in the percentage change in distance traveled (left panel) and the percentage change in non-essential visits given a 20% increase in the number of confirmed COVID_19 cases after the CPAC announcement in high and low Trump vote share counties. We obtain these estimates by estimating models like those for 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 for Table 2. Each plotted estimate includes 95% confident intervals, and standard errors are clustered at the county level.

with such guidelines can be the difference between life and death for many, strict enforcement may be necessary to induce compliance.

4.4. 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 US and its reflection in how individuals consume and 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.

We next examine 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. Fig. 7 presents the estimates for high and low Trump vote share counties from a difference-in-difference specification similar to the one for 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 2020 and running until March 31, 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 of the COVID-19 exposure at CPAC, reducing daily distance traveled and vis-

its 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 politicians on “their side” have been affected. This is not to say that people in lower Trump vote share counties are not also changing their behavior during this period as a result of these and other related events, but rather that the people in high Trump vote share counties are reacting *more* than the people in low Trump vote share counties.

4.5. 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 between the two is 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 that recommended a more cautious approach to the pandemic from their trusted news sources, they would change their beliefs and behaviors. The second channel suggests that regardless of what information they are exposed to, they would not change their beliefs or behavior. Of course, both channels could be at play.

While the results in Figs. 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 to COVID-19 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. Panel A of Fig. 8 presents binned scatterplots relating the search share for COVID-19 on the average ratio of Fox News searches to MSNBC News searches on Google in the DMAs

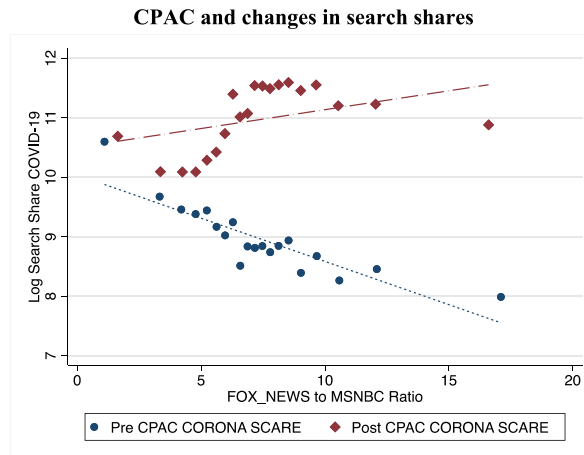
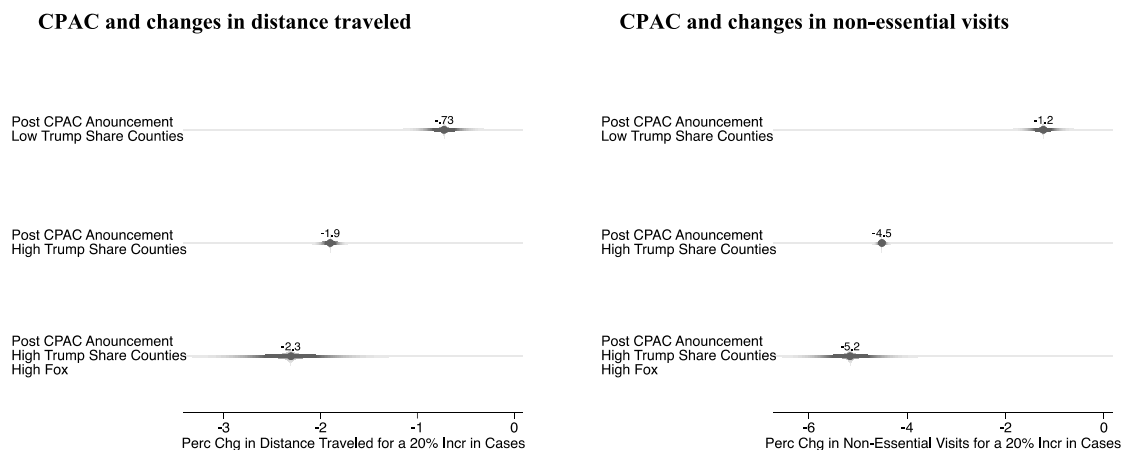
Panel A: COVID-19 scare at CPAC and risk perceptions based on news media viewership**Panel B: COVID-19 scare at CPAC and changes in social distancing behavior for high Trump & high Fox News viewership**

Fig. 8. The role of the media - Trump vote share and behavior changes. We provide two sets of analyses to examine the media's role in affecting risk perceptions using the CPAC score. Panel A provides binned scatterplots 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. We 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 of COVID-19 in the DMA in each plot. We focus on the impact of CPAC on the relation between our measures and the Fox News ratio by partitioning pre and post-CPAC event searches. In Panel B, we examine the differential change between high and low Trump share counties in social distancing behavior and risk perceptions based on news viewership. Specifically, we plot 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 Fig. 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 for 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.

