Political Geography 106 (2023) 102939

Contents lists available at ScienceDirect

Political Geography

journal homepage: www.elsevier.com/locate/polgeo

Full Length Article

Geographical analysis of political epidemiology: Spatial quantification of simultaneity between politics and pandemics

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ARTICLE INFO

Keywords:
Territorial analysis
Spatial quantification
Political epidemiology
COVID-19
R
Political partisanship
Polarization
Retrospective voting
Prospective voting
2020 US presidential elections
Residential mobility
Work mobility
Transportation mobility
Essentials mobility

ABSTRACT

Using the sequence of events in 2020, we study simultaneity between political behavior and pandemics. Capitalizing on spatial quantification to untangle simultaneity between politics and pandemics with county as the basic territorial unit, we examine the *politics-on-pandemic* impact from the outbreak to Election Day. The relations seem more directional than bidirectional and limited in time. Bigdata for 250 M US citizens and tens of thousands of county-days indicate an initial partisan effect on the R reproduction coefficient via a range of mobility types, which disappeared after the outbreak. Then, we quantify the opposite *pandemic-on-politics* pattern in the form of COVID-19's effect on the 2020 elections, with data for 150 M voters. Our spatial analyses offer scant support for simultaneity in the relations between political behavior and COVID-19. If there is an effect of pandemics on politics, it is often insignificant and never of meaningful magnitude.

1. Introduction

The question of human behavior—and in particular its political aspects—and their relations to the epidemiological world has risen as acutely important during the COVID-19 pandemic (Parolin & Lee, 2021; Josephson et al., 2021; Druckman et al. 2020). Links between pandemics and political behavior could run both ways, though. Politics may influence the pandemic, and the pandemic may influence politics. 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. Abiding by remain in place orders diminishes the likelihood of spreading the disease. Conversely, when people leave their homes, the disease is more likely to spread. Likewise, the pandemic with its human, social, economic and health ramifications may have an impact on the political world, and specifically on political behavior in the form of voting. This raises the question of simultaneity between politics and pandemics.

Research in the social sciences often involves issues of simultaneity (King et al., 1994). When there is influence between variables on different sides of an equation model, which means that predictors (right hand variables) do not simply influence the outcome variable on the left side of the equation, it is a case of simultaneity (Wooldridge, 2013, pp. 82–83). Simultaneity may stem from the fact that predictors are endogenous. They not only influence the outcome variable but are also influenced by it. Alternatively, left hand and right hand variables may be codetermined (Merton, 1968). When predictors and the explained variables are related—in the sense that they are from the same issue area—simultaneity may often be at play (Shvetsova, 2003). In such cases, disentangling causality may prove particularly complicated, despite the fact that statistical frameworks have been developed to deal with such endogeneity (Freedman & Sekhon, 2010).

We capitalize on spatial quantification to untangle simultaneity between politics and pandemics, using county as the basic geographical unit. We build on previous work that highlighted the importance of spatial and geographical analysis of the pandemic, from

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https://doi.org/10.1016/j.polgeo.2023.102939
Received 18 October 2022; Received in revised form 4 May 2023; Accepted 3 July 2023
Available online 21 July 2023

territorialization of the pandemic, social and class variance in infections and death, social distancing and spatial implications for politics and governance at the national, subnational and supranational levels (Dodds et al., 2020). We build on extant work and expand it with considerably improved data, which helps us improve our inferences about the intricate relations between politics and pandemics. This is not limited just to the examination of simultaneous relations between the two, but also the underlying pathways through the formalization of links between politics and infection rates. Our research design is also uniquely conducive to a thorough examination of the effects of a host of political predictors, some of them purely political such as partisanship and others as markers for political effects, such as levels of education as a marker for class. Our significantly improved database allows us to capitalize on geographical variance in the exploration of those different aspects. As the bigdata provided by Google is at the aggregate level and thus requires analyses at the county level, we provide several tests for the necessary ecological assumptions. In particular, we provide robustness tests for the effects of key predictors such as partisanship and education, using subsamples of counties with a small population that are homogenous on the relevant variables.

The COVID-19 pandemic during 2020 and the fact that the presidential elections cooccurred that same year provide researchers with an exceptional opportunity to delve into the much-debated relations between political behavior and the pandemic. By most counts, the world of politics and the world of epidemics are distinct realms. Unlike institutions and social outcomes (Shvetsova, 2003), for instance, politics and epidemiology are, at least supposedly, discrete. The analytical edge we have in understanding the links between them stems from the fact that both the pandemic and the political behaviors associated with it can be broken down spatially to different geographical regions, and it is the spatial aspect that determines both. For politics, spatial variables determine how votes are counted. And in epidemiology, spatial variables are critical for the spread of the disease and a host of its implications and associated policies. Lockdowns and stay at home orders, for instance, may be national, but for the most part are determined regionally (Woolf, 2022) and based on epidemiological variables measured spatially. We build on work that has used geographical analyses to investigate the politics of the pandemic (Vlados & Chatzinikolaou, 2021) in different parts of the world, including Norway (Gulbrandsen, 2022), Italy (Coletti & Filippetti, 2022) and Nigeria (Anazonwu et al., 2021).

Capitalizing on our innovative framework, we are able to explore a set of crucial questions: Did politics, such as in the form of partisanship (that had preexisted before the pandemic), influence the pandemic? Did this effect happen through mobility, which was a distinctly political behavior during the pandemic? Was there a mutual effect, whereby COVID-19 influenced political behavior in turn? And was there a temporal effect, wherein as time went by such effects fluctuated spatially between different parts of the nation?

For the purposes of this project, we are interested in quantifying two specific relations over time. The *politics-on-pandemic* impact: the extent to which politics in the form of political partisanship (measured as voting patterns in 2016) influenced the spread of the pandemic from the outbreak in March to Election Day in November via mobility. As partisanship is measured as voting patterns (in 2016, 2012, or as an average from 2000 to 2016), hereinafter we use political partisanship and voting patterns interchangeably when discussing the *politics-on-pandemic* impact. Then, the *pandemic-on-politics* impact is the extent to which the pandemic influenced political behavior and thus the outcome of the presidential elections. We use bigdata for approximately 250 M US citizens and 150 M US voters. Spatially modelling the effects, we find that instead of simultaneity, the initial impact of political partisanship, as reflected in voting patterns, on the spread of COVID-19 via mobility patterns disappeared quickly never to be reciprocated by an effect in the opposite direction. We find little evidence that the pandemic influenced voting patterns.

