Pandemic Politics:
COVID-19 as a New Type of Political Emergency

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Abstract

Does a state of emergency necessarily contract human behavior? In times of security crises, for instance, citizens overcome their divides. Our analysis explores the relationship between county-level partisanship in the United States during COVID-19 and mobility. We provide an original theoretical analysis to distinguish pandemic politics from politics in times of emergency as we had known them. Our framework helps reconcile previous contradictory findings about this type of emergency politics. Such a frame is needed as it has been a century since the last major global pandemic, and since Coronavirus may not be the last. There are five reasons to distinguish COVID-19 from previously familiar types of emergency politics: psychological, national sentiments, policy-, elite-, and time-related. Our extensive mobility bigdata (462,115 county*days from March-August 2020) are uniquely informative about pandemic politics. In times of pandemic, people literally vote with their feet on government actions. The data are highly representative of the US population. At the pandemic outbreak, our exploratory innovative analysis suggests, political divides are exacerbated. Later, with mixed messages about the plague from party leadership, such exceedingly partisan patterns dissipate. They make way to less politically-infused and more educationally, demographically and economically driven behavior.

Keywords

pandemic politics; COVID-19; emergency politics; political partisanship; rally around the flag; US President; mobility patterns; political ideology; residential mobility; workplace mobility; retail & recreation mobility

Introduction

Emergency situations change human conduct and alter the course of politics. The range of possible behaviors narrows in the face of an emergency. At the individual level, people fight or flight (Cannon 1932; Jansen et al. 1995). At the political level, people close ranks, coalesce and come together (Mueller 1970). COVID-19 is an emergency situation and an international crisis. The US presidency has been directly involved, including president Trump falling ill with it himself. As such, COVID-19 satisfies the conditions of an emergency where we would expect to find a distinct pattern of politics where people close ranks, coalesce and come together (Feinstein 2016). Our goal is to examine whether emergency politics in times of a global pandemic resembles what we know in terms of psychological and political reactions to emergency situations. We do that by examining the relationship between county-level political partisanship and mobility during the first two waves of the pandemic in the USA from March-August 2020.

Literature on emergency situations discusses large scale political and psychological reactions such as the rally-round-the-flag effect. Emergency situations trigger closing the ranks nationally which may include various manifestations of national pride and displays of patriotism. They lead to cohesion in the nation (Sigelman and Conover 1981). Yet, in many ways the opposite is true in the case of COVID-19. Some aspects of political life, and some political conflicts, not only endured but intensified. While partisanship and political sophistication affect reactions of different groups within society to other national emergency situations as well (Baum 2001), the extent to which the reaction to COVID-19 in America was political was far broader. Accounts in the literature diverge as to the effect of COVID-19 (Lipsitz and Pop-Eleches, 2020; Yam et al., 2020) and surveys suggest temporally changing patterns of public opinion about the pandemic (Byocoffe et al. 2020). Accordingly, we aim to resolve existing inconsistencies and characterize pandemic politics and their key patterns over time, thus expanding beyond extant literature theoretically, in terms of number of observations, range of mobility types, the effect of education and time period studied (Gollwitzer et al. 2020). We define Pandemic Politics as politics of a national emergency stemming from a global pandemic.

First, we provide analyses to explain pandemic politics and most importantly distinguish them from politics in times of war or other national security emergencies, typically characterized by rally-round-the-flag effects. Before COVID-19, it has been a century since the last major pandemic hit the world, and made a major impact in the United States and other western Democracies, in the form of the Spanish Flu. COVID-19 threatened both political elites and the public. Unlike wars or terrorist attacks (Kemmelmeier and Winter 2000; Sulfaro and Crislip 2002), the leadership and the public knew scarcely little about pandemics. Accordingly, partisans' positions on COVID-19 were not well established. Unlike familiar topics on the political agenda, people's minds were not set with respect to their positions on the plague.

Furthermore, as the Spanish Flu followed on the heels of World War I, apart from a few exceptions, students of politics were more concerned with the politics of a global war than with the politics of a global illness (Watterson and Kamradt-Scott 2016). A century hence, much has changed in the political sphere at both the domestic and international levels, which suggests that what we did know about politics in times of pandemic during the Spanish Flu may not apply. Thus, theory on pandemic political emergency is thin. As we elaborate below, at the levels of psychological accounts and national sentiments as well as the range and complexity of required policies and degree of elite discord, there are key differences between politics in times of pandemic and other types of emergency politics. Additionally, the time dimension of a pandemic is materially different from that of other crises, which is evident in the temporal patterns of pandemic politics.

Second, in order to investigate the nature of politics in times of pandemic, we provide an in-depth and comprehensive empirical picture of pandemic politics in the USA. The analyses explore the relationship between county-level partisanship and reports of personal mobility. Our outcome variable is based on extensive data for five distinct types of mobility. In times of COVID-19, mobility is a massive behavioral referendum on government actions. Mobility taps the key issue at the interface of citizen and state during the COVID-19 crisis—the extent to which people were allowed to physically move from place to place. Our results suggest that behavioral public reaction—in the form of mobility of various sorts—is acutely partisan at the outbreak of the pandemic, which is the opposite of familiar rally around the flag reactions to emergency. This, however, makes way over time to behavioral patterns reflecting how demographics and education take center stage and where partisanship is relegated a more marginal effect. This change is at least partly attributable to mixed and even contradictory signals from president Trump and members of his administration about the pandemic (see online appendix for details on the press coverage of the administration's reaction to COVID-19). As the pandemic persisted, partisan behavior attenuated when the administration sent mixed signals about the disease. We conclude with some general thoughts about politics in times of zoonotic disease epidemics as well as in times of other natural disasters, such as environmental crises.

COVID-19: A Political Emergency

COVID-19 is an emergency situation and an international crisis. The unfolding events were sudden in nature. With the realization of the existence of the pandemic and soaring infection and death rates, conditions deteriorated rapidly at least in some parts of the country, such as the State of Washington and New York City. Some of the policy measures that were put in place to fight the disease—including quarantine, travel bans and social distancing—were dramatic and abrupt as well. Those measures were adopted sequentially over a tight timeline and dramatically changed daily life (Hsiang et al. 2020).

Figure 1 illustrates how the presence of COVID-19 came about quickly and intensely, at scales similar to war or international conflict. There were radical policy changes at different levels of government; the public and the media were consumed with the topic; and, all those coincided with dramatic changes in how and to what extent people moved about. This was reflected in the overall number of cases (in log scale) denoting the pandemic spread (in Red); the share of COVID-19 related articles out of the overall daily articles based on data harvesting of the New York Times (U.S. and NYC-region sections) (in Purple); the number of states imposing school closures (in Yellow) and stay-at-home orders (in Green); and, the increase in time spent at home compared to 2/15/2020 (in Blue). Our original data suggest that between February 15-March 22, as the number of cases rose from nearly zero to almost 1,000,000 nationwide, coverage of the pandemic in the New York Times rose from 10% to over 80% of the articles in the US and NY sections. The number of states with school closures jumped from 0 to 51 (including Washington, DC). The number of states with stay-at-home orders was nearly 50 by early April. Those changes were associated with dramatic declines in workplace and transit mobility. The pandemic that appeared almost overnight overwhelmed life in a range of different ways, satisfying the conditions of an emergency where we would expect to find a distinct pattern of politics.

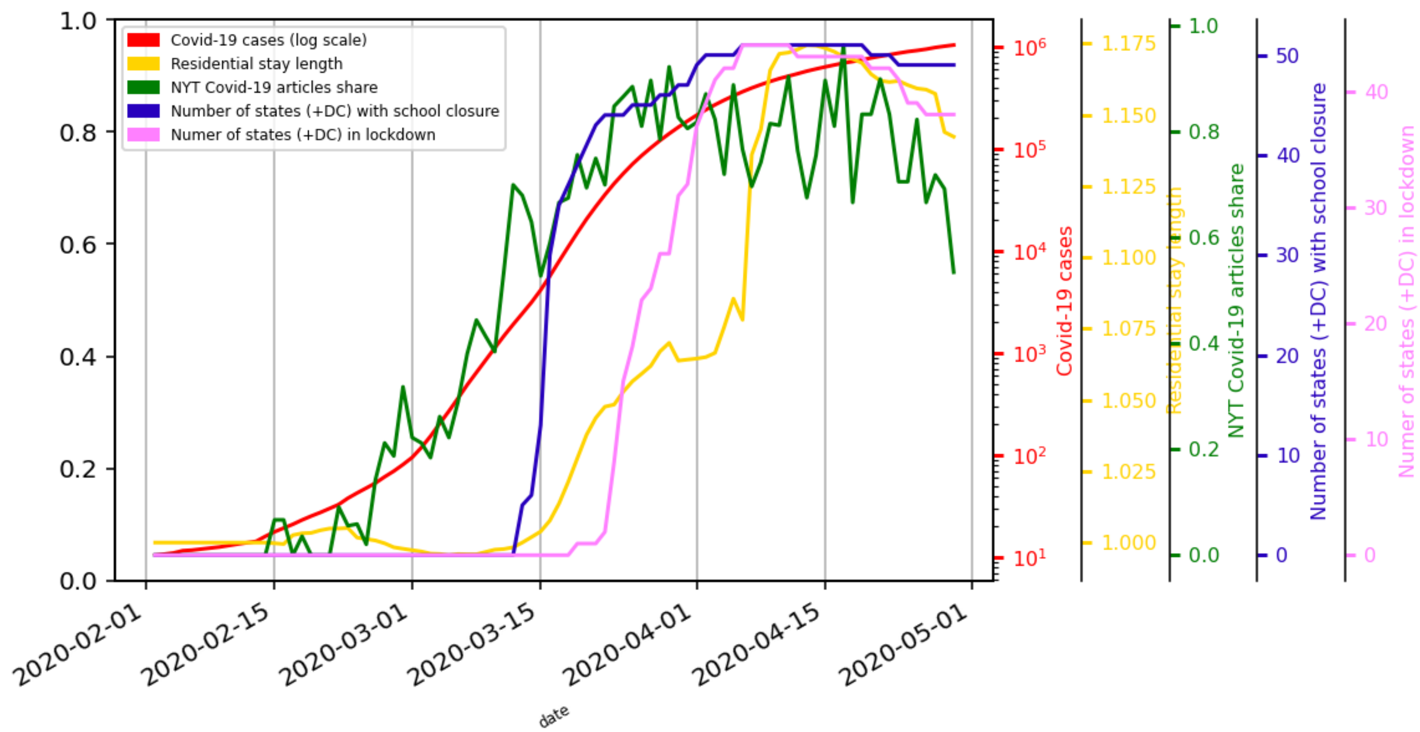


Figure 1 - Indications for the Sudden Nature of the Repercussions of COVID-19

The literature in political psychology and in political science on emergency situations mentions large scale political phenomena, which would take shape under such circumstances. Beyond a spike in presidential approval ratings, emergency situations lead to more cohesion within the nation, even across political parties (Sigelman and Conover 1981). Yet, no such cohesion transpired during the COVID-19 crisis. Let us delve into the range of theoretical frameworks explaining emergency politics as we had known them, and try to decipher why politics of a national emergency stemming from a global epidemic are so profoundly different in the USA from what we know from other types of emergency politics.

Theory

Given the nature of the pandemic, there are several dimensions along which the emergency of COVID-19 is distinct from national security situations, such as wars or terrorist attacks. Several discrepancies—ranging from psychological accounts and national dimensions of the emergency to the range and complexity of required policies, degree of elite discord and time dimensions—help explain why COVID-19 would not elicit emergency politics of the type we were familiar with, and instead would generate a different set of political patterns.

The crisis of the pandemic spans both the international and the domestic arenas (Stapley 2012). Yet, the strong national sentiments standardly dominating the political reactions to emergency situations are absent. Pandemics are not like wars, where enemies tend to be clear and where heroic narratives and protagonists are more likely. Unlike many battlefields, endless rows of hospital beds rarely leave consistent stories to tell or historical narratives to study. The rhetoric of some of the world's leaders notwithstanding (Benziman 2020), there is no sense of a distinct enemy comparable to an adversary in a war situation. This is also the reason why the logic of a diversionary war would not apply in the case of a global pandemic (Levy 1989), further diminishing the likelihood of a rally effect.

Indeed, there are certain aspects of politics in times of pandemic that contradict a strong national sentiment. Social, economic and political ramifications of pandemics are far reaching, hard to overlook and pertain to humanity as a whole. It is these global and universal aspects that may be the critical element. Not only does the story of pandemics not serve and is hardly woven into a national project, but the common human experience of suffering with no clear enemy may be contradictory to national sentiments. When caring for each other, medically or otherwise, is such a major theme, commonalities across the human race are underscored. Yet, it is national projects that determine collective consciousness, form national identity, and govern the content of school curricula. Threatening as they are, pandemics do not make it into national identities, narratives and curriculums. Unlike wars, they do not necessarily trigger the same set of national reactions at the social and individual levels. Thus, in terms of national sentiments, there is little reason to expect pandemics to bring about the standard set of emergency politics, as we know them.

Different theories explain the emotional and cognitive underpinnings of the reactions to a national emergency. Such psychological motivations would lead people in the face of a salient emergency—such as the 9/11 attacks—to affiliate themselves with the American president and with other institutions of government and culture. Those institutions provide a sense of safety and security and have a symbolic role. A range of psychological motivations are key to this political effect. First, scholarship on this topic has focused on rational calculations of success. This is a realist perspective evaluating the chances of military action (Eichenberg 2005; Voeten and Brewer 2006). Yet, such calculations are difficult in the face of a global pandemic such as COVID-19. Furthermore, popular perceptions of security threats about maintaining national security are also influential (Kohut and Toth 1994; Western 2005) as well as the international context within which the political emergency unfolds (Chapman and Reiter 2004). However, the international context for the pandemic, at least in its first few months, but also later, was a mixture of national and international reactions.

The psychological effect of COVID-19 is different in other ways as well. Such psychological motivations—related to terror-management, uncertainly, motivated-social-cognition or uncertainty-management –may be less at play when what is at stake is an epidemic rather than an international conflict in the form or a war or a terrorist attack (Greenberg, Solomon, & Pyszczynski, 1997; Jost, Glaser, Kruglanski, & Sulloway, 2003; Van den Bos, Poortvliet, Maas, Miedema, & Van den Ham, 2005; Doty, Peterson, & Winter, 1991).