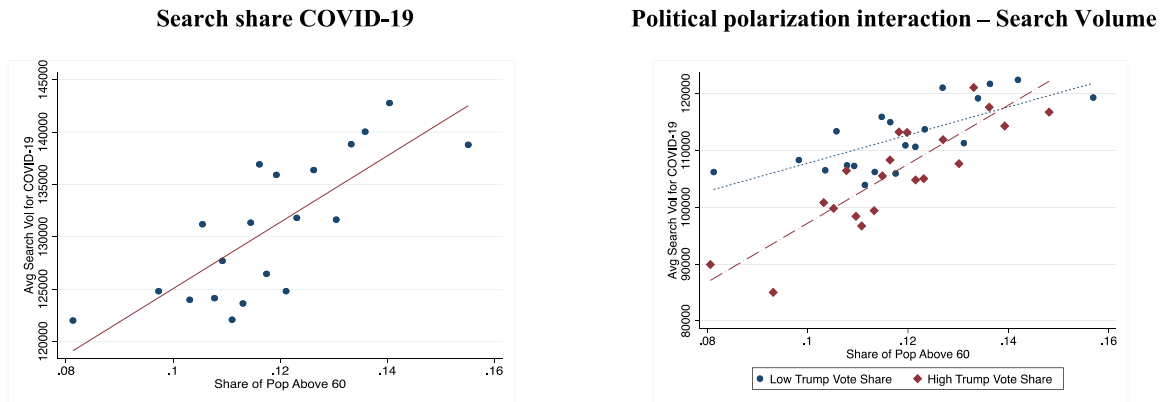
during 2019. Each of the plots controls for the log number of confirmed cases, population density, income per capita, population, the day of the week, and the number of days since the first case in the DMA.

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. Panel A of Fig. 8 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 relation-

ship post-CPAC, consistent with Fox News viewers playing catchup once their "own" are affected.

Second, in Panel B of Fig. 8, we present estimates from a model similar to that in Fig. 7, but where we add an interaction of high Trump vote share with high Fox News viewership from the Nielsen NLTV data. We examine the differential changes between high and low Trump vote share counties in behavior based on Fox News viewership. Specifically, we plot the cumulative change in the percentage change in distance traveled (left panel) and the percentage change in non-essential visits given a 20% in-

Panel A: Search share COVID-19



Panel B: Percentage change in distance traveled

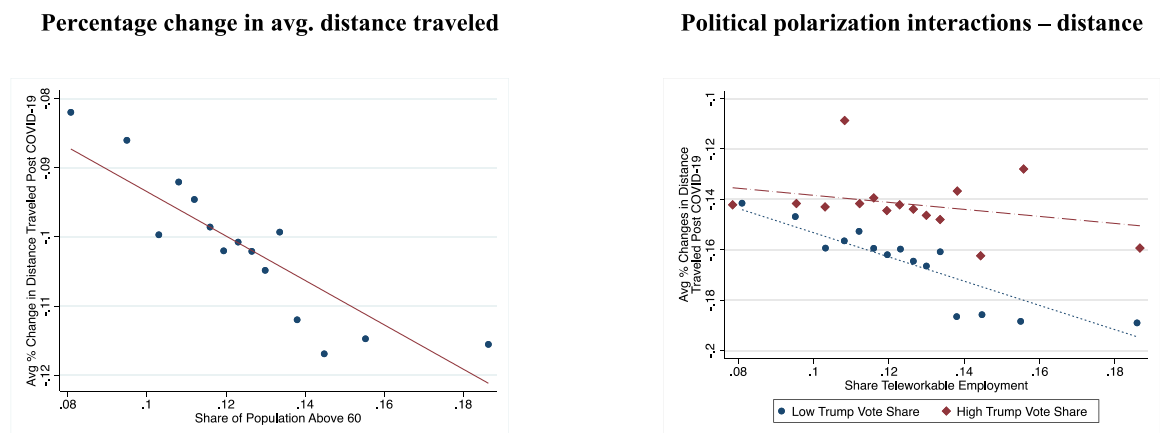


Fig. 9. Risk perceptions and share of the population over age 60. We examine the relation between the share of the population over age 60 and search share (Panel A) and changes in the daily distance traveled (Panel B). For each measure, we examine both the fundamental relation (left column) and the differential effect based on high Trump VS. The search share panels are measured at the Nielsen DMA level, while the daily travel distance change is measured at the county level. In each of the plots, we 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 COVID-19 case in the DMA or county.

crease 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 using models like those implemented in columns (1) and (2) of Table 2. Specifically, we augment the models by using a post-CPAC indicator and interacting it with the base variables used in the regressions for 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.