2. Theory and literature review

Scholarship has examined the relations between a range of political variables and COVID-19. Governments play a role in monitoring and controlling the spread of the pandemic with policies they put in place (Hsiang et al., 2020) such as risk mitigation strategies in schools (Lordan et al., 2020) as well as locally (Bonaccorsi et al., 2020; Woolf, 2022), nationally (Holtz et al., 2020; Chiu et al., 2020) and internationally (Barak et al., 2021; Ruktanonchai et al., 2020). This includes emergency politics (Yam et al., 2020) and the degree of elite discord about the pandemic as reflected on Twitter (Green et al., 2020), which would affect how it is covered by the media and in public opinion. Apart from elites, the pandemic influenced political minorities, discrimination, prejudice and stigma (Wlliamson et al., 2020; Ferrante & Fearnside, 2020; Rzymski & Nowicki, 2020). The media has also influenced the spread of the disease via its effects on social distancing (Kim et al., 2020).

One of the most consequential features of politics is political partisanship. Levels of polarization in the United States mean that partisanship has a distinct effect in almost all aspects of life. Beyond the profound influence of partisanship on electoral politics and electoral behavior (Achen & 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 & Nall, 2017; Huber & Malhotra, 2017). 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 influences support for mail-in voting during the pandemic (Lockhart & et al., 2020). Partisanship also had an effect on the spread of the pandemic, at least initially (Gollwitzer et al., 2020; Sommer & Rappel-Kroyzer, 2022a, 2022b).

We build on this work and expand its scope in several key respects. First, this work is limited in time to the first waves of the pandemic. Second, it puts a normative burden on members of one of two major US parties. Third, education has played a major role in American politics during the Trump era. If controlled for, level of education may attenuate the effect of partisanship on the pandemic, particularly as time went by. Fourth, the cellular phone data that is limited to approximately 15% of the population and is used in many of those studies can be augmented at this point to over 70% of the population with data that were made available more recently and for a range of different types of mobility: Residential, Work, Retail & Recreation and Parks mobilities. Lastly, any examination of links between political behavior and pandemics remains incomplete without the complementary examination of the opposite effect, that from pandemics to politics. The latter is particularly important given the presidential elections that took place in the fall of 2020 and the fact that an incumbent president lost a reelection bid, possibly as a consequence of COVID-19.

With respect to education, during the Trump era, whites with no college education cemented the base of the Republican party. The link between education and partisanship has been established (Thiede & Brown, 2013) and specifically during COVID-19 (Brzezinski et al., 2020). What is more, even before the Trump era, levels of education were linked to mobility patterns during emergencies. Thus, when education—which in the Trump Era is a marker for class in America—is controlled for, partisanship may lose much of its effect via mobility on growth rate.

Furthermore, how such an effect changes over time is important. Some literature suggests that the partisan effect would subside quickly, giving way to social, demographic and economic structures. Such variables would take the place of politics in the context of mobility 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 & Peek, 2004). As time goes by, this would lead us to hypothesize that the effect of partisanship would diminish. This also suggests that there is little reason to expect such a partisan effect to rebound at any point in time between the outbreak and Election Day. Conversely, at the elite levels, we know that partisanship had a lasting effect on policies, including at the state level (Woolf, 2022). Thus, how the effect changed over time can go either way, with partisanship's effect increasing at the level of the mass public as it did at the level of elites (Woolf, 2022), or subside as time went by, as earlier studies of natural disasters, including in the United States, suggest (Fothergill & Peek, 2004; Sommer et al., 2023; Elhadad & Sommer, 2022).

Let us delve into the links between political behavior and epidemiological measures. When citizens abide by remain in place orders, the likelihood of spreading the disease diminishes. Conversely, when people leave their homes, the disease is more likely to spread. To model the effect of political behavior on epidemiology via mobility, we use the SIR (susceptible-infected-recovered) model.

Let:

$$S = S_t := \textit{number of susceptible individuals}$$

$$I = I_t := \textit{number of infected individuals}$$

$$R = R_t := \textit{number of recovered individuals}$$

$$N: = \textit{Overall population}$$

$$b := \textit{average daily number of contacts for each individual}$$

And define:

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

Then:

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

Let us define b in terms of mobility drop. For each mobility type $j \in \{\textit{work}, \textit{transit}, \textit{retail and recreation}, \textit{essentials}, \textit{residential}\}$, let:

$$M_j := \textit{base number of individuals in site}$$

$$d_j^t := \frac{M_j^t - M_j}{M_j} \Longrightarrow M_j^t = M_j\left(1 + d_j^t\right)$$

And let:

$$a_j := \textit{the probability an interaction will cause an infection}$$

Spatial aspects are of key importance here as they determine the link between different types of mobility and infection rates, with different formalizations in the case of residential mobility (the amount of time people spent staying home) as opposed to the other types of mobility as defined by Google:

1. For Residential Mobility:

Let $a_{res} := \textit{the number of people one person will infect in an hour}$

$$b_t = \sum_j a_{res}(24 - M_{res}) + \varepsilon = \sum_j a_j\left(24 - M_j\left(1 + d_j^t\right)\right) = \sum_j a_j M_j\left(1 + d_j^t\right) - 24a_j + \varepsilon$$

Define $x_{res}^t := 1 + d_{res}^t, p_{res} = a_{res}M_{res}$, then:

$$b_t = \sum_j p_{res}x_{res}^t + \varepsilon$$

$$\Rightarrow \frac{\frac{\partial i}{\partial t} + \frac{\partial r}{\partial t}}{s_t i_t} = \sum_j p_{res}x_{res}^t + \varepsilon$$

$$\Longrightarrow \textit{Growth rate} = \sum_j p_{res}x_{res}^t + \varepsilon$$

According to stage 1

$$d_{res}^t = q_{res}v + \varepsilon_{res}^{'}$$

And thus

$$\textit{Growth rate} = \sum_j p_{res}\left(q_{res}v + \varepsilon_{res}^{'}\right) + \varepsilon$$