The key difference at the level of psychological reactions is the core emotions a pandemic elicits, compared to other major emergencies. When it comes to a national security, anger is the driving force behind the standard reaction of rally around the flag (Lambert et al. 2011). People close ranks and the public becomes more cohesive because of a shared sense of anger directed towards a common enemy. Pandemics on the other hand, raise anxiety. Motivated-social-cognition and uncertainty-management are key to situations where anger is elicited, but pandemics cause anxiety. Anger is not a key reaction to such events (Kamradt-Scott 2020). In the case of COVID-19, instead of reacting with anger (like in the case of a national security crisis), citizens react with anxiety towards the plague and its health, social and economic ramifications. Such a reaction would lead individuals to seek the familiarity of their leader and of their political "home" in the form of their political party. In order to reduce anxiety and feel safe, people would act in a partisan fashion, taking the cues from their party on how to react to the pandemic, with the goal of reducing the sense of anxiety.

While anxiety may open people up to new information regarding the source of threat, it is possible that in the particular information environment of COVID-19—where people's physical movement and human interaction were severely limited—Republicans and Democrats trusted different sources of information about the unfamiliar threat. This may be doubly true when people spent most of their time indoors, obtaining their information from their favorite TV channels and social media platforms, where eco chambers may further sustain initial preconceptions and partisan biases. Consequently, anxiety lead Republicans and Democrats to different information, and thus to profoundly different mobility patterns.

Beyond the deep influence of partisanship on electoral politics and electoral behavior (Achen and Bartels 2016), it also influences a range of social and political life in America, including places of residence and even dating choices (Mason 2015; Huddy et al. 2015; Noel 2013; Mummolo and Nall 2017; Huber and Malhorta 2017). Indeed, in the context of COVID-19, political partisanship is known to play a role in the extent to which social distancing measures are adhered to (Grossman et al. 2020) and influenced support for mail-in voting during the pandemic (Lockhart et al. 2020). The contraction of political spectrums, familiar from other types of political emergencies, would *not* be present in the case of Pandemic Politics in America. Instead, partisanship in the USA would soar, at least at the outbreak.

H1: Instead of closing ranks, COVID-19 would lead initially to partisan reactions among the public.

The pandemic is also distinct from familiar types of emergency politics such as wars in the sense that the actions needed to deal directly with the emergency are diverse and, in many cases, highly complex. In a state of war, the president would win support for his actions related to the international crisis. Job approval of president George W. Bush skyrocketed shortly after 9/11. Yet, the public does not provide the president with a cart blanche. As far as other policies are concerned—policies that are not related to the emergency situation itself—the level of support may be considerably lower (Lindsay and Smith 2003).

In order to deal with a pandemic, the range of government actions is immense, and spans anything from the health system to economic stimuli and from schools to infrastructure. In a state of war, the president would win support for his actions related to the international crisis. The complexity, obscureness and wide range of such government actions necessary to deal with a pandemic decrease the likelihood that people would feel a strong sense of solidarity. In familiar types of national emergency such as wars, people would not bridge their ideological and partisan divides when it comes to policies that do not concern fighting the enemy. The complexity of the emergency and the required actions and policies needed to fight COVID-19 suggests that such support is even less likely in the case of politics in times of pandemic. The implications would also be felt at the level of elites.

In terms of elite discord, according to indexing theories, elite discussion is consequential for emergency politics (Sigal 1973; Bennett 2011). Elite debates determine the parameters of public discussion of political and policy matters. In particular, it is the degree of political (dis)agreement at those levels that makes a difference for how the elite debate develops, for how it is covered by the media and then for its effects on public opinion. The reaction to COVID-19 was distinctly of elite *dis*cord (Green et al. 2020). Elite criticism was high both among political elites and the media (Groelingg and Baum 2008). There is little reason to expect the public to behave differently (Berinsky 2009; Zaller 1992; Baker and Oneal 2001; Oneal and Bryan 1995). In the case of COVID-19, the political positions and various motivations of factions within elites were different. The political differences between Republicans and Democrats on a range of questions ranging from mask wearing to social distancing and to the mere severity of the public health emergency were significant. Most parties did not have a readymade response to pandemics, as they are a new type of emergency, different from wars or terrorist attacks. It is very unlikely that elite disunity of this magnitude would transpire in a national security crisis.

H2: Due to disunity in their ranks, elites would produce mixed messages about COVID-19

The time dimension of a pandemic is materially different from that of other crises. Pandemic's arrival is sudden and it spreads quickly. Yet, it lingers. The development of Covid-19 vaccines, which was remarkably short, took 12 months, but still faces the challenges of wide acceptance, dissemination and administration. With social, economic, political and international ramifications, the crisis could last much longer. Other crises, however—such as a Hurricane landfall or a terrorist attack, for instance—arrive and disappear quickly.

The time dimension of politics in times of pandemic is closely linked to partisan and ideological effects. Partisanship and ideology are key organizing principles, that are critical for how people perceive politics, how they organize political information and how they operate and behave politically (Jacobson 2013). This would include how people cast their vote (Hill and Huber 2018; Bartels 2000), how they determine and form their policy views (Broockman and Butler 2017), and how they evaluate members of other political groups (Iyengar and Westwood 2015). Beyond the very broad influence of partisanship on electoral politics and electoral behavior (Achen and Bartels 2016), it also influences a broad range of social and political life in America. Partisanship would influence perceived credibility (Nicholson 2012), issue attitudes (Levitin and Warren 1979), and support for government actions, even in the case of rather complicated policies (Rudolph and Evans 2005). In this case, however, neither party nor ideology provided a clear guide on how to form positions regarding the pandemic itself and the policies to deal with its ramifications (Barber and Pope 2019; Achen and Bartels 2016; Box-Steffensmeier and De Boef 2001).

There are unique temporal patterns, such as repeated waves, which we deem an essential feature of the time dimension. Since the first case was diagnosed in the USA in late January 2020, and despite variations during the waves of the pandemic, COVID-19 cases and deaths increased incessantly. As this was persistent and increasing over time, it would take time for the elites to form their positions on it. Furthermore, in such circumstances, when the public is mostly a tabula rasa, cues from the party are particularly potent for the positions the public would form. Yet, with no consistent signal from the party (H2 above), with time, the impact of partisanship on people's perception of the pandemic would fade. As time goes by, and given inconsistent cues from partisan leadership about the pandemic (Bisbee and Lee 2020), behavioral patterns would change (Ansolabehere et al. 2008; Lewis-Beck et al. 2008.). If cues from the party are unclear, given the novelty of the topic, the party would lose its significance as a solid guide to forming positions on the pandemic (Ahler and Broockman 2018). During the emergency, without a consistent leader, the partisan group would lose its way. Mixed messages from the president would result in a diminished effect for partisanship (Brody and Page 1972; Page and Jones 1979). This is true for various topics, but is doubly true for a novel issue on the political agenda such as COVID-19 (Markus and Converse 1979). Extant literature provides limited such overtime analysis, and covers a period only up to May 2020, where partisanship still consistently influenced mobility (Gollwitzer et al. 2020).

H3: As time goes by, the effect of partisanship would wane.

The impact of a natural emergency can be fully understood only when social, demographic and economic structures are brought into the picture as well. This was shown to be true in work that studied mobility and evacuations during natural disasters in general (Mileti 2001; Morrow 1997; Cutter et al. 2003; Wisner et al. 2004) and in the United States specifically (Fothergill et al. 1999; Fothergill and Peek 2004). Levels of education, for instance, were linked to mobility patterns during emergencies (Thiede and Brown 2013) and specifically during COVID-19 (Brzezinski et al. 2020). Education is also associated with voting patterns in the United States. The demographic that stood out the most during the Trump era was Whites with no college education, which has increasingly become a key constituency in the Republican Party base. While extant literature does not delve into this effect on COVID-19 (Gollwitzer et al. 2020), such a demographic would impact political behavior even when controlling for ideology and partisanship. This effect would be stable over time. Conversely, as time goes by, and with inconsistent party messaging, politics' effect would diminish. It would make way to the effects of economics, demographics and education variables (Morrow 1997). Since we also control for different types of political minorities (e.g., % African Americans and % Hispanics) and to avoid multicollinearity, we hypothesize an effect for the size of the group with no college education. It is true that the Republican base in the Trump era was heavily populated by *Whites* with no college education, but we opted for a specification for people with no college education of *all* racial groups, in order to avoid high levels of correlation with the political minority variables that we also specify in our models.

H4: The constituency of people with no college education would have a clear effect. This effect would persist over time.

Data and Methods

Our outcome variables are different types of mobility. The study of mobility during COVID-19 offers important solutions to many of the methodological problems that characterize social science research into the citizen-state interface. The first key issue has to do with sampling (Verba 1996; Cuddeback et al. 2008). While statistical inference allows us to extrapolate from samples to the population, a gamut of biases—ranging from selection procedures to inference methods—lead to probabilistically accurate results (Thiem 2007). On top of the probabilistic nature of the results, other issues such as replicability are hard to overcome. We have near complete data for mobility for a huge sample, which likely represents the entire US population.

The Google mobility data we use come from users who have opted-in to Location History for their Google Account. As opting-in to Location History is one out of many choices made when singing up for a Google account, it is reasonable to expect that most people do so with little attention, and almost automatically as a part of a long list of choices they make at the time they open an account. Further validation comes from the fact that the data we used are aggregated and anonymized data similar to Google's widely used services for popular times, wait times, and visit duration for various places. As data for wait times are largely accurate and are based on similar means of mobility data collection and storage, we have good reason to believe the same is true for the data we use. As such, our data take the meaning of representative sample to a new level at least in terms of the numbers of people we have data for. It is, indeed, a bigdata sample, which also means it is likely representative of the US population. Hence, issues of sampling abate. What is more, given that Google has hundreds of millions of users in the US alone, and while only a subset of those opt into Location History, the data we have are bigger—probably by orders of magnitude—and more reliably representative than data in extant literature that are based on 15 million users and are provided by an intermediary software company, Unacast (Gollwitzer et al. 2020).

Secondly, in terms of measurement, social scientists often examine proxies for the variables we wish to measure. In experiments, for instance, to elicit particular emotions, the researcher may present the subjects with certain stimuli, under the assumption that those stimuli generate particular reactions and not others. Likewise, in public opinion surveys, in order to circumvent biases related to social desirability, for instance, questions would tap the issues indirectly in order to measure politically sensitive variables such as racism (Nederhof 1985). Such constraints often lead to use proxies, rather than to directly measure the variable of interest.

With mobility data, instead of using proxies for how states regulate mobility or how citizens react to those regulations, we have a measure that taps the exact interface of citizens and state and on a pivotal issue during the pandemic—moving from place to place. Thirdly, the gaps between the measured variables and actual behavior are often hard to overcome (Padel and Foster 2005; Zaller and Feldman 1992). Gaps between attitude and behavior or between verbal response and actual conduct is largely solved when it comes to mobility data. Rather than asking people about their attitudes towards mobility restriction measures the state put in place, and instead of counting on their word with the host of biases that may be associated (e.g., social desirability), we measure the actual behavior of citizens directly, accurately and aggregately. Which leads us to the final methodological point. Social scientists have widely studied individual level data to learn about mass behavior. However, there are intrinsic and thorny issues related to such extrapolations. There are well documented cases of meaningful difference between micro-level individual behavior to macro-level political conduct (Mansfield and Sisson 2004). Mobility is organized as county-level data and thus allows us to look at the political landscape at the macro level and overcome issues related to extrapolating from individual conduct to mass behavior. In sum, mobility data provide a unique opportunity methodologically and theoretically to investigate pandemic politics. We use aggregate data at the county level, with predictors and outcome variables measured at that level as well.

The time period we study includes the first two waves of COVID-19 in the USA, from March-August 2020. Our dependent variable is mobility data as collected by Google. Google used their aggregated cellular data to provide the changes in 6 types of mobility for each day in each county as compared to the baseline of a standard value for that day of week based on the median value from the 5-week period before the pandemic hit America, from January 3-

February 6, 2020. Compared to extant literature where 2 types of mobility are studied (e.g., Gollwitzer et al. 2020), our analyses benefit from data for 6 types of mobility. The stated motivation for Google in making the data publicly available is to assist in research related to COVID-19 and in sound policymaking. Data are collected at the level of google accounts. Accordingly, the information is for anyone who uses a google account either on their phone or on their computer. Data, thus, are not limited to the Android market penetration, with the caveat of the opting-in option mentioned above. There might be some minimal shifts due to variance in privacy settings, but for the most part our bigdata sample should be highly representative of the US population.

Five types of mobility—retail and recreation, groceries and pharmacies, parks, transit stations and workplaces—measure the change in number of people visiting certain types of locations over 24 hours compared to the baseline. If, for example, the average number of attendants in transit station on Mondays between January 6th and February 3rd in New York county, NY was 2 million, and on Monday, March 16th the number of attendants in transit stations in that county was 500,000, the value for New York county, NY for March 16th would be 0.25.

The residential mobility—as termed by Google—indicates the change in the average amount of time people spent in their homes, in the same granularity (county*day) compared to the same baseline. That is, if, for example, people in New York county, NY had spent on average 16 hours of the day in their homes on Mondays between January 6th and February 3rd, and on Monday, March 16th they spent on average 22 hours, the value for New York county, NY for March 16th would be 1.375. Residential mobility shows a change in duration of time stayed home, which is how Google uses this term, rather than referring to moving households, that is, moving to a new residential location.

Generally, the more people of a certain county took Covid-19 restrictions seriously, the larger values we would expect in the residential mobility and the smaller the values in other types of mobility as measured by Google. When the amount of data in a day/county is too small to keep anonymity, data were not provided for that day/county by Google. Yet, such cases are relatively rare, guaranteeing near completeness of data coverage. All variables are described in Table 1. The coverage figures describe the entire database; in some of the models estimated, rejection of outliers or the overlap (or lack thereof) between variables created minimal levels of data omission. Where that was the case, it is indicated in the specific chart or figure.