Fig. 8, Panel B, 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

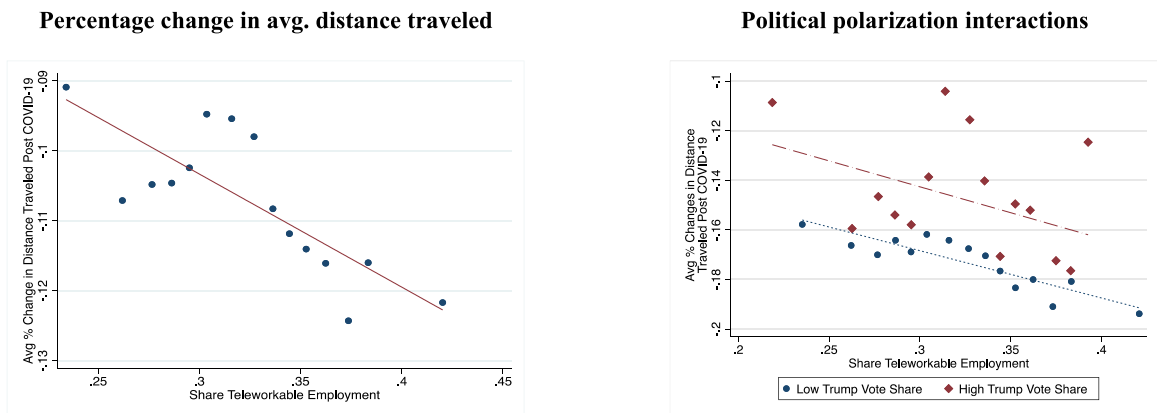


Fig. 10. Social distancing behavior and teleworking. We examine the relation between social distancing behavior and the share of the workforce that is easily done at home (Telework). The Telework measure is obtained from [Dingel and Neiman \(2020\)](#). They classify the feasibility of working at home for all occupations and merge this classification with occupational employment counts for the US. In the left column, we examine the fundamental relation while in the right column, we examine the differential effect based on high Trump vote share counties. In each of the figures, we 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 COVID-19 case in the DMA or county.

subsequent work by [Bursztyn et al. \(2020\)](#), who demonstrate using a quasi-natural experiment that within the Fox News viewership, people in DMAs who watched the Sean Hannity program more than Tucker Carlson (who acknowledged the dangers of COVID-19 early 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 change in consumption, 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 the mainstream views channel suggested above.

That said, as can be seen in [Fig. 5](#), 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 percentage change in visits to non-essential businesses that is still ten percentage points lower from high Trump vote share counties, the confidence interval for the estimates does contain zero, at least in the most conservative specification that includes county and state by day fixed effects while also controlling for COVID cases and deaths. This result indicates that we cannot reject the null hypothesis that high Trump vote share counties completely caught up to low Trump vote share counties in terms of behavior changes, suggesting that the effect is driven primarily by the media source channel, rather than the rejection of mainstream views channel. In other

specifications, we reject the null of complete catchup, suggesting that the rejection of the mainstream views channel may be active. Thus, we do not feel it is appropriate to rule out this channel fully.

4.6. 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 population age, focusing on the population over the age of 60, and the ability to work from home in a county. [Fig. 9](#) graphically depicts the relation between the share of the county population over the age of 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. For each of the figures, we control for the log number of confirmed COVID-19 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 years old). 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 years old); this effect is muted (if not erased) in high Trump vote share areas.

4.7. Telework ability

In [Fig. 10](#), we graph the estimates from a similar analysis examining the relation between changes in behavior and the share of the workforce in the area that can

easily conduct work from home (“Telework,” Dingel and Neiman, 2020).²³ 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. We find that in areas where a larger share of employment can be done via telework, 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. Specifically, holding all else equal, the change is smaller in high Trump vote share counties.

5. 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 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 shares in the 2016 presidential election to local COVID-19 cases. We document a muted response to preliminary COVID-19 cases in high Trump vote share areas. This is evident despite state governments imposing a variety of school and business closures and stay-at-home mandates, with a catchup in attention only after the virus 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 COVID-19 crisis. Our findings suggest that risk perceptions and—consequently—choices may be shaped through a political screen, rendering 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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²³ Dingel and Neiman (2020) classify the feasibility of working from home for all occupations and merge this classification with occupational employment counts for the US.

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