2. In the case of Work, Transit, Retail & Recreation and Essentials mobility, interactions between people from different households take place. Thus, the spatial organization of these types of mobility means that they relate to infection rates differently. The following modelling applies:

for $j \in \{\textit{work}, \textit{transit}, R\&R, \textit{essentials}\}$.

$$b_t = \sum_j a_j \frac{\binom{M_j^t}{2}}{\binom{N}{2}} + \varepsilon = \sum_j a_j \frac{M_j\left(1 + d_j^t\right)\left(M_j\left(1 + d_j^t\right) - 1\right)}{N(N-1)}$$
$$= \sum_j a_j \frac{M_j}{N(N-1)}\left(1 + d_j^t\right)\left(\left(1 + d_j^t\right) - \frac{1}{M_j}\right) + \varepsilon$$

Define $x_t := 1 + d_j^t, p_j^1 = a_j\frac{M_j}{N(N-1)}, p_j^2 = -a_j\frac{1}{N(N-1)}$, then:

$$b_t = \sum_j p_j^1 x_j^{t2} + p_j^2 x_j^t + \varepsilon$$

$$\Rightarrow \frac{\frac{\partial i}{\partial t} + \frac{\partial r}{\partial t}}{s_t i_t} = \sum_j p_j^1 x_j^{t2} + p_j^2 x_j^t + \varepsilon$$

$$\Longrightarrow \textit{Growth rate} = \sum_j p_j^1 x_j^{t2} + p_j^2 x_j^t + \varepsilon$$

According to stage 1

$$d_j^t = q_j v + \varepsilon_j^{'}$$

And thus

$$\textit{Growth rate} = \sum_j p_j^1\left(1 + q_j v + \varepsilon_j^{'}\right)^2 + p_j^2\left(1 + q_j v + \varepsilon_j^{'}\right) + \varepsilon$$

With the politicization of a range of issues related to COVID-19 in the USA right from the outbreak—including mask wearing and social distancing—at least initially, partisanship's effect should be distinct from other variables known to influence the pandemic. Partisanship would not, however, have a direct effect on the pandemic. The effect would be via what amounted to another type of behavior, which was distinctly political during the pandemic: mobility. Changing mobility patterns according to fluctuations in state regulations due to COVID-19 was a political act (Gollwitzer et al., 2020). Yet, the spatial aspect here is critical: when modeled with mobility types that do not involve close contact between individuals, such as parks mobility, we should observe little effect for partisanship on the spread of the disease. Thus, this is a form of validation for the effect of political behavior on epidemiology via mobility.

H1. *Ceteris paribus*, partisanship would influence the spread of the pandemic through its effect on mobility. This effect would be diminished when we control for education and as time goes by.

As for the opposite direction, the *pandemic-on-politics* effect, extrapolating from the economic logic underlying prospective and retrospective voting (Reed & Cho, 1998; Key, 1955, 1966; Born et al., 2017;

Singer & Carlin, 2013; Elinder et al., 2015), we would expect an effect for the pandemic on politics in general and on voting behavior in particular. In economic voting, it is economic policy and economic performance that influence voting behavior. By the same logic, epidemiological metrics should have an effect on voting patterns. The geographical variance in terms of the severity of the pandemic is substantial and thus conducive to the research design we develop. Some parts of the country were hit considerably harder than others and some were hit closer to Election Day than others. In those parts of the country where the pandemic hit particularly hard—or particularly close to the elections—this logic would suggest an electoral impact.

Spatial aspects related to different geographical units may be crucial. Compared to the previous election round, the difference in vote share should tilt against an incumbent president in those places where the pandemic was most severe and the memory of its impact freshest in people's minds (Healy & Malhotra, 2009).

The competing hypothesis would revolve around political tribalism. It is possible that in a polarized era, policy concerns take the backseat and, thus, do little to drive voting behavior. As such, there would be little effect for policy. Republicans (Democrats) would vote for (against) a Republican incumbent, epidemiology notwithstanding. This may be particularly true for an external shock such as COVID-19, where policy measures may be opaquer than economic issues, and the ideology behind them less clear.

If policy is the key driver, we would expect to find an effect, *ceteris paribus*, for the pandemic on election outcomes in different geographical units (counties in our case). Conversely, if political tribalism is the key driver, no effect for the pandemic should appear on Election Day.

H2. Controlling for alternative effects, those counties hit the hardest by COVID-19 (according to various epidemiological metrics) and closest to Election Day, would see the greatest decline in 2020 voting for Trump.

3. Data and methods

Leveraging their spatial organization by county, we use Google COVID-19 Community Mobility Reports,. The stated motivation for Google in making the data publicly available was to assist in research related to Corona and in sound policymaking. The data provide information about movement trends in several categories including: retail & recreation, groceries and pharmacies, parks, transit stations, workplaces, and residential. Google's core measure compares mobility for each day to a pre-pandemic baseline. Values are reported as a positive percentage (more mobility than baseline) or negative (less mobility). The baseline is a standard value for that day of the week based on the median value from the 5-week period Jan 3 – Feb 6, 2020. Residential mobility shows a change in duration. Retail & Recreation, groceries and pharmacies, parks, transit stations and workplace mobility measure a change in total visitors. In the first five categories, the values denote the change in percentage from the baseline, in the amount of people visiting places of that category, that is, places with similar characteristics for purposes of social distancing guidelines. For instance, under mobility in parks, included are national forests, campgrounds and observation decks. Places grouped under transportation were related to transit including transit stations, taxi stands, car rental agencies, highway rest stops, subway stations and sea ports. In the residential category, the values denote the change in the amount of time people stayed in their homes out of each 24 h. Residential mobility is thus a complement of the other categories of mobility and shows a change in duration. For example, if people in New York county, NY had spent on average 16 h of the day in their homes on Mondays between January 6th and February 3rd, and on Monday, March 16th they spent on average 22 h, the value for that county for March 16th would be 1.375. Retail & Recreation, groceries and pharmacies, parks, transit stations and workplace mobility measure a change in total visitors.

County level election data were obtained from County Presidential Election Returns 2000–2020 of the MIT Election Data and Science Lab. Demographic variables (e.g., percent over 65 years old) and economic variables (e.g., household income and unemployment rates) at the county level were also obtained from the MIT database. COVID-19 data were obtained from the New York Times COVID-19-data page on GitHub.