Outcome Variables

Variable name	Description	Units	Range	Granularity	number of observations	% of counties covered (daily ave. where applicable)	number of days for which data are available
Residential stay length (in Fig. 1)	see description in text. Data in this figure is smoothed over 7-days	fraction	0-inf	county*day	208,653	86%	88
Residential stay length	see description in text	fraction	0-inf	county*day	227,711	42%	194
Work mobility	see description in text	fraction	0-inf	county*day	451,826	84%	194
Parks mobility	see description in text	fraction	0-inf	county*day	97,995	18%	194
Transit mobility	see description in text	fraction	0-inf	county*day	169,976	32%	194
Pharmacy and groceries mobility	see description in text	fraction	0-inf	county*day	278,669	52%	194
Retail & recreation mobility	see description in text	fraction	0-inf	county*day	306,668	57%	194

Independent Variables

Variable name	Description	Units	Range	Granularity	number of observations	% of counties covered (daily ave. where applicable)	number of days for which data are available
States with school closure	Number of states mandating school closures (where schools are closed in part of the state, the value for that state is share of population in the counties where schools are closed)		0-51	day	4,488	100%	88
States in lockdown	Number of states in lockdown (where part of the state is in lockdown, the value for that state is share of population in the counties in lockdown)		0-51	day	4,488	100%	88
Covid 19 cases (in Fig. 1)	Accumulated number of Covid-19 confirmed cases for the entire U.S., smoothed over 7 days		0-overall pop.	day	88	-	88
Covid 19 cases (in other tables)	Accumulated number of Covid-19 confirmed cases, smoothed over 7 days		0-overall pop.	county*day	471,303	88%	194
Trump-Clinton vote share	Vote share difference between Donald Trump and Hillary Clinton in the 2016 presidential elections	fraction	(-1)-1	county	469,726	87%	194
Time index	Number of days from outbreak start (March 14th)		0-180	day	471,334	88%	194
Weekend	weekday indicator. 0 - weekday, 1 - weekend	bit	0/1	day	471,334	88%	194
African-American share	share of African Americans in county population	fraction	0-1	county	471,334	88%	194

Hispanic share	share of Hispanics in county population	fraction	0-1	county	471,334	88%	194
Asian / Pacific islander share	share of Asians/Pacific islanders in county population	fraction	0-1	county	471,334	88%	194
Population density		people / square mile	0-inf	county	471,334	88%	194
Median household income		$/year	0-inf	county	471,147	88%	194
State-mandated business closures	Estimation of share of retail/recreation business activity allowed according to Covid-19 state regulation	fraction (grades)	0, 0.25, 0.5, 0.75, 1	county*day	471,214	88%	194
Ticket split precent	share of votes which split the ticket between the presidential race, gubernatorial race and House race in the county in 2016 (and 2014). Proxy measure for county polarization			county	451,429	84%	194
Following CDC press release	Indicator whether the CDC has issues a press release concerning COVID within 3 days	bit	0/1	day	471,334	88%	194

Table 1: Variable Descriptions, Units, Range, Granularity and Coverage

Figure 2 provides an initial intuition for patterns of mobility and their potential links to politics. Larger decrease in workplace mobility (i.e., more people avoided going to work) is indicated in the series of maps by purple hues. Increases in mobility are indicated in green. The six maps indicate the geographic disparity of mobility change in one week day (from 00:01AM to 00:00 midnight) over March and early April. Mobility is normalized so that each county is colored according to difference from average mobility index of that day over all counties.

Observing how mobility changes during the first few weeks of the outbreak, a familiar pattern—both between and within states—emerges. As time goes by, it is Democratic counties and states that turn purple (i.e., people move less). Conversely, counties and states voting mostly Republican turn from white (stable mobility) to green (i.e., people move more compared to the average). Where more Republicans reside, we see higher levels of mobility, the rise of the pandemic notwithstanding. Importantly, it was not the temporally-changing geographically varying presence of the pandemic that generated those discrepancies. Several hot spots at the outbreak were Democratic strongholds, but the mobility-partisanship link was unrelated. Specifically, counties turn purple (i.e., less mobility) in Democratic counties hit hard by the pandemic (e.g., NYC and Seattle) as well as those relatively spared the brunt of the plague at this stage (such as Chicagoland and south Florida). This link of mobility to partisanship, rather than to the severity of the plague, is further examined in the multivariate analyses below.

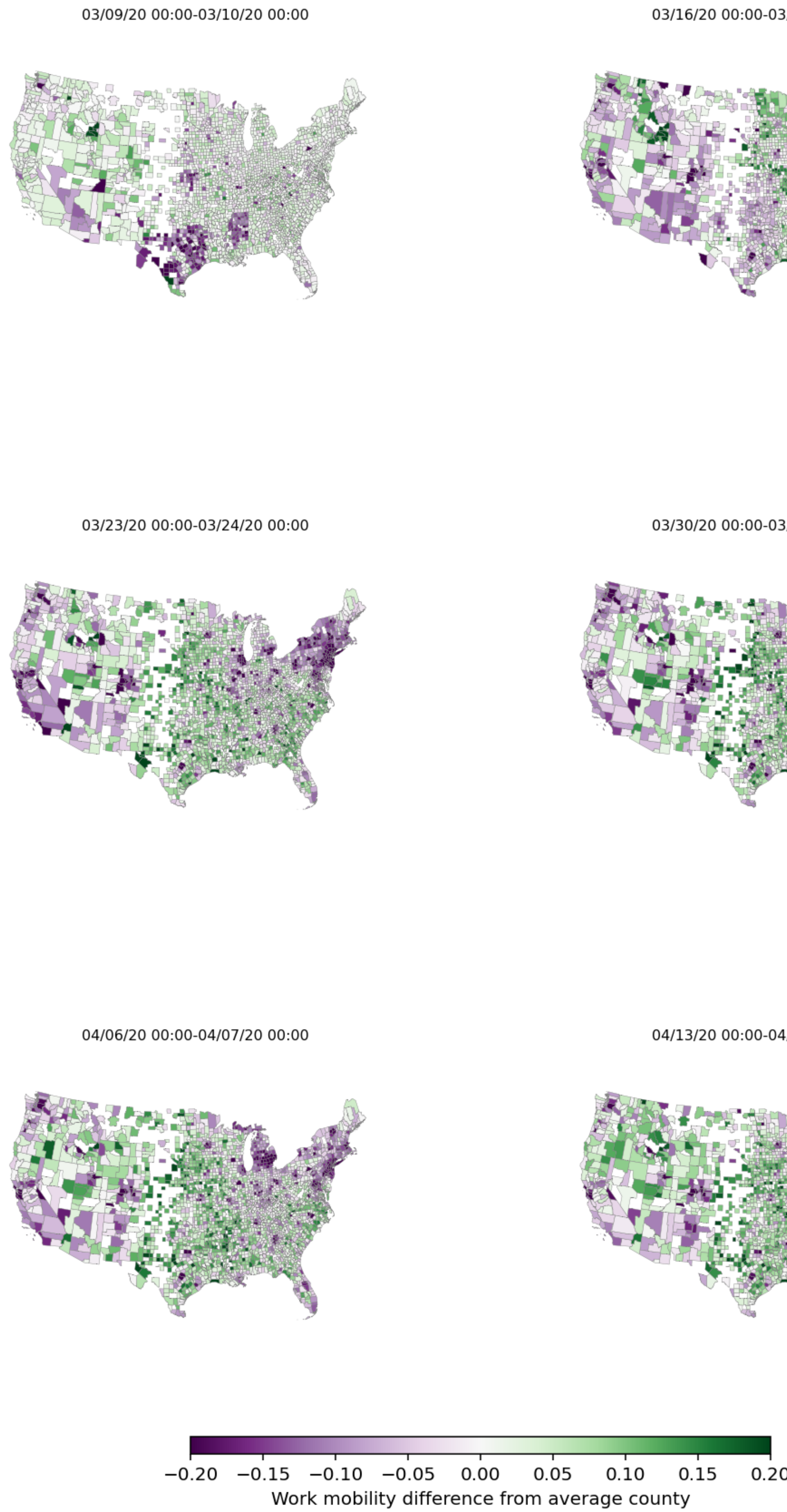

03/09/20 00:00-03/10/20 00:00
03/16/20 00:00-03/17/20 00:00
03/23/20 00:00-03/24/20 00:00
03/30/20 00:00-03/31/20 00:00
04/06/20 00:00-04/07/20 00:00
04/13/20 00:00-04/14/20 00:00
−0.20 −0.15 −0.10 −0.05 0.00 0.05 0.10 0.15 0.20
Work mobility difference from average county

Figure 2 - Workplace Mobility Change over the First 6 Weeks of COVID-19

County level election data were obtained from County Presidential Election Returns 2000-2016 of the MIT Election Data and Science Lab. Demographic variables (e.g., % >65 years old) and economic variables (e.g., household income and unemployment rates) at the county level were also obtained from MIT. COVID-19 data were obtained from the New York Times COVID-19-data page on GitHub and included numbers of cases and deaths. Per capita number of cases was compiled by dividing the number of cases by the size of the respective population. As for ideological polarization, we used two separate measures. Since measures for polarization at the state level, which are typically based on measures such as DW-Nominate Scores, are applicable to the district but not to the county level, we looked at the share of split tickets in the county. In addition, we used the 538 polarization measure, which includes Political Elasticity Scores.

Data for messages at the level of the federal government, by President Trump and members of his administration and by the CDC, were obtained from a range of websites, all listed in the Online Appendix. The CDC variable is coded 1 for dates when the CDC released a public statement about the pandemic and for the next 2 days. Data were harvested for all White House press conferences of the White House Coronavirus Task Force during March and April 2020 with specification for the different speakers attending and coding the content of the message by the speaker regarding COVID-19 as highly serious, moderately serious, neutral, moderately dismissive or highly dismissive.

The state-level COVID-19 regulations were processed mainly from Ballotpedia.org's "Documenting America's Road to Recovery" project, as well as the plethora of state-level reopening plans available online or news reports concerning them. Sources for state-level COVID-

19 regulations are listed in Part 2 of the Online Appendix. For robustness, these data were juxtaposed with data from Adolph et al. (2020). We report the results of OLS and nested regression models specifying a time counter since the beginning of the pandemic. In addition to the time counter, we accounted for the effect of time by smoothing COVID-19 data over a 7-day period to avoid daily noise due to testing and reporting patterns over a week. We also controlled for weekdays or weekends. The findings are robust to a range of model specifications, controls for time and severity of the pandemic, different predictors, sources of data and functional forms. Some additional robustness tests are available in Parts 4 and 5 of the Online Appendix.

Results

The effect of COVID-19 on party and national leadership is apparent. Two exchanges during the April 21st White House Coronavirus Taskforce press conference illustrate this. In the first, when Robert Redfield, Director of the Centers for Disease Control and Prevention, is asked by a reporter to address a piece in the Washington Post, where he is quoted as saying: "there's a possibility that the assault of the virus on our nation next winter will actually be even more difficult than the one we just went through," (Washington Post, April 22, 2020) he confirms and says that this would be due to the possibility of cooccurrence with the flu. Yet, as soon as Dr. Redfield makes this statement, president Trump says: "And you may not even have corona coming back, just so you understand. Doctor, would you like to explain that." However, Dr. Redfield begs to differ, even when the Vice President joins president Trump in prodding him.

Moments later, equally fundamental disagreements among the members of the administration about the pandemic transpire. President Trump says: "it is estimated it might not come back at all, Jeff. It may not come back at all." Only to be followed by Dr. Fauci, director of the National Institute of Allergy and Infectious Diseases, who could not contradict the chief executive more clearly by saying: “No. There will be coronavirus in the fall”. Such contradictory messages, however, were not unique to the April 21st press conference. Data we harvested for press conferences during the first two months of the pandemic suggest that such inconsistency was the rule. Whether due to lack of preparation, different political incentives, or since the virus was a truly historical challenge of unparalleled proportions, there is a systematic pattern of members of the administration sending mixed messages about it.

For a more complete picture, in line with H2, Figure 3 shows the tone towards COVID-19 in statements made by president Trump and key officials in the administration in White House press conferences during March and April 2020. The tone (on the horizontal axis) ranges from highly dismissive of the risks to the left to highly serious about them to the right. Number of appearances with this tone is on the vertical axis and colored bars correspond to each of the main administration officials. The president has changed his mind on the topic repeatedly, sending messages highlighting the risks of the pandemic interchangeably with messages ignoring or downplaying them. The same is true for Vice President Pence, who in addition served as the head of the Corona task force after replacing Secretary of Health and Human Services Alex Azar in this position in late February. While on the individual level, some of those officials were relatively more coherent (e.g., Dr. Fauci tends to treat the pandemic as highly serious), cues on the pandemic are profoundly convoluted. The mixed nature of the messages from the administration persisted throughout the period (see Figure A1 in online appendix for the temporal variation).

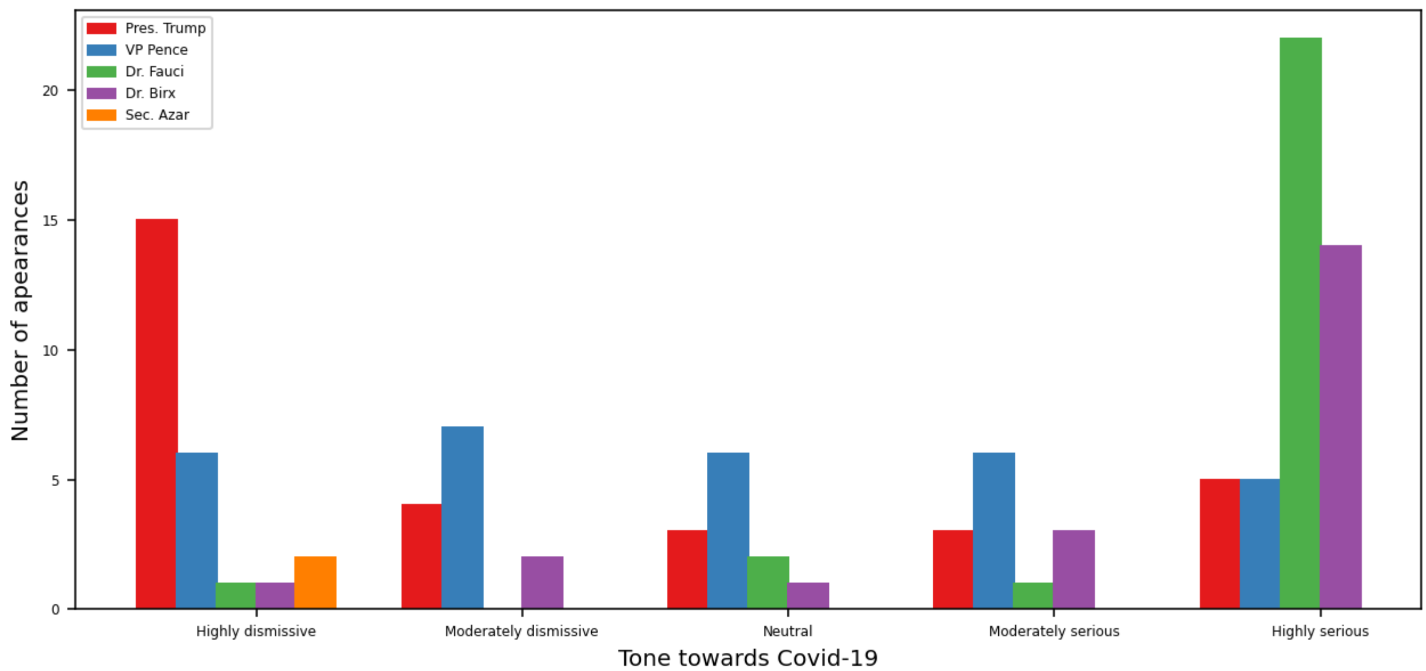


Figure 3 – Tone towards COVID-19 in Taskforce Press Conferences

Switching now from elites to the public, Figure 4 presents tight links between pronouncements by party leadership and mobility, disaggregated by partisanship. The top panel in Figure 4 disaggregates residential mobility patterns by quantile of Republican votes from blue in the most Democratic counties (top quantile) to the least Democratic ones in red (bottom quantile). Values greater than zero on the vertical axis indicate people stayed home more. Values less than zero indicate people's mobility *outside* their homes increased. In the bottom panel is the number of words per speaker in press conferences over time, with the red line for President Trump, and the rest denoting VP Pence, Dr. Fauci and Dr. Birx. Similar analysis using the number of sentences or questions answered reveal the same picture: it is in the second week of March, when the volume of public discussion of COVID-19 by the leadership grows, that mobility patterns diverge according to partisanship. Republicans move much more than Democrats along with the significant growth in President Trump's discussion of the topic.