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. The sources for state-level COVID-19 regulations are listed in the Online Appendix. To provide for higher levels of robustness, these data were juxtaposed with data from the database State-level social distancing policies in response to the 2019 novel coronavirus in the US. In order to evaluate the severity of state regulations regarding business, school and other closures we measured them on a 0–1 score on 4 categories that correspond to types of mobility: work, Retail & Recreation, parks and outdoors, schools and transit. The initial value for every state in every category was 1.5, as even after full reopening no segment of the economy went completely back to normal. When stay-at-home orders take effect, the score is set to 0. For the reopening process we went over the reopening plans and implementations of each state and marked for each day, the degree to which the sector is open according to state regulations. Values fall along the range of 0.25, 0.5, 0.75, 0.9 and 1, with 1 denoting full reopening, subject to health limitations.

4. Results

For the *politics-on-pandemic* effect, our theory suggests that partisanship affects mobility, which in turn affects infection rates. Accordingly, we first examine the effect of partisanship on mobility from the outbreak through Election Day. We control for education and a range of other variables with data for approximately 250 M US citizens. For each mobility type, two regression models were estimated at the county level – with and without a control for education in the county (*Share of College Degree Holders*). In Fig. 1, points indicate OLS regression coefficients for data covering the outbreak period. Lighter points indicate the size of the coefficients in models not controlling for education. Darker points indicate coefficient size in models where education levels are controlled for. Since ideology/partisanship is of particular interest for us, arrows indicate the change in the effect of this variable.

During the outbreak, the effects of partisanship on mobility of different types in Fig. 1 is statistically significant and substantively reasonable. The panels present coefficients (dots) and 95% confidence intervals (whiskers) of regression models predicting 6 different types of mobility, from top left: Residential (that is, the increase in time spent at home), Work, Parks, Transit, Retail & Recreation and Essentials. The size of the coefficient is on the horizontal axis. Models control for % under age 24, % over age 65, time since the beginning of the pandemic, weekend, % minorities (black and Hispanic), size of population, median income in the county, gender equality, state closures, % Evangelicals and federal allocation of special COVID-19 funds. Specifying a time counter since the beginning of the pandemic, the models also account 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 and for weekdays or weekends. Variables are normalized and numbers of observations and R^2 values for each model are reported in each panel.

The vote-share difference between Trump and Clinton in 2016 had a negative and significant correlation with residential mobility. In those counties where more people voted Republican, people abided less by stay-at-home orders at the outbreak. This is the second largest effect, after median income. In the model for Retail & Recreation mobility (the change in the amount of time people spent in Retail & Recreation activities compared to a pre-pandemic baseline in mid-February), the effect of partisanship is approximately twice as large, and is the most

Fig. 1. Partisanship, education and different types of mobility during the outbreak.

substantial. The arrows highlight how controlling for education dramatically reduces this effect. For instance, in Workplace mobility, the change in the effect size of the partisanship coefficient on mobility is a 70% drop (from 0.13 to 0.04), in a regression model controlling for education as opposed to a model that does not. In sum, partisanship has a distinct effect on various types of mobility at the outbreak, but this effect is attenuated when controlling for education. This attenuation, however, does not mean the elimination of the effect of partisanship, which still has a significant and positive effect even after controlling for education. The findings are robust, for instance to a range of model specifications and different predictors (e.g., with and without an education predictor), and types of sampling (e.g., a subsample of small counties where education is homogenously distributed as we show below).

Let us now attend to the second stage effect, that of mobility on the pandemic. Fig. 2 suggests a strong relation at the outbreak between mobility (on the horizontal axis) that involves human interaction and COVID-19, on the vertical axis, where growth rate is lagged by 5 days. Sensitivity tests for other lags for growth rate were applied, but the effect was comparable. Plus, the 5 day lag is epidemiologically the most accurate and reasonable (Omer & et al., 2020).

Panels range from top left: Residential, Work, Parks, Transit, Retail & Recreation and Essentials, as retrieved from Google. Bubble size is proportional to county population and color indicates the presidential election result in the county in 2016, from blue (most pro-Clinton counties) to red (pro-Trump). Each panel also reports the regression equation and the R^2. The strongest effects and explanatory power are registered in the models estimated for the Residential, Workplace and Retail & Recreation mobilities with R^2 of 0.41, 0.42 and 0.43 respectively.

Residential mobility (top left panel) is negatively correlated with growth rate of COVID-19 at the outbreak. As people stayed home more, the growth rate of the disease decreased. Correspondingly, Retail & Recreation mobility had a positive effect. As people moved about more for Retail & Recreation purposes—doing shopping or going to the gym—infection rates soared. Conversely and as a form of validation for the modeling strategy through the SIR model, where mobility types that do not involve close proximity between individuals are concerned, and which relate mostly to outdoor activity (e.g., parks mobility), there is no noticeable effect on rates of COVID-19, also indicated by the negligible

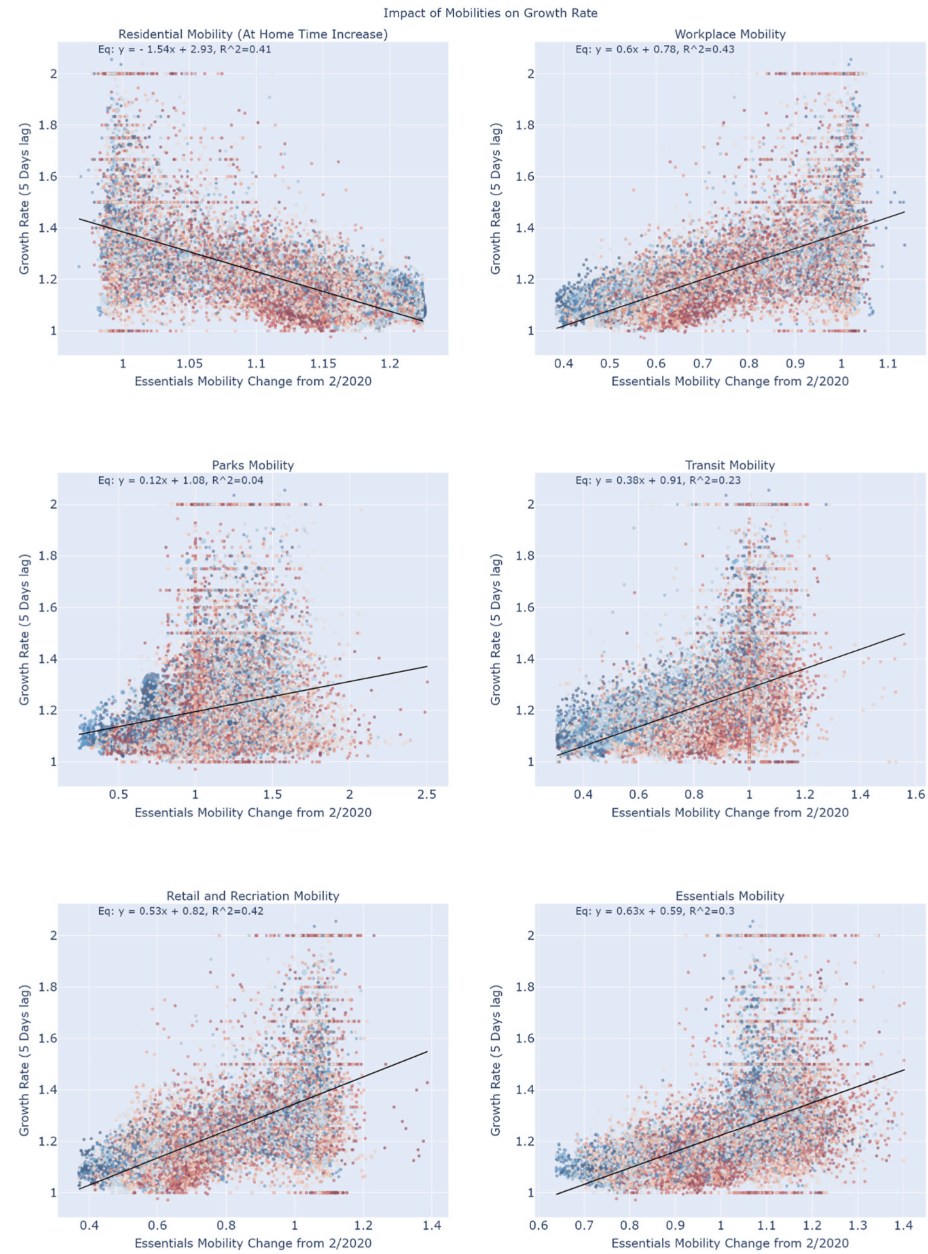

Fig. 2. Effect of 6 different types of mobility on the R growth rate with a 5-day lag at the outbreak.

$R^2 = 0.1$ for the corresponding regression model.

Now that both the effect of partisanship on mobility and the effect of mobility on COVID-19 at the outbreak are established, let us formalize the effect of partisanship on COVID-19 via mobility. This modeling strategy and model specifications are based on the formalization of the SIR model presented above and the 2-stage process by which ideology influences mobility, which in turn influences epidemiological growth.

To test models for the effects of partisanship on epidemiology via mobility, we estimated several SIR-based 2-stage regression models on the first wave of COVID-19 in the United States, over a period of 120 days starting March 1, 2020 with data for the 20% most populated counties. Those counties represent about 70% of US population, which amounts to 250 M citizens.

The effects of ideology and other factors on the epidemiological growth rate during the outbreak, via a range of mobility types is presented in Fig. 3, both with and without controlling for education. The first three panels present the results for the effects via Residential, Work and Retail & Recreation mobilities. The effect through Parks mobility is also presented. Models for the effects of partisanship on the pandemic via Residential, Work and Retail & Recreation mobilities have a strong explanatory power. Their R^2 ranges from 0.8 to 0.85. Conversely, and as expected, the model via parks mobility has a negligible explanatory power of 0.2. Variables are normalized.

The effect of education is substantial in its own right and in terms of its attenuation of partisanship's effect. Lighter points indicate the size of regression coefficients in models specifying all variables without controlling for education. Darker points indicate coefficient size in models where education levels are controlled for. Arrows indicate the change in the effect of partisanship without (tail of the arrow) and with (head of the arrow) a control for education. When education is controlled for, the effect of partisanship shrinks considerably. This attenuation, however, does not mean the elimination of the effect of partisanship, which still has a significant effect even after controlling for education.

Without controlling for education, the effect of partisanship on the growth of COVID-19 via Residential mobility is the second largest in the model. The 0.07 coefficient on the Republican-Democrat 2016

Fig. 3. Effect of political partisanship on COVID-19 growth rates modeled through various mobilities at the outbreak.

differential in the county indicates that with an increase of 1% towards Republicans on a spectrum of 0–100%, the R reproduction coefficient grows by 0.07%, controlling for all alternative explanations (aside from education). As R is exponential, this effect may be substantial. More specifically, the difference in the normalized margin variable between a purely Republican and a purely Democratic county is 1. Let's take a country where voters voted overwhelmingly Democrat in 2016 and where R = 0.99 (suggesting a pandemic growth rate that is under control, even slightly shrinking) and compare it to a matching county with purely Republican voters (but otherwise identical). The difference in COVID-19 growth rate between those two counties at the outbreak would be substantial. Mathematically, the difference would be 0.06, yielding an R = 1.06 in the otherwise identical, yet Republican, county. In other words, while growth rate in the Democratic county is under control, its Republican "twin" would experience a pandemic that is rampant.

The effect of partisanship on the pandemic growth rate via Retail & Recreation mobility is even more substantial. It is the coefficient with the largest effect. When computing the effect of partisanship on COVID-19 growth rate through Retail & Recreation mobility (Fig. 3), the 0.011 unnormalized coefficient on the Republican-Democrat 2016 differential indicates that with an increase of 1% towards the Republicans on the margin spectrum, the R reproduction coefficient grows by 0.1%, controlling for all alternative explanations (aside from education). Compared to an overwhelmingly Democratic county where R = 0.99, a matching county that is dominated by a Republican constituency, would experience a pandemic that is out of control. The difference would be 0.1, yielding R = 1.09 in the matching Republican county.