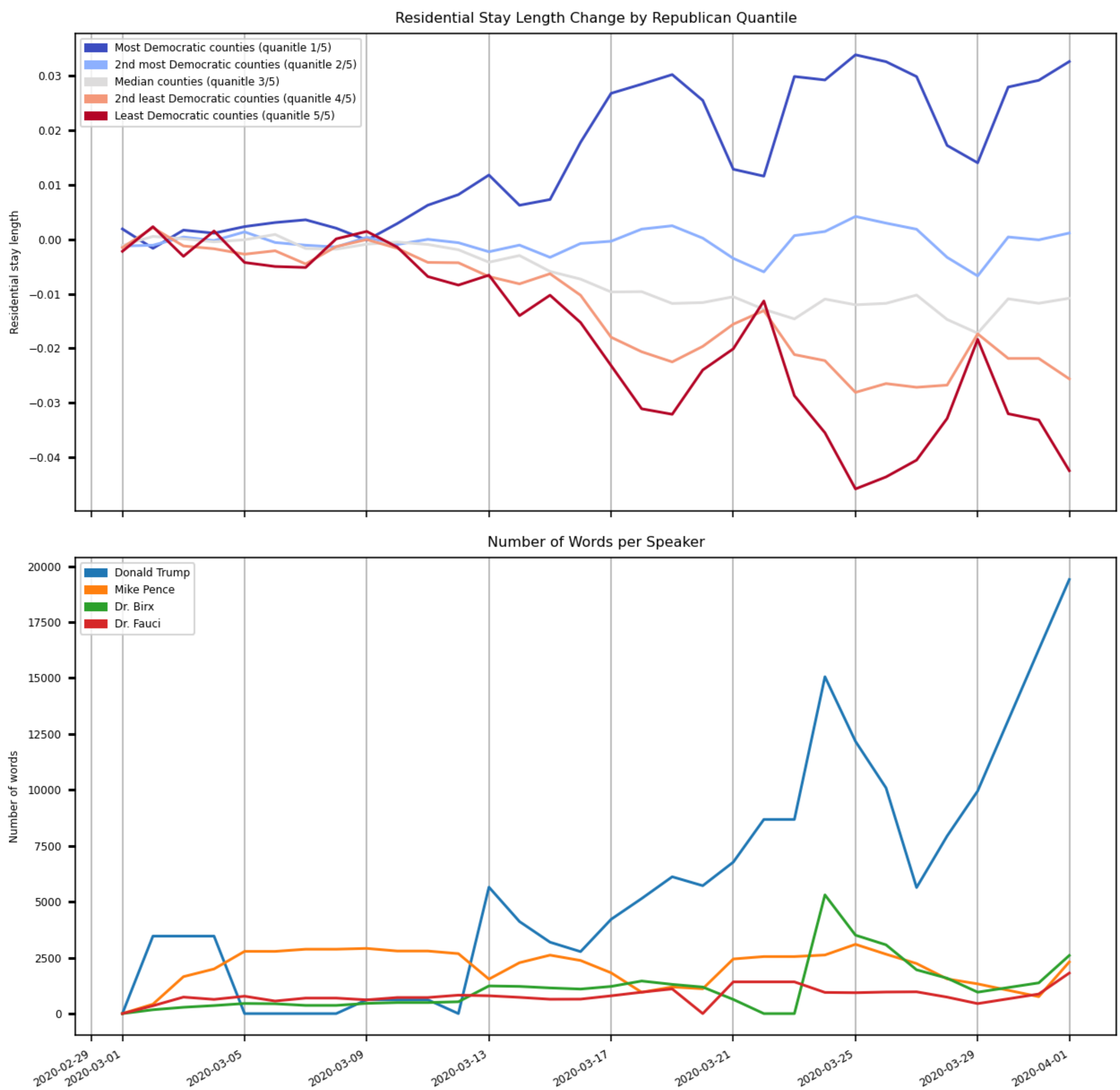


Figure 4 – Messages from Party Elites and Mobility Change by Party

To what extent was the dramatic change in mobility (blue line in Figure 1) related to partisan patterns?

Figure 5 illustrates with a bivariate analysis how mobility changes in relation to the dominant partisanship in the county. X-values denote the share difference between Donald Trump and Hilary Clinton in the 2016 Presidential elections in the county. Y-values denote average deviation of the county from the average time-at-home increase per day. Each point marks a county. Supporting H1, the 2016 election outcome alone explains 40% of between county variance in how much time people stayed home.

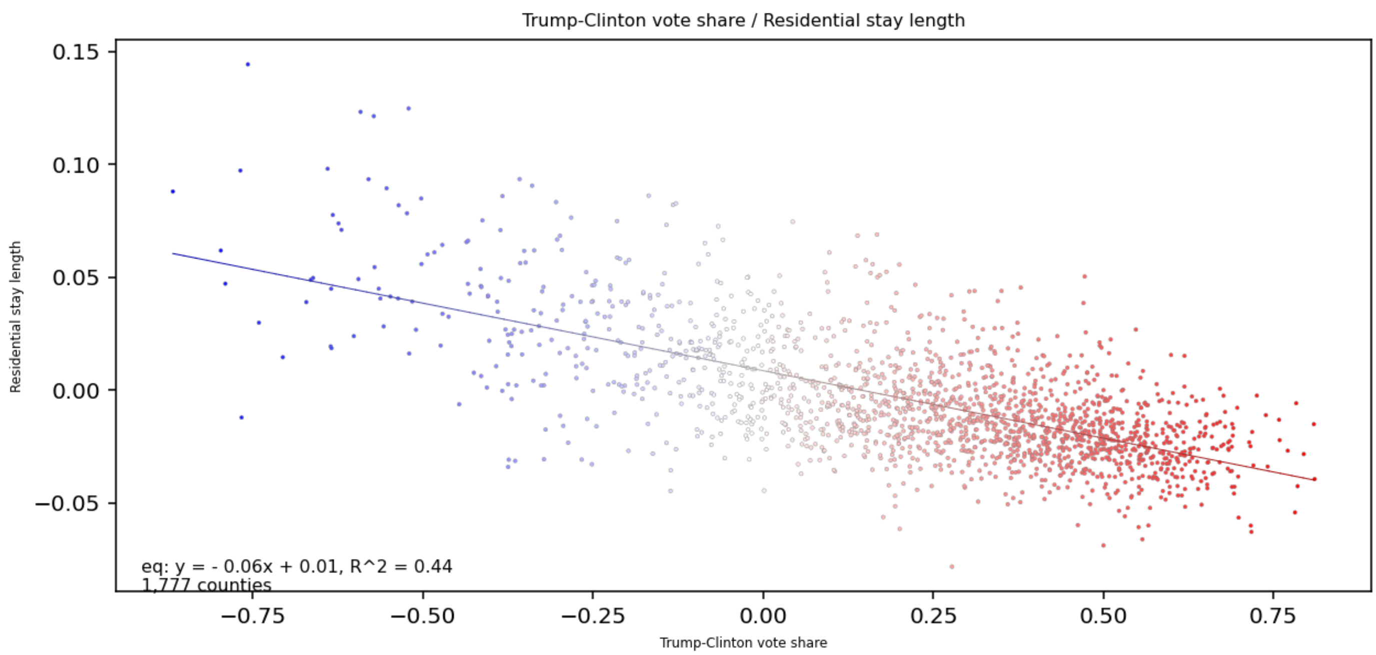


Figure 5 - Increase in Home Duration and Trump-Clinton Disparity in the 2016 Presidential Elections

To test the robustness of the link between politics and mobility, and further delve into the intricacies of pandemic politics, let us switch to multivariate models. Figure 6 presents the results of coefficients for multivariate regression models for the 6 types of mobility—Retail & recreation (top-left panel), Essentials (top-right), Parks (middle-left), Transit (middle-right), Workplace (bottom-left) and Residential (bottom-right). On the horizonal axis is the size of the coefficient with the dashed red lines indicating a coefficient of zero. Coefficients for each variable (variables are listed on the vertical axis of each panel) are represented as a point with 95% confidence intervals (whiskers around the point). We control for the number of COVID-19 cases. Alternative measurements, such as cases per capita, yielded substantively similar results. In addition, the models control for time elapsed since the first outbreak in the US, average household income, percent minorities in the county, state regulations, the timing of CDC statements and polarization. Both independent and dependent variables are normalized. For Residential mobility, the effect size of partisanship is the second largest and the model explains 46% of the variance. In the models for Retail & Recreation, Workplace, Transit and Essentials, the effect size for the Trump-Clinton differential is the largest of all predictors. In these variables, the model explains 13-33% of the variance in mobility. The only exception is Parks mobility, where Republican partisanship *decreases* mobility and merely 18% of the variance is explained. Parks mobility is included to provide a complete picture of all mobility types, but it is distinct from other types of mobility due to its nature.

Consistently and systematically, partisanship is correlated with mobility. In fact, judging by effect size, partisanship has the highest influence of all tested variables in almost all mobility types. In counties where more Republicans reside, levels of mobility are higher, *ceteris paribus*. This effect is robust to a range of model specifications.

See Table A1 in online appendix for models without the predictor for number of cases, which given the SIR model may be endogenous to mobility. According to the SIR Model for the spread of infectious diseases, let:

$$S = S_t \coloneqq number\ of\ suceptible\ indeviduals$$
$$I = I_t \coloneqq number\ of\ infected\ indeviduals$$
$$N \coloneqq Overall\ population$$
$$k \coloneqq fraction\ of\ infected\ indeviduals\ recovering\ each\ day$$
$$b \coloneqq average\ number\ of\ contacts\ for\ each\ individual\ \text{equation}\ per\ day$$

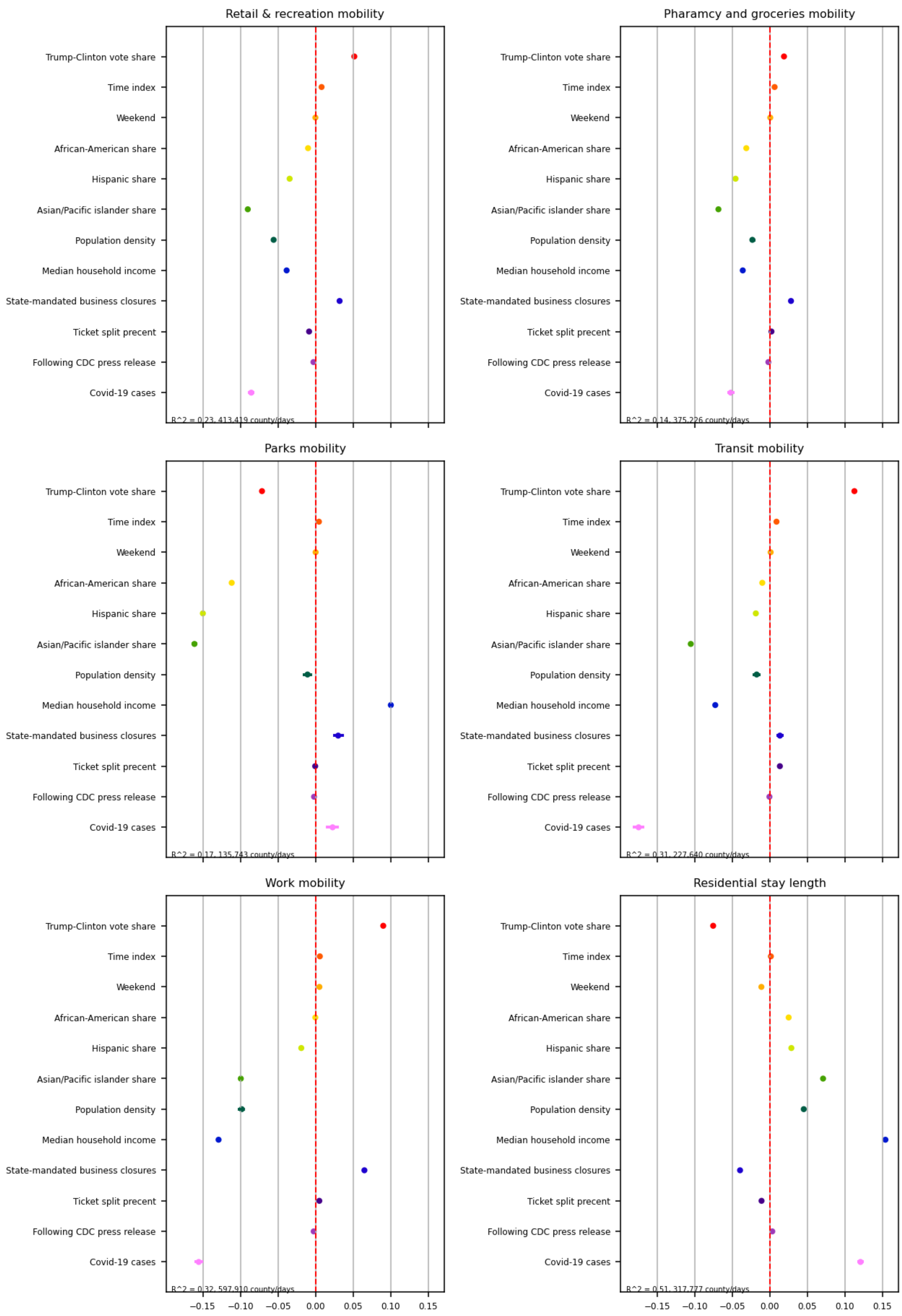
And define:

$$s = \frac{S}{N}, i = \frac{I}{N}$$

Then the differential equation would be:

$$\frac{\partial i}{\partial t} = bs_t i_t - ki_t$$

The differential equation suggests that interactions between susceptible and infected ($s_t i_t$), which inevitably increase along with mobility, would influence the rate in which the disease would spread ($\frac{\partial i}{\partial t}$). Yet, results remain substantively the same notwithstanding whether the control for number of cases is omitted or not. The results are robust when taking clustering into account, as the nested models (counties within states) in Table A6 in the online appendix show.