Those results, however, overestimate the effect of partisanship on the pandemic, since the model is underspecified and controlling for education significantly reduces the impact of partisanship. As the arrows in the different panels indicate, for Residential, Work, and Retail & Recreation mobility, not only is the drop in the effect of partisanship substantial when controlling for education, but the effect of the latter is sizeable. Indeed, in both the Work and the Retail & Recreation models, the effect of education is the predictor with the largest or second largest effect in absolute value.

When controlling for education in the models in Fig. 3, the impact of ideology drops by approximately 40% on the growth rate via residential mobility and Retail & Recreation mobility. The drop is even more dramatic in the work mobility model. There, without controlling for education the effect size of ideology is 0.125, which is, as seen before, quite substantial. But when controlling for education the effect of ideology drops by over 70% to 0.04. According to the theoretical framework that we developed based on the SIR model, in Retail & Recreation and Work mobilities we may expect to see quadratic relationships between the independent variables and the growth rate. We tested this formulation empirically as well. Model specification and interpretation in this case are considerably more cumbersome as they include as right-hand variables multiplication terms of every pair of independent variables. Yet, there is no significant corresponding improvement in the explanatory purchase of the model. Hence, we reported here the linear version.

While partisanship may be considered a pure political effect, education as a marker for class is also a political effect, and in particular in the Trump Era. Thus, if education has an effect, this effect is another effect of politics broadly defined. Accordingly, to delve into the effect of education and to test the robustness of our findings, we reran the analyses with a sample consisting only of counties with a population size <30 K and which are at the top or bottom 20% of the distribution of the education variable. While the number of observations is smaller as a result, this subsample allows us to flash out more clearly the effects of education. Figure A1 (in the Online Appendix) presents the results of the impact of ideology on different types of mobility. Apart from residential mobility, where the data are too limited which leads to particularly large standard errors, we find a similar effect overall: conservative ideology increased levels of mobility, with education attenuating this effect, which is true even in this subsample of smaller counties that are homogenous on the education variable.

The panels in Figure A2 (in the Online Appendix) represent the effects of mobility of different types on the R Growth Rate in the same subsample of counties. The effects, again, are like those in the overall population. Lastly, we test the effects of ideology and education on growth rate in this subsample. Again, in Figure A3 (in the Online Appendix) other than residential mobility, where data are limited and thus standard errors are inflated, the effect of ideology is significant and in the anticipated direction. What is more, even in this subsample, where the distribution of education is more homogenous, partisanship's effect is attenuated when education is controlled for. Yet, here as well partisanship's effect remains significant.

To delve into the effect of partisanship and to further test the robustness of our findings, we reran the analyses with a different subsample now consisting only of counties with a population size <30 K and which are at the top or bottom 20% of the distribution of the partisanship variable. Figure A4 (in the Online Appendix) presents the results of the impact of ideology on different types of mobility. We find a similar effect overall: conservative ideology increased levels of mobility, with education attenuating this effect, which is true even in this subsample of smaller counties that are homogenous on the partisanship variable.

The panels in Figure A5 (in the Online Appendix) represent the effects of mobility of different types on the R Growth Rate in the subsample of counties selected for homogeneity in partisanship. The effects are like those in the overall population. Lastly, we test the effects of partisanship and education on growth rate in this subsample. Again, in Figure A6 (in the Online Appendix), the effect of ideology is significant and in the anticipated direction. What is more, even in this subsample, where the distribution of partisanship is more homogenous, its effect is attenuated when education is controlled for.

Yet, as time went by, the strong connections both between ideology and mobility and between mobility and growth rate—that we observed for the outbreak—subsided. Fig. 4 shows the temporal shift between mobility and epidemiology. Each panel presents the results for a month, between the outbreak and Election Day. On the horizontal axis are levels of residential mobility and on the vertical axis is growth rate with a 5-day lag. The size of each bubble is proportional to the population size of the county and the color indicates the 2016 presidential elections result, ranging from blue (most Clinton-leaning counties) to red (Trump-leaning). Univariate OLS regression results appear within each panel.

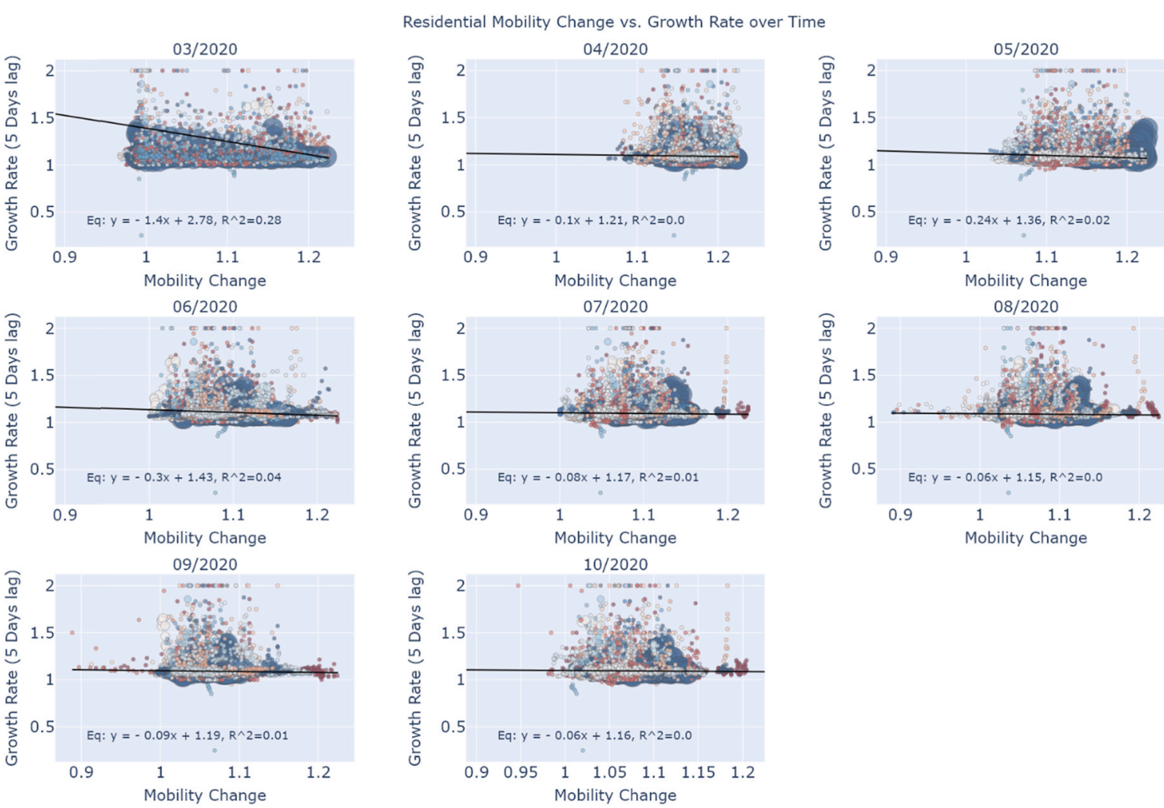

Fig. 4. Mobility's effect on growth rate subsides quickly with time.

Fig. 5. The impact of partisanship and other factors on the pandemic growth rate in weekly intervals throughout 2020 to election day.

The effect of Residential mobility on growth rate gradually disappeared as time went by. In March (top left panel), the effect was substantial, with a regression coefficient of 1.41 and explanatory power of approximately 30% of the variance between counties in growth rate. That coefficient shrinks tenfold in April, and remains within the same order of magnitude or even shrinks further. From July onward, this coefficient is almost indistinguishable from zero. As the colors of the bubbles indicate, the dominant ideology in the county is related to mobility, in particular from April onward when the blue counties move visibly less than red ones. Yet, this has no bearing on the growth rate of COVID-19, due to a ceiling effect. As time went by and as all counties started exhibiting some level of behavioral change, the little variance between levels of change lead to a diminishing effect on growth rate. After the outbreak, people across the ideological spectrum and across the country stayed home more. Mobility, thus, lost most of its explanatory value, so that the remaining variance in growth rate was likely explained from April onward by other variables, such as mask wearing, quality of medical care, population density or even disparities in climate conditions. In sum, after the outbreak, mobility had a smaller influence on the pandemic.

Regression models estimated for the period from the outbreak to Election Day tell a similar story for the dwindling effect of partisanship

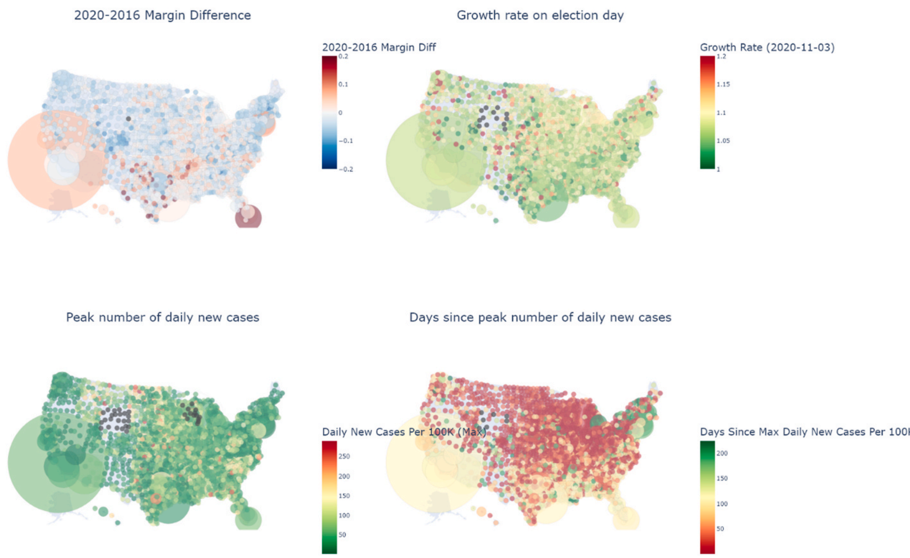

Fig. 6. COVID-19 hotspots and election differentials.

on the pandemic via mobility. The coefficient for the effect of partisanship/ideology on the R growth rate over time in Fig. 5 is high initially (H1). The top three panels present coefficients (lines) and 95% confidence intervals (shaded areas) of 2-stage regression models predicting growth rate through 3 different types of mobility: Residential, Work and Retail & Recreation in weekly intervals between March 7, 2020 and Election Day.

To 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.

The size of the coefficients for each of the weekly models is on the vertical axis. Only a subset of the coefficients appear in the figure for models that control for % under age 24, % over age 65, time since the beginning of the pandemic, weekend, % minorities (black and Hispanic), size of population, median income in the county, gender equality, state closures, % Evangelicals and federal allocation of special COVID-19 funds. The bottom panel shows the explanatory power (R^2) of the 3 models in weekly intervals through the same time period.

Calculated via all three types of mobility (Residential, Work and Retail & Recreation), the impact of political behavior in the form of ideology on the pandemic reaches a peak in mid-March. Yet, the size of the coefficient shrinks by more than 50% shortly thereafter. Indeed, the only time when it bounces back is in June, when it reaches approximately 50% of the effect size of March. From that point onward, the effect diminishes to being almost indistinguishable from zero. R^2 values for the different models (in weekly intervals) indicate that while the explanatory power of the models stems not just from the partisanship predictor, the overall pattern remains the same. Using mostly political, sociological and demographic variables, the models explain the growth rate of the pandemic reasonably well only in March.

The spatial quantification presented here provides clear evidence for the limited effect over time that partisanship had on the pandemic, at least when modeled with county as the basic geographical unit. As far as the *politics-on-pandemic* impact is concerned, the initially strong partisan effect on the growth rate of the pandemic via mobility disappeared shortly after the outbreak. It never regained its power throughout the year to Election Day. This suggests that over time, partisanship did not increase its effect on the mass public as it did at the level of elites (Woolf, 2022). Instead, the effect of partisanship subsided as time went by, as earlier studies of natural disasters, including in the United States, suggested (Fothergill & Peek, 2004).