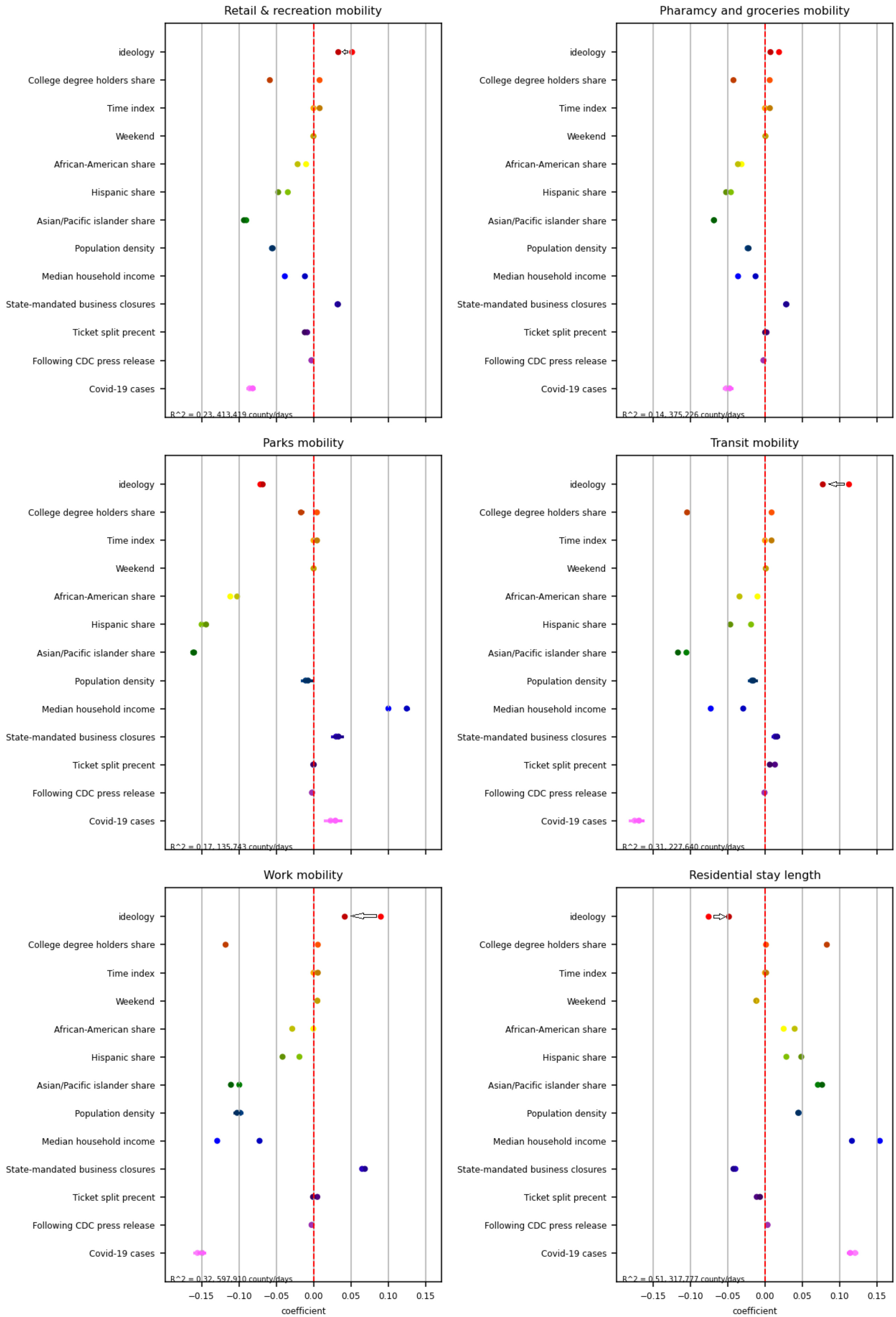


Retail & recreation mobility
Pharamcy and groceries mobility
Parks mobility
Transit mobility
Work mobility
Residential stay length
Trump-Clinton vote share
Time index
Weekend
African-American share
Hispanic share
Asian/Pacific islander share
Population density
Median household income
State-mandated business closures
Ticket split precent
Following CDC press release
Covid-19 cases
R^2 = 0.23, 413,419 county/days
R^2 = 0.14, 375,226 county/days
R^2 = 0.17, 135,743 county/days
R^2 = 0.31, 227,640 county/days
R^2 = 0.32, 597,910 county/days
R^2 = 0.51, 317,777 county/days
−0.15 −0.10 −0.05 0.00 0.05 0.10 0.15
coefficient

Figure 6 - Multivariate Mobility Regression Models

To test H4 and control for education but avoid high levels of multicollinearity with the partisanship/ideology predictor (due to the increasing correlation between the education variable and the Republican base during the Trump administration), we add an education variable to the model but specify a measure for partisanship that preceded the Trump era. Instead of the 2016 Trump-Clinton county differential, we use the comparative vote share of Romney and Obama in 2012. To the extent that the election of Donald Trump ushered in a new era in American politics, the Romney-Obama differential is a good measure for pre-Trump partisanship. Importantly, the findings are robust when the Trump-Clinton variable is used instead.

Models in Figure 7 support H4 and highlight how controlling for education dramatically reduces the effect of partisanship. Points indicate coefficients. Lighter points indicate the size of the coefficients for all variables without controlling for education. Darker points indicate coefficient size when education levels are controlled for. Arrows indicate the change in the effect of partisanship. For instance, in Workplace mobility, the change in the effect size of the partisanship coefficient is a 52% drop (from .23 to .11). The meaningful effect of education is robust also when taking clustering into account, as the nested models (counties within states) in Table A7 in the online appendix show.


Retail & recreation mobility
Pharamcy and groceries mobility
Parks mobility
Transit mobility
Work mobility
Residential stay length
ideology
College degree holders share
Time index
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African-American share
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−0.15
−0.10
−0.05
0.00
0.05
0.10
0.15
coefficient

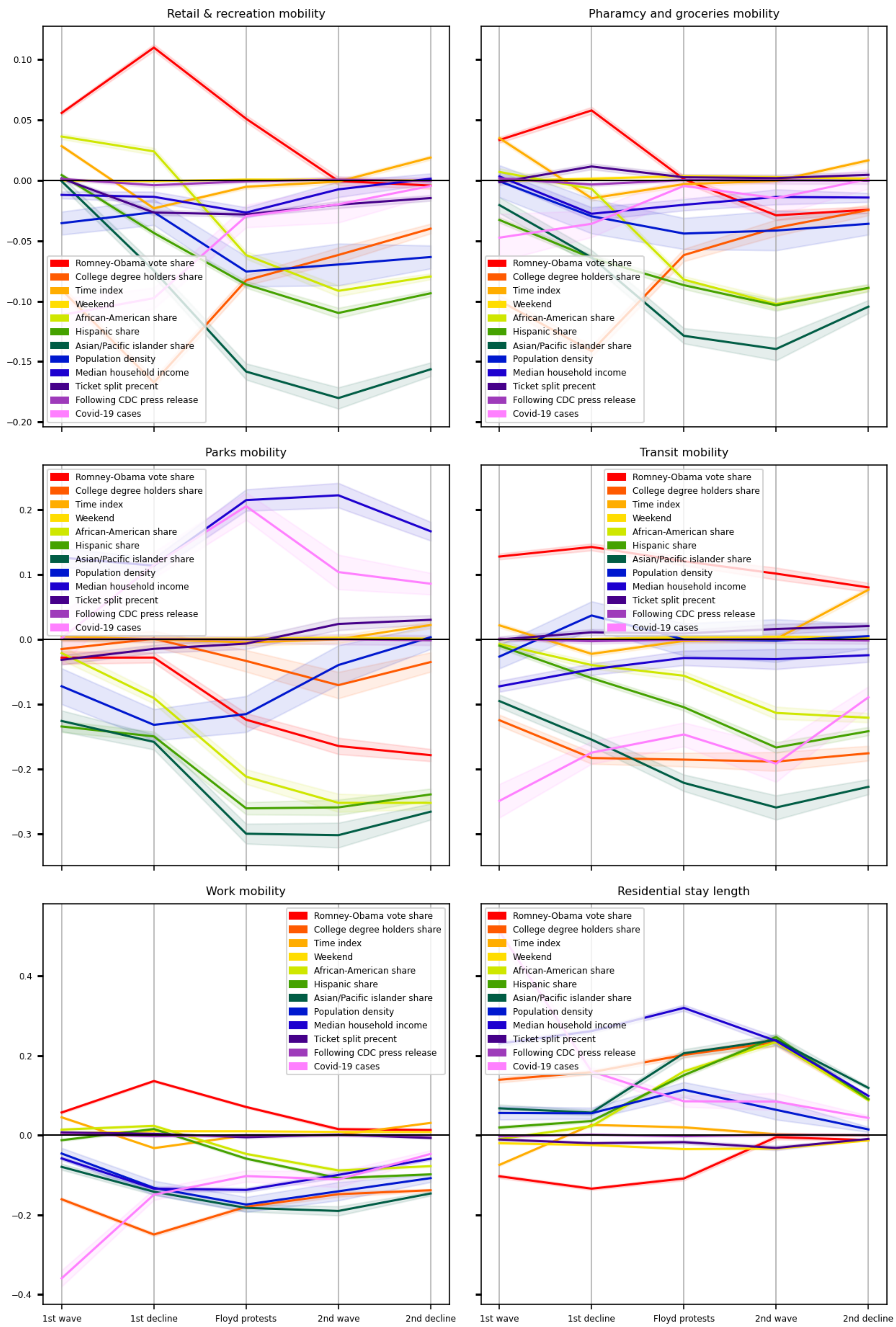
Figure 7 - Shrinkage in Partisanship's Effect when Controlling for Levels of Education

We established that pandemic politics are a new type of political emergency, with patterns unfamiliar heretofore: instead of closing ranks, behavior was excessively driven by politics. To test H3, we need to examine to what extent those patterns were stable over time. As time went by, numbers of cases rose from under 1000 nationally in early March (beginning of period in Figure 1) to over 5 million by mid-August, which is the end of our dataset.

We separate the pandemic into five consecutive time-segments. The 1st Wave segment (3/1-4/11) is the outbreak of the pandemic in the USA, 4/11 being a local maximum of daily cases in the NY Times 7-day rolling average. 1st Decline (4/1-5/24) is the decline of the first wave. Following the deaths of George Floyd and Breonna Taylor, the pandemic temporarily took the political backseat to a nationwide protest movement. Political focus was almost exclusively on questions related to the politics of race and social justice; this is the third segment, Floyd Protest (5/24-6/28). 2nd Wave (6/28-7/20) covers the rise of the 2nd wave (again, 7/21 being the local maximum of daily cases in the NYT 7-days average). And 2nd Decline, is from 7/21-8/8, when the 2nd wave waned. There may be different viewpoints on when the 1st wave ended or when the protests subsided. Hence, we conducted sensitivity tests for the dates demarcating those periods. Results presented here remain robust.

Figure 8 outlines how the effects of the key predictors changed over time between the different segments. For clarity, coefficients of only a subset of key variables are included (Figure A3 shows also coefficients for state-regulation variables). The time segment is on the horizontal axis and the size of the coefficient is on the vertical axis. For Retail & Recreation, Workplace and Residential mobility, the effect of partisanship (red line) converges to zero over time. This effect nearly vanishes as the pandemic persists. For instance, the effect of partisanship on Residential mobility (i.e., time stayed at home) in 2nd Decline is indistinguishable from zero and is more than 99% smaller in effect size than in 1st Decline. What seemed like a uniform effect for partisanship for the entire period in Figure 6, turns out to have a considerably more convoluted pattern over time. In support of H1, for most types of mobility, the effect of partisanship is significant in the first wave. In support of H3 and H4, the coefficient on % with no college education is relatively stable over time—as are the coefficients on most other demographic, education and economic variables—whereas partisanship declines as time goes by. The effect of partisanship reduces from 1st Wave to 1st Decline and then towards the Protests season. In the 2nd wave, the ideological effect largely dissipates in several of the mobility types. The decline in the effect of partisanship on Retail & Recreation mobility was dramatic, where it plummets 92% from a coefficient of .11 (SE=.001) in the 1st Decline to a negligible .009 (SE=.002) in the 2nd Decline. Conversely, demographic, economic and educational effects remain significant, with coefficient sizes that do not waver much. These effects are robust to a range of model specifications (see Table A2 for models for the 5 periods without the number of cases predictor, which may be endogenous to mobility according to the SIR model). Temporal effects were present but slightly attenuated when taking clustering into account, as the nested models (counties nested within states) in Table A8 in the online appendix show.

The temporal changes in the geographical spread of the disease, where Democratic parts of the country were hit earlier and Republican regions later, do not account for the partisan component in mobility. Mobility-partisanship link remains stable, even when those temporal changes in levels of cases are controlled for, measured in more than one way.



Retail & recreation mobility
Pharamcy and groceries mobility
Parks mobility
Transit mobility
Work mobility
Residential stay length
Romney-Obama vote share
College degree holders share
Time index
Weekend
African-American share
Hispanic share
Asian/Pacific islander share
Population density
Median household income
Ticket split precent
Following CDC press release
Covid-19 cases
1st wave
1st decline
Floyd protests
2nd wave
2nd decline

Figure 8 - Shrinkage in Partisanship's Effect over Time

Discussion and Conclusions

Unlike much of the literature in political science and political psychology about emergency political situations, pandemic politics was a different type of political emergency in the United States, at least during the first two waves of COVID-19 (from March-August 2020). Discrepancies in psychological reactions, elite discord, complexity of policies, national sentiments and the time dimension suggest that in this type of political emergency, political spectrums do not simply contract and partisans do not simply bridge their gaps leading to a rally-round-the-flag effect. Instead, in light of a persistent pandemic that increases in intensity over time, American elites scrambled to form a consistent position. Furthermore, the initial public reaction to the outbreak, that was profusely political, dissipated as time went by. The effects of education, demographics and economics endured.

Reconciling some debates in the literature about politics in times of pandemic (Lipsitz and Pop-Eleches, 2020; Yam et al., 2020), two key effects were critical to understanding politics in the time of COVID-19: demographics and time. First, a constituency that has shifted politics in America was critical. The reflection of the political realignment that materialized with Trump in the form of a demographic with no college education is influential in the COVID-19 era. Second, elites fail to form consistent partisan positions. With the increasingly mixed cues from the leader of the party, President Trump, and his administration, the effect of partisanship waned (Bartels 2000). During this political emergency, with a national emergency that increases in intensity, and without consistent leadership, the partisan group lost its cohesion and over time, the effect of partisanship subsided. As the United States was not the only country to experience such a polarizing moment—see the examples of Brazil, India and Israel, among many others—our theory and findings shed important light on the interface of politics and pandemics.

Our analysis of pandemic politics reveals how the impact of a natural emergency can be fully understood only when social, demographic and economic structures are brought into the picture. This was shown to be true in work that studied mobility and evacuations during natural disasters in general (Cutter et al. 2003; Wisner et al. 2004) and in the United States specifically (Fothergill and Peek 2004). As time goes by, and with inconsistent party messaging, politics makes way to the effects of economic, demographic and educational infrastructure (Brzezinski et al. 2020; Gollwitzer et al. 2020).

Our study of mass behavior at the aggregate level contributes to our understanding of the political psychology of such mass phenomena (Brown 1954). Instead of a survey-based technique to establish valuations, which would indicate individuals' stated preferences, our macro-level behavioral analysis indicates their revealed preferences, as we study their actual mobility patterns (Samuelson 1938; 1943). Our research is also in line with recent survey-based global research identifying correlations between national identity and support for public health (Van Bavel et al. 2020). Accordingly, theoretical advances and empirical findings from our behavioral analyses of mobility during COVID-19 shed light on survey results from the same period. Aggregate data from 1928 polls from January-October 2020 (Boycoffe et al. 2020) suggest that during the outbreak of the pandemic, the public was equally divided in approving president Trump's response. On March 20, for instance, 46.5% approve while 46.8% disapprove. By August 8, 58.2% disapprove and only 37.9% approve. The behavioral evidence we present here, that is based on a bigdata sample representative of US population, suggests an important potential insight into those survey results. Democrats, who showed lower mobility throughout the period, conceivably likewise did not change their disapproval of Trump in surveys as time went by. It is among Republicans, who initially moved more but whose mobility then declined over time, where people switched from the approval to the disapproval camp.

This project was limited to the study of mobility, which in the context of COVID-19 was a quintessential political behavior. Yet, the interface of pandemics and politics is broader, and future research should explore additional facets. For instance, more standard types of political behavior may be affected. The presidential elections of 2020, cooccurring the same year as COVID-19, are a good example. It is possible that the pandemic had something to do with the failure of an incumbent president to win reelection, a relatively rare event in American politics. Likewise, it is possible that typical political variables, such as ideology, may affect key epidemiological variables, such as infections rates. As such, the possibility of simultaneous relations between pandemics and politics should be explored, and in particular their fluctuations over time. Finally, the politics of the vaccination campaign, where questions of partisanship, political minorities and mandates are key, are of particular interest for those concerned with the interface of politics and pandemics. While partisan patterns during the vaccination campaign are clear (Weisel 2021), comparison to our research is invaluable for several reasons. Vaccinations are a familiar political question. As such, unlike the pandemic at its outbreak, vaccinations are not a novel and unfamiliar emergency. Likewise, the issue of vaccines surfaced when the pandemic was already a familiar topic, at least a year into the crisis, which puts the politics of the pandemic in a different context.

World Health Organization records show over 180 million cases worldwide, of which over 33.5 are in the US, by mid 2021, with COVID-19 and its Delta variant gathering momentum in the developing as well as in parts of the developed worlds. As Pandemic Politics lingers, it becomes important to understand it theoretically and empirically. The persistent pandemic circumstances, which grow over time, generate a new type of emergency politics at the levels of elites and masses alike. If the political and psychological aspects of Pandemic Politics are acknowledged and if their patterns are studied and heeded to when governments work to fight the disease, more informed decisions can be made (Hsiang et al. 2020; Barak et al. 2021). What is more, even if after COVID-19 there were no more major disasters related to zoonotic diseases, a natural disaster due to global warming may be the next big challenge humanity is going to endure. Deeper understanding of emergency politics of *various* sorts may be particularly useful in such times.

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Appendix

1. **Data for Federal Government Messages:**

Data for messages at the level of the federal government, and in particular by President Trump, were obtained from a range of websites, all listed here (all websites were accessed last during September 2020):

https://slate.com/news-and-politics/2020/05/trump-smearing-fauci.html

https://www.reuters.com/article/us-health-coronavirus-china-cdc-exclusiv/exclusive-u-s-axed-cdc-expert-job-in-china-months-before-virus-outbreak-idUSKBN21910S,

https://www.politico.com/news/2020/03/17/how-trump-shifted-his-tone-on-coronavirus-134246

https://www.politico.com/news/2020/03/17/how-trump-shifted-his-tone-on-coronavirus-134246

https://www.washingtonpost.com/politics/2020/04/28/yet-again-trump-pledges-that-coronavirus-will-simply-go-away/

https://www.washingtonpost.com/politics/2020/04/28/trump-continues-refuse-accept-deadlines-coronavirus-pandemic/

https://www.reuters.com/article/health-coronavirus-usa/trump-to-meet-with-drugmakers-as-us-sees-more-coronavirus-cases-idUSL1N2AV0EP

https://www.theguardian.com/world/2020/mar/05/trump-coronavirus-who-global-death-rate-false-number

https://www.rollingstone.com/politics/politics-features/covid-19-test-trump-admin-failed-disaster-995930/

https://www.rollingstone.com/politics/politics-features/rolling-stone-timeline-coronavirus-america-982944/

https://www.politico.com/news/2020/03/17/how-trump-shifted-his-tone-on-coronavirus-134246

https://www.washingtonpost.com/politics/2020/04/28/yet-again-trump-pledges-that-coronavirus-will-simply-go-away/

https://edition.cnn.com/2020/03/17/politics/fact-check-trump-always-knew-pandemic-coronavirus/index.html

https://www.nytimes.com/2020/03/17/us/politics/trump-coronavirus.html

https://www.washingtonpost.com/politics/2020/04/28/yet-again-trump-pledges-that-coronavirus-will-simply-go-away/

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https://www.washingtonpost.com/politics/2020/04/28/yet-again-trump-pledges-that-coronavirus-will-simply-go-away/, https://www.politico.com/news/2020/05/01/masks-politics-coronavirus-227765

https://edition.cnn.com/2020/04/06/politics/donald-trump-coronavirus-history-health-economy/index.html

https://www.washingtonpost.com/politics/2020/04/28/yet-again-trump-pledges-that-coronavirus-will-simply-go-away/

https://www.washingtonpost.com/health/2020/04/21/coronavirus-secondwave-cdcdirector/,

https://www.whitehouse.gov/briefings-statements/remarks-president-trump-vice-president-pence-members-coronavirus-task-force-press-briefing-30

https://www.washingtonpost.com/politics/2020/04/28/yet-again-trump-pledges-that-coronavirus-will-simply-go-away/

https://thehill.com/homenews/administration/495343-white-house-risks-backlash-with-coronavirus-optimism
https://thehill.com/homenews/coronavirus-report/497324-fauci-real-coronavirus-death-toll-almost-certainly-higher-than
https://thehill.com/homenews/administration/503003-pence-panic-over-second-coronavirus-wave-overblown, https://www.wsj.com/articles/fauci-warns-of-coronavirus-resurgence-if-states-dont-adhere-to-safety-guidelines-11592338771
https://www.theguardian.com/us-news/2020/jun/25/trump-fauci-redfield-cdc-coronavirus-messages
https://www.cnn.com/2020/07/01/politics/donald-trump-masks-coronavirus/index.html
https://www.politico.com/news/2020/07/05/hahn-coronavirus-trump-infection-348954
https://www.politico.com/news/2020/07/14/trump-urges-americans-to-wear-masks-361836
https://deadline.com/2020/07/donald-trump-chris-wallace-fox-news-sunday-2-1202989272/
https://www.cnbc.com/2020/07/20/trump-says-coronavirus-masks-are-patriotic-after-months-of-largely-resisting-wearing-one.html
https://www.cnbc.com/2020/07/21/trump-warns-us-coronavirus-outbreak-will-probably-get-worse-before-it-gets-better.html
https://news.sky.com/story/coronavirus-trump-praises-impressive-doctor-who-said-alien-dna-is-used-in-medical-treatments-12038448

2. **State-Level Data Compilation:**

The list of sources for state-level COVID-19 regulations includes (all websites were accessed last during September 2020):
https://ballotpedia.org/State_government_reopenings_after_coronavirus_(COVID-19)_lockdowns,_2020
https://www.maine.gov/covid19/restartingmaine
https://accd.vermont.gov/covid-19/business/restart
https://www.covidguidance.nh.gov/
https://www.mass.gov/info-details/reopening-massachusetts
https://reopeningri.com/
https://portal.ct.gov/Coronavirus/Covid-19-Knowledge-Base/Latest-Guidance
https://forward.ny.gov/
https://abc7ny.com/reopen-new-jersey-nj-covid-19-plan-to/6188416/
https://www.governor.pa.gov/process-to-reopen-pennsylvania/
https://governor.maryland.gov/recovery/
https://coronavirus.dc.gov/reopendc
https://www.vdh.virginia.gov/coronavirus/frequently-asked-questions/phase-1-safer-at-home/
https://www.nc.gov/covid-19/staying-ahead-curve/phase-1-faqs
https://backontrack.in.gov/2348.htm
https://www.michigan.gov/documents/whitmer/MI_SAFE_START_PLAN_689875_7.pdf
https://coronavirus.illinois.gov/sfc/servlet.shepherd/document/download/069t000000BadS0AAJ?operationContext=S1
https://governor.wv.gov/Pages/The-Comeback.aspx
https://www.wpsdlocal6.com/coronavirus_news/gov-beshear-releases-reopening-requirements-for-phase-1/article_b11e50ee-9182-11ea-9a72-2be2d6f6e1dd.html
https://kentucky.gov/Pages/Activity-stream.aspx?n=GovernorBeshear&prId=156

https://kentucky.gov/Pages/Activity-stream.aspx?n=GovernorBeshear&prId=156
https://www.wcpo.com/rebound/timeline-ohio-kentucky-and-indiana-reopening-plans
https://www.wmcactionnews5.com/2020/04/27/mayors-shelby-county-municipalities-join-strickland-harris-covid-meeting-announce-reopening-plans/
https://www.commercialappeal.com/story/news/2020/04/30/memphis-shelby-county-back-business-phase-1-reopening/3056838001/
https://www.asafenashville.org/wp-content/uploads/2020/09/Updated_RoadmapforReopeningNashville_09_01.pdf
https://www.wsfa.com/2020/04/28/alabama-economy-reopen-phases-starting-thursday-pm/
https://mn.gov/covid19/for-minnesotans/stay-safe-mn/stay-safe-plan.jsp
https://ndresponse.gov/sites/www/files/documents/covid-19/ND%20Smart%20Restart/Additional%20Resources/NDSmartRestartPlan.pdf
https://www.health.nd.gov/news/burgum-announces-move-next-phase-nd-smart-restart-plan
https://covid.ks.gov/ad-astra-a-plan-to-reopen-kansas/
http://www.artesianews.com/1857312/new-mexicos-phased-reopening-plan-outlined-in-full-detail.html
https://covid19.colorado.gov/sites/covid19/files/COVID-19%20Safer%20at%20Home%20PHO%20Guidance%20%282%29.pdf
https://trib.com/news/state-and-regional/health/state-of-wyoming-announces-widespread-business-closures-in-response-to/article_fd9b3090-536e-5e55-902e-0585322740a2.html#tracking-source=home-top-story
https://www.nps.gov/yell/learn/news/20015.htm
https://billingsgazette.com/lifestyles/recreation/yellowstone-reopens-after-7-week-pandemic-closure/article_7ee5df78-eb18-56b9-b913-8bbfce372218.html
https://coronavirus.utah.gov/utahs-health-guidance-system/
https://www.sfgate.com/news/editorspicks/article/California-counties-Stage-2-reopen-restaurants-new-15291096.php
https://twitter.com/GavinNewsom/status/1278406469663158272
https://www.sfgate.com/news/editorspicks/article/Alameda-Contra-Costa-Stage-2-reopen-Santa-Clara-15270829.php
https://en.wikipedia.org/wiki/COVID-19_pandemic_in_Nevada
https://www.kptv.com/news/31-oregon-counties-approved-2-not-approved-for-phase-1-reopening/article_830068f4-9606-11ea-a22f-efd1f5c1cc4f.html
https://www.oregon.gov/newsroom/Pages/NewsDetail.aspx?newsid=36749
https://govstatus.egov.com/reopening-oregon
https://www.statesmanjournal.com/story/news/2020/05/21/oregon-state-park-campgrounds-reopen-june-9-limited-services/5235940002/
https://www.king5.com/article/news/health/coronavirus/coronavirus-phase-2-counties-washington-state/281-cdcc2a2e-05f3-4564-ad0f-892d4d4b09c4
https://www.q13fox.com/news/pierce-snohomish-counties-approved-for-phase-2-reopening-king-county-granted-modified-phase-1
https://www.kpq.com/chelan-and-douglas-counties-approved-to-move-into-modified-phase-1/
https://www.nwpb.org/2020/05/27/kittitas-county-can-moves-to-phase-2-reopening-three-weeks-after-outbreak-paused-application/
https://www.union-bulletin.com/news/health_fitness/coronavirus/walla-walla-county-approved-for-phase-2-economic-reopening/article_5487fa88-6b25-5b7b-aca9-358b9cd64c43.html

https://www.king5.com/article/news/health/coronavirus/washington-state-coronavirus-covid-19-pandemic-updates/281-81f6547d-75e1-45e7-a276-2dab244a85b0
https://www.bigcountrynewsconnection.com/local/asotin-county-approved-for-move-into-phase-3-of-safe-start-re-opening-plan/article_47acf7d0-ab7e-11ea-a806-4363bc632acd.html
https://www.thedailyworld.com/news/grays-harbor-countys-phase-3-variance-approved/
https://www.usatoday.com/storytelling/coronavirus-reopening-america-map/

3. Data Harvesting of Media Coverage

Using selenium, a python scraping framework, we downloaded all articles from the *New York Times* (*NYT*) website. The *NYT* website allows for systematic iteration over all articles, which facilitates scraping. For each article, we scraped HTML meta tags, title, author, body, links, images and image captions. We then filtered only articles with the meta type PT(piece type)=article, to filter out videos and interactive material which is not usable and can distort our analysis (such as detailed election results). To determine which articles are relevant to COVID-19, the "news keywords" metatag in the article's HTML was used. Using this tag, the website owner or editor are able to inform news aggregators, particularly, Google news, under what keywords the article should be grouped. While Google has officially dropped support for this meta tag, it is still widely used by websites, specifically the ones we researched. This method is superior to searches over the article's title or body, as it follows the decision of the site editor herself.

This framework provides a considerably more complete picture of the network. We do not look at specific articles assuming they represent the entire corpus, nor do we even look for all the data concerning the subject of discussion (as done, for instance, by *Lexis-Nexis*). Rather, we extract the universe of newspaper articles. We differentiate between the topics of those texts ourselves and do so based on the actual data in its entirety. This allows us to perform qualitative analyses on the share of texts concerning our subject of the entire corpus, and compare between texts that concern our subject and those that do not. There is no sampling involved, and thus biases typically associated with inference are avoided. Furthermore, as we download and scrape the entire archive, the risk of having a biased selection of texts to analyze is essentially marginal. While obviously the web archive does not contain everything ever published, texts which are missing or have less informative metadata are either older or in places the website owner put less emphasis on. The articles available to harvest from the newspaper websites are the ones the publisher and editor decided to put on their online archive. We avoid those articles that the elites involved (e.g., editors and owners, politicians, regulators, campaigners) were least interested or vested in. Lastly, and relatedly, by avoiding a third-party tool (such as *Lexis-Nexis*) we have full knowledge and control over what was retrieved, how and why. There is less risk of selection biases, which the researcher is not even aware of, that would be embedded within the third-party tool we would have otherwise used.

The harvested *NYT* pieces totaled 11,213, of which 4,917 were COVID-19 articles. The 5 most popular sections included US (1768 articles), Opinion (1283), World (946), Arts (905) and Business (817). On weekdays, the NYT averaged 176 articles a day, and on weekends 77.

On top of the standard textual fields such as article title, subtitle and full text, our scraping framework enabled harvesting of metadata invisible to the user but highly informative of the article, such as its tag, how it is summarized for social media entries, etc. On top of this information, we harvested image captions and links, which enabled constructing the network structure of the articles.

4. Complementary Analyses

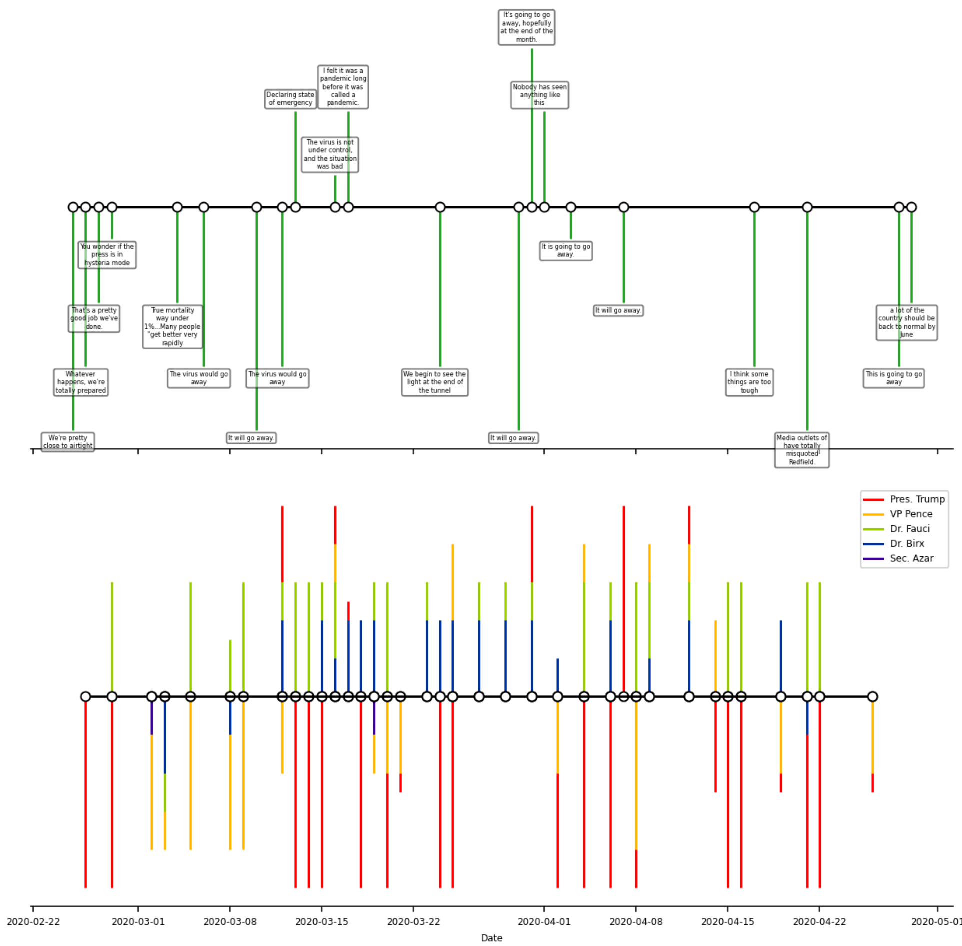
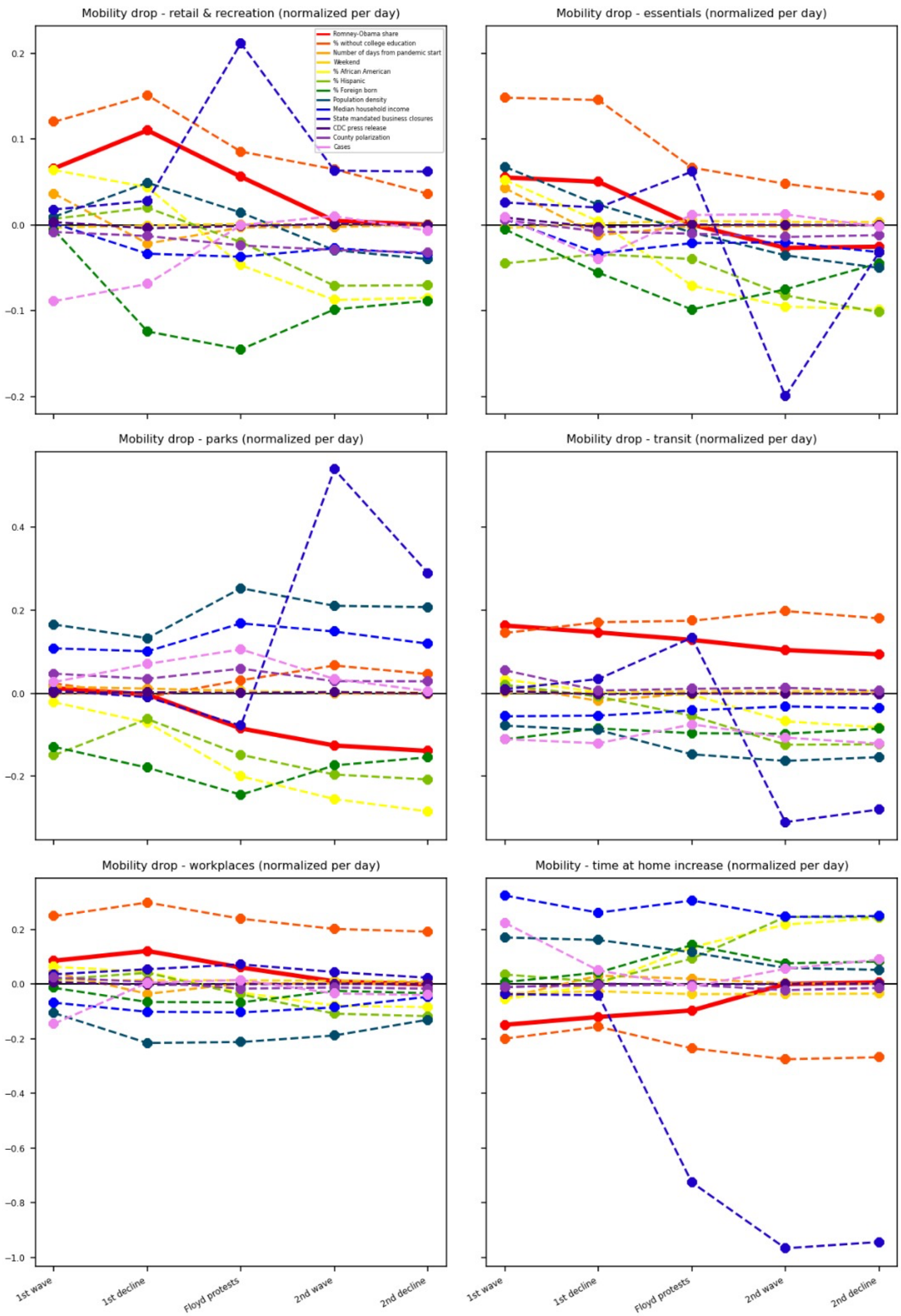


Figure A1 - Timeline of Statements by President Trump and His Administration Officials Regarding COVID-19. The top panel presents a timeline of notable statements by president Trump, where statements belittling the pandemic, promoting unscientific medication etc. are below the line and statements highlighting the pandemic above it. The lower panel describes the tone of the five top briefers in the COVID-19 task force daily briefings during March and April. Above the line are referrals which highlighted the risks in the pandemic and below it are referrals that belittled those risks.



Mobility drop - retail & recreation (normalized per day)
Romney-Obama share
% without college education
Number of days from pandemic start
Weekend
% African American
% Hispanic
% Foreign born
Population density
Median household income
State mandated business closures
CDC press release
County polarization
Cases
Mobility drop - essentials (normalized per day)
Mobility drop - parks (normalized per day)
Mobility drop - transit (normalized per day)
Mobility drop - workplaces (normalized per day)
Mobility - time at home increase (normalized per day)
1st wave
1st decline
Floyd protests
2nd wave
2nd decline

Figure A2 - Shrinkage in Ideology's Effect over Time including State-Regulation Variables. Coefficients of key indicators as they relate to the various types of mobility over the 5 periods of the COVID-19 pandemic. Solid line connects ideology/partisanship coefficients in each period.

	Residential		**Retail & Recreation**		**Transit**		**Workplace**	
	Ideology/partisanship	**Ideology/partisanship & Education**	**Ideology/partisanship**	**Ideology/partisanship & Education**	**Ideology/partisanship**	**Ideology/partisanship & Education**	**Ideology/partisanship**	**Ideology/partisanship & Education**
Trump-Clinton share	-0.132 (0.001) ***		0.086 (0.001) ***		0.192 (0.002) ***		0.149 (0.001) ***	
Romney-Obama share		-0.08 (0.001) ***		0.056 (0.001) ***		0.122 (0.002) ***		0.068 (0.001) ***
% without college education		-0.136 (0.002) ***		0.077 (0.001) ***		0.165 (0.003) ***		0.199 (0.001) ***
County polarization	-0.015 (0.002) ***	-0.014 (0.002) ***	-0.011 (0.001) ***	-0.013 (0.001) ***	0.016 (0.003) ***	0.012 (0.003) ***	0.012 (0.001) ***	0.005 (0.001) ***
% African American	0.012 (0.001) ***	0.033 (0.001) ***	0.016 (0.001) ***	0.0 (0.001) ***	0.016 (0.002) ***	-0.018 (0.002) ***	0.061 (0.001) ***	0.021 (0.001) ***
% Foreign born	0.069 (0.002) ***	0.061 (0.002) ***	-0.09 (0.002) ***	-0.089 (0.002) ***	-0.081 (0.003) ***	-0.092 (0.003) ***	-0.046 (0.002) ***	-0.035 (0.002) ***
% Hispanic	-0.006 (0.002) ***	0.039 (0.002) ***	0.016 (0.001) ***	-0.007 (0.001) ***	** -0.006 (0.002) ***	-0.051 (0.002) ***	0.049 (0.001) ***	* 0.003 (0.001) ***
State-mandated business closures	-0.147 (0.003) ***	-0.159 (0.003) ***	0.064 (0.002) ***	0.067 (0.002) ***	** 0.017 (0.005) ***	0.023 (0.005) ***	0.118 (0.002) ***	0.13 (0.002) ***
CDC press release	0.001 (0.0)	0.001 (0.0)	-0.002 (0.0) ***	-0.002 (0.0) ***	0.001 (0.001)	0.001 (0.001)	-0.001 (0.0)	-0.001 (0.0)
% 65 years and older	-0.117 (0.002) ***	-0.102 (0.002) ***	0.076 (0.002) ***	0.073 (0.002) ***	-0.053 (0.004) ***	-0.062 (0.004) ***	0.174 (0.002) ***	0.168 (0.001) ***
Population density	0.119 (0.003) ***	0.11 (0.003) ***	-0.004 (0.003) ***	0.003 (0.003) ***	-0.166 (0.005) ***	-0.148 (0.005) ***	-0.171 (0.003) ***	-0.152 (0.003) ***
Median household income	0.256 (0.001) ***	0.201 (0.002) ***	-0.046 (0.001) ***	-0.016 (0.001) ***	-0.123 (0.002) ***	-0.054 (0.003) ***	-0.134 (0.001) ***	-0.045 (0.001) ***
Number of days from pandemic start	0.004 (0.0) ***	0.004 (0.0) ***	0.005 (0.0) ***	0.005 (0.0) ***	0.009 (0.001) ***	0.009 (0.001) ***	0.003 (0.0) ***	0.002 (0.0) ***
Weekend	-0.023 (0.0) ***	-0.024 (0.0) ***	-0.0 (0.0)	-0.0 (0.0)	0.003 (0.001) ***	0.003 (0.001) ***	0.012 (0.0) ***	0.012 (0.0) ***
const	0.576 (0.001) ***	0.649 (0.002) ***	0.174 (0.001) ***	0.133 (0.001) ***	0.316 (0.002) ***	0.235 (0.003) ***	0.312 (0.001) ***	0.201 (0.001) ***
R^2	0.6	0.61	0.3	0.3	0.35	0.35	0.43	0.45
F Value	14310	13880	5368	5170	4124	3932	14660	14820
Prob (F statistic)	.0	.0	.0	.0	.0	.0	.0	.0
N	123735	123735	164569	164569	101195	101195	251223	251223
Standard Errors in Parentheses * p<.05; ** p<.01; *** p<.001								

Table A1: Residential, Retail & Recreation, Transit and Workplace Mobility (***without*** number of cases)

	1st wave (March 1-April 11)	1st decline (April 12-May 24)	Floyd protests (May 25-June 28)	2nd wave (June 29-July 20)	2nd decline (July 21-August 8)
Romney-Obama share	-0.163 (0.004) ***	-0.126 (0.002) ***	-0.102 (0.003) ***	-0.006 (0.004)	0.002 (0.004)
% without college education	-0.164 (0.006) ***	-0.136 (0.003) ***	-0.221 (0.004) ***	-0.257 (0.006) ***	-0.253 (0.007) ***
County polarization	-0.022 (0.006) ***	-0.014 (0.003) ***	-0.009 (0.004) *	-0.028 (0.006) ***	-0.018 (0.007) **
% African American	-0.088 (0.005) ***	-0.023 (0.002) ***	0.115 (0.003) ***	0.197 (0.005) ***	0.226 (0.006) ***
% Foreign born	0.036 (0.007) ***	0.057 (0.004) ***	0.148 (0.006) ***	0.093 (0.008) ***	0.105 (0.009) ***
% Hispanic	-0.019 (0.006) **	-0.025 (0.003) ***	0.067 (0.004) ***	0.211 (0.006) ***	0.217 (0.007) ***
State mandated business closures	-0.036 (0.001) ***	-0.044 (0.001) ***	-0.788 (0.023) ***	-1.112 (0.061) ***	-1.052 (0.069) ***
CDC	-0.012 (0.002) ***	0.001 (0.001)	-0.003 (0.001) *	0.0 (0.002)	0.001 (0.002)
% 65 years and older	-0.22 (0.008) ***	-0.155 (0.004) ***	-0.125 (0.006) ***	-0.139 (0.008) ***	-0.11 (0.01) ***
Population density	0.191 (0.009) ***	0.171 (0.006) ***	0.104 (0.008) ***	0.069 (0.012) ***	0.067 (0.013) ***
Median household income	0.309 (0.006) ***	0.242 (0.003) ***	0.289 (0.004) ***	0.226 (0.006) ***	0.231 (0.007) ***
Number of days from pandemic start	-0.044 (0.003) ***	0.034 (0.001) ***	0.021 (0.001) ***	0.003 (0.002)	0.001 (0.002)
Weekend	-0.035 (0.001) ***	-0.027 (0.001) ***	-0.038 (0.001) ***	-0.037 (0.001) ***	-0.036 (0.001) ***
const	0.595 (0.006) ***	0.696 (0.003) ***	0.514 (0.005) ***	0.548 (0.008) ***	0.503 (0.009) ***
R^2	0.63	0.68	0.68	0.63	0.6
F Value	2457	5730	4937	2309	1715
Prob (F Statistic)	.0	.0	.0	.0	.0
N	20034	37605	32819	19242	16279

Standard Errors in Parentheses
* p<.05; ** p<.01; *** p<.001

Table A2: Residential Mobility over Time (***without*** number of cases)

5. Clip Legends

Clip 1 shows change over time in mobility using a sequence of maps of the United States
Clip 2 highlights the meaningful shrinkage in the coefficient on ideology once percent with less than college education in the county are controlled for in the multivariate regression.

6. Nested Models Analyses

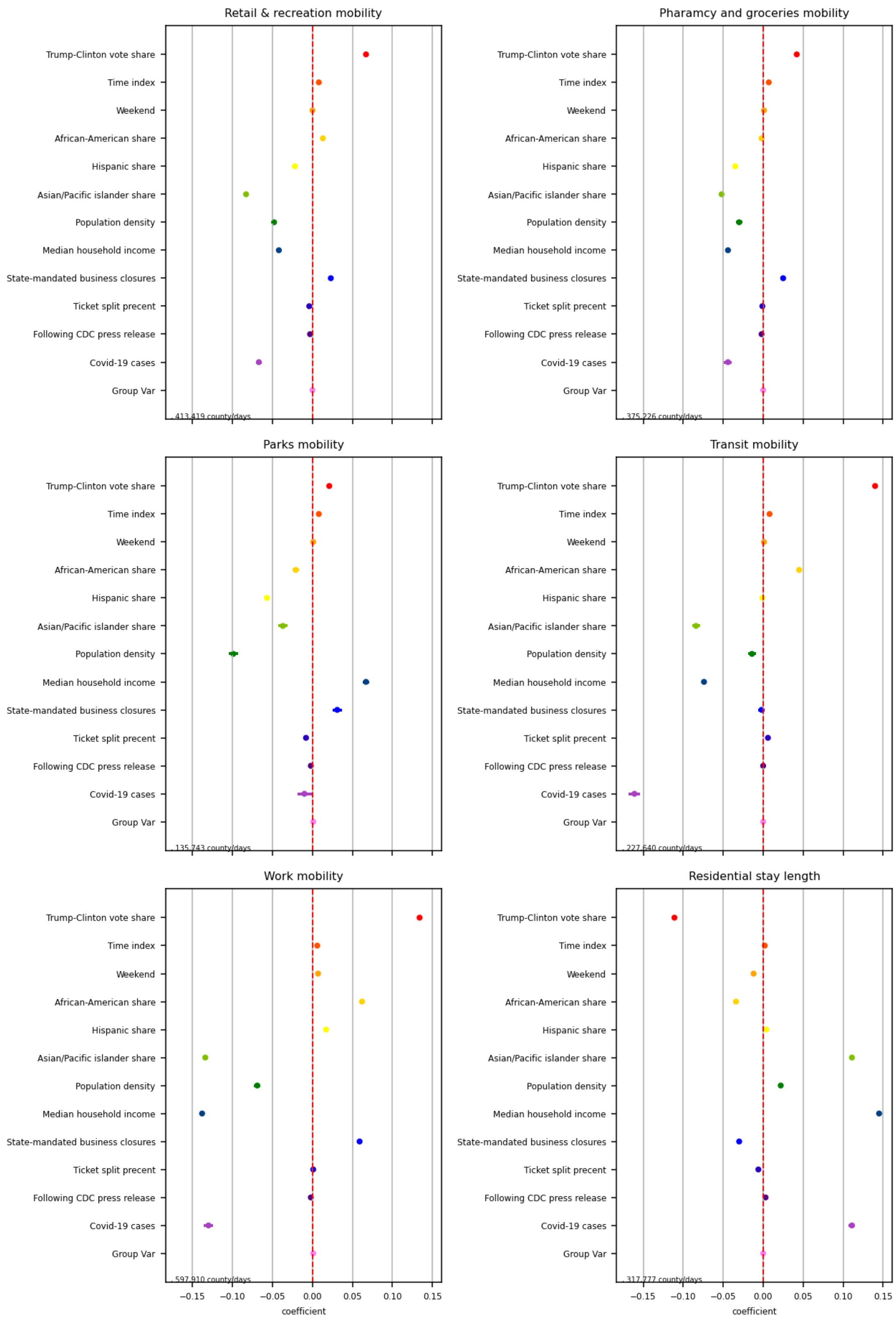


Figure A6 - Multivariate Mobility Nested Regression Models

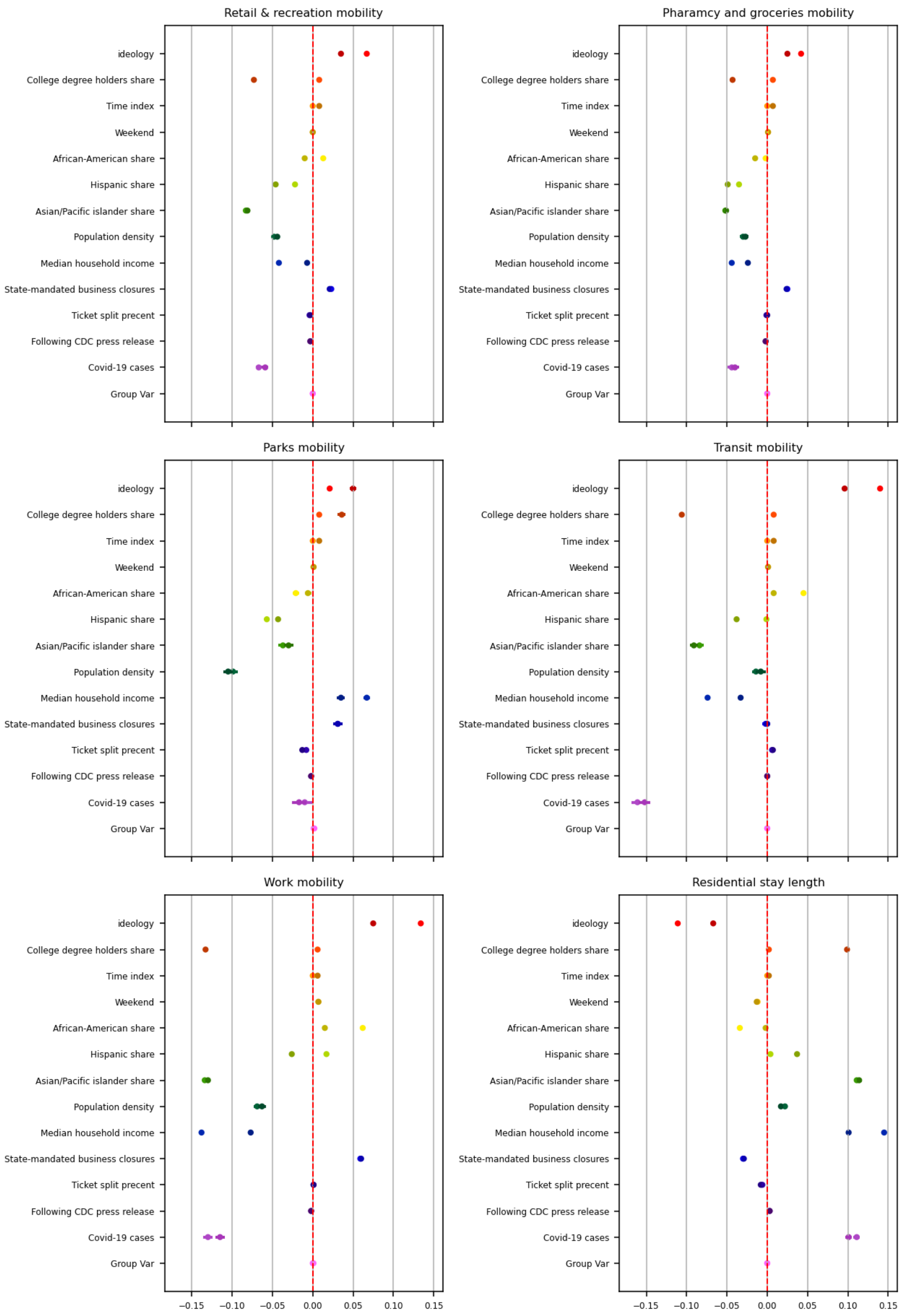

Retail & recreation mobility
Pharamcy and groceries mobility
Parks mobility
Transit mobility
Work mobility
Residential stay length
ideology
College degree holders share
Time index
Weekend
African-American share
Hispanic share
Asian/Pacific islander share
Population density
Median household income
State-mandated business closures
Ticket split precent
Following CDC press release
Covid-19 cases
Group Var
−0.15
−0.10
−0.05
0.00
0.05
0.10
0.15
coefficient

Figure A7 – Nested Models for Shrinkage in Partisanship's Effect when Controlling for Levels of Education

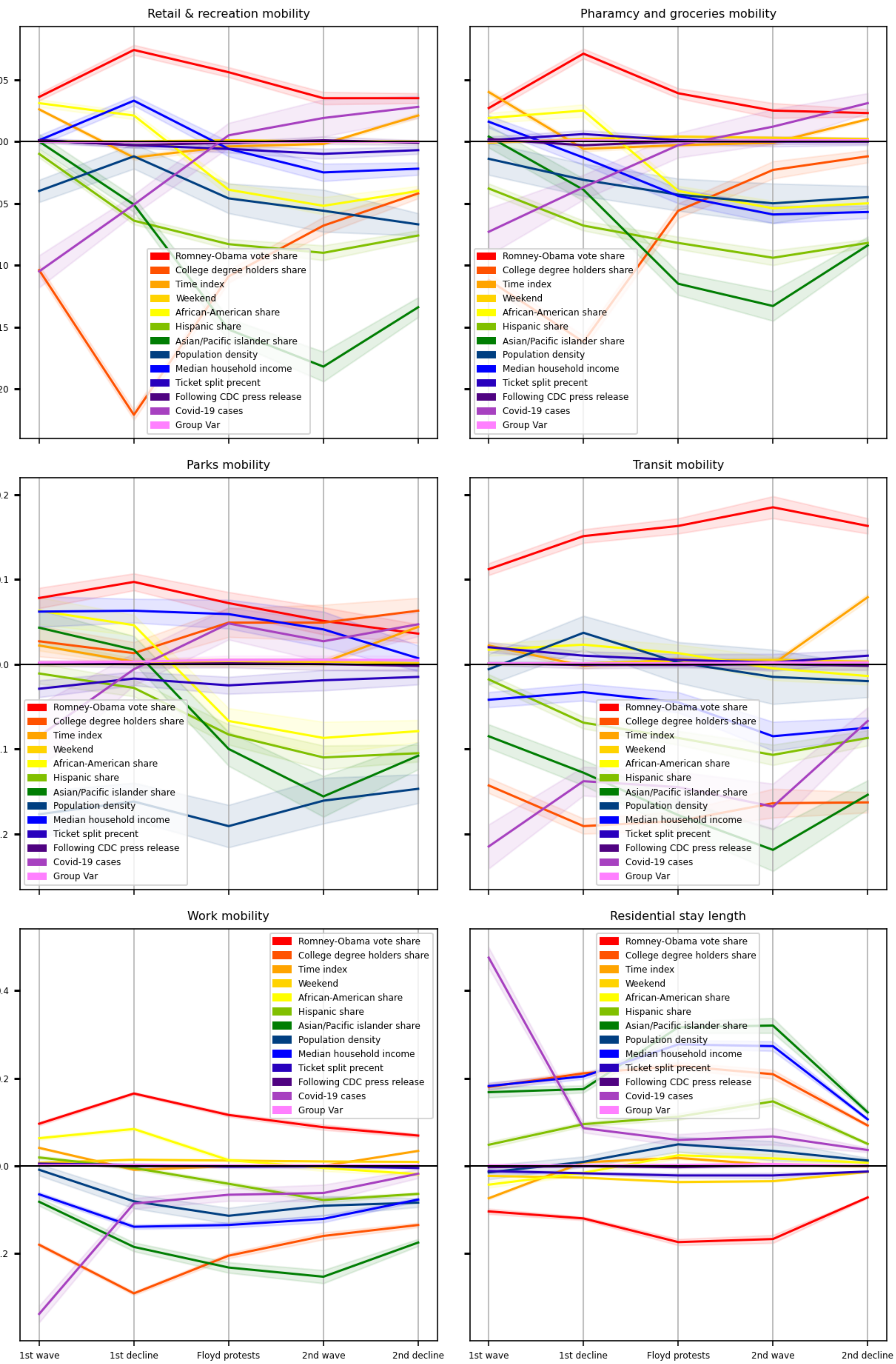

Retail & recreation mobility
Pharamcy and groceries mobility
Parks mobility
Transit mobility
Work mobility
Residential stay length
Romney-Obama vote share
College degree holders share
Time index
Weekend
African-American share
Hispanic share
Asian/Pacific islander share
Population density
Median household income
Ticket split precent
Following CDC press release
Covid-19 cases
Group Var
1st wave
1st decline
Floyd protests
2nd wave
2nd decline

Figure A8 - Shrinkage in Partisanship’s Effect over Time (Nested Models)