Let us now turn to the opposite direction: the effect of COVID-19 on politics—the *pandemic-on-politics* effect. The US Presidential Elections are the most important event on the political calendar. With a strong economy under his wings and enjoying incumbency advantage, in early 2020 president Trump's reelection prospects seemed reasonable. Yet, he lost. In the intervening months, the country was hit by a global pandemic, disrupting all aspects of life for prolonged periods of time and in the most fundamental of ways, including taking the lives of hundreds of thousands of Americans. Was Trump's electoral defeat attributable to the disease? With nearly 9.5 M infected and over 230 K dead by Election Day, COVID-19 had wreaked havoc in America under the Trump Administration. The economic and social tolls of the pandemic by November of 2020 are still hard to accurately compute. Conversely, the pandemic was perceived by many as beyond the control of any specific state, government or leader since it was a global event, affecting almost all the countries in the world. Were votes cast on Election Day affected by the pandemic, its severity or any of its characteristics? If so, the pandemic clearly influenced political behavior.

To delve into the extent to which COVID-19 influenced election outcomes, let us take advantage of its geographical organization. We first look for some level of correlation between COVID-19 growth rates in different parts of the country on Election Day and the 2016–2020 differential in election outcomes. If voting were largely retrospective, those places hit hardest by the pandemic would be the ones where president Trump would lose the most support.

Fig. 6 suggests little correlation, *prima facie*, between various epidemiological variables and the shift from 2016 to 2020 in election outcomes. On the top left is a map representing the voting differentials by county between the presidential elections in 2020 and in 2016. Each county is represented by a bubble, whose size is proportional to its population. Trending red are those counties where Trump gained votes and blue are the ones where he lost votes compared to 2016. White counties are those with no meaningful change in voting patterns. The map on the top right indicates the R coefficient in each county on Election Day. In green counties, the pandemic is largely under control. It is growing in yellow counties and rampant in those counties painted in red. The map on the bottom left indicates the peak number of daily new cases (per 100 K people) in the county over the pandemic. Green indicates a relatively low number whereas red indicates a high number. The bottom right map indicates the number of days elapsed since the peak described in the previous map was reached. Red indicates small number of days, that is the peak was in the recent past, whereas green indicates large number of days, i.e., the peak was in the more distant past.

The pandemic hotspots on Election Day do not seem to be the counties where Trump suffered the most dramatic electoral losses. Results remain the same when we use a host of other epidemiological measures to gauge the severity of the pandemic in the county, including days since peak number of daily new cases and peak number of daily new cases. Those epidemiological measures at different points in time—closer to Election Day and at earlier points since the pandemic started in early 2020—do not correlate with electoral changes. In fact, some of the correlations may be the opposite of what we would expect; certain parts of the Midwest United States, where the number of days since the peak number of daily new cases was the highest, are in fact those where Trump lost votes compared to 2016. In sum, at least by an initial inspection, it is hard to see how epidemiological variables changed with electoral shifts.

To obtain a more robust estimate for the effects of the pandemic on voter behavior, we estimated multivariate regression models. The outcome variable for the regression models is the Republicans to Democrats margin difference comparing 2020 to the mean of the elections in 2000–2016. This approach using the mean presidential vote allows us to average out the impact of individual candidates such as Biden or Clinton. In addition to various controls, all models specified an epidemiological indicator of some kind. The epidemiological variables included: Growth rate on election day, Peak growth rate, Average daily growth rate during month leading up to election day, Days elapsed since peak daily growth rate, Days elapsed since peak cumulative cases, Days elapsed since peak in active cases, Days elapsed since peak in daily new cases, Cumulative cases by Election Day, Active cases by election day, Daily new cases by Election Day, Peak cumulative cases, Peak active cases, Peak daily new cases, Cumulative cases during month leading up to Election Day, Active cases during the month leading up to Election Day, and Average daily new cases during month leading up to Election Day. A discrete model was estimated for each of those COVID-19 indicators separately as reported in Table 1, adding up to 16 different models. Of all the variables specified in each model, Table 1 reports the results only for the coefficient of the epidemiological measure. This coefficient answers the question around the *pandemic-on-politics* effect. The general specification for all models in the table is the following, with the epidemiological measure changing between them:

vote differential = b_1*ideology + b_2*education + b_3*% under 24 + b_4*% over 65 + b_5*% African Americans + b_6*% Hispanics + b_7*density + b_8*household income + b_9*Duncan Index + b_{10}*closures + b_{11}*% Evangelicals + b_{12}*CARES Act expenditure per capita + b_{13}*Epidemiological Measure.

Only the b_{13} coefficients in the different models (and their standard errors) are reported in Table 1. In almost all models, the b_{13} coefficient fails to meet standard levels of statistical significance. In only 4 of the models, this coefficient is statistically significant. The effect size in those models, however, suggest a marginally substantive effect. In sum, failing to find support for H2, we see that the effect of the disease on election outcomes was virtually zero.

One reason for why our results diverge from existing literature—at least by our measures despite its devastating effect across the country, COVID-19 had little effect on political behavior related to election outcomes—is the fact that we specify a wide range of epidemiological measures. We believe this approach is justified, as it is not clear what aspect of the pandemic was linked to politics. Observing the gamut of epidemiological indicators and their effects provides us with a picture that is more complete and comprehensive, and yet more convoluted, than previously available. It suggests that when examined on its multitude facets, the pandemic had an inconsistent, and substantively insignificant, effect on voting in 2020. Another reason may be the discrepancy between the overall effect of the pandemic on American politics studied in previous scholarship on the topic, an overall effect which may have been more substantial, and the effect on the local level. What happened on the national level may have had an effect on voters. The local level of the pandemic, however, which is the one we study in depth, seems to have had little effect.

Table 1
OLS Regression Models
Pandemic-on-politics effects
DV: 2020 vote vs. Mean Presidential Vote 2000–2016

Regression model #	Epidemiological variable specified in the model	Coefficient	Standard Error
Model #1	Institutional Continuity in Voting	−0.874 ***	0.248
#2	Growth Rate (2020-11-03)	17.3553	9.795
#3	Growth Rate (Max)	0.3028	0.872
#4	Growth Rate (2020-10-03 - 2020-11-03)	1.5574	3.638
#5	Days Since Max Growth Rate	−377.8049	578.585
#6	Days Since Max Cases Per 100 K	3172.2136	8261.435
#7	Days Since Max Daily New Cases Per 100 K	1112.3445 ***	524.006
#8	Days Since Max Active Cases Per 100 K	1009.1434	533.574
#9	Cases Per 100 K (2020-11-03)	−0.0003	0
#10	Active Cases Per 100 K (2020-11-03)	−0.0036 ***	0.002
#11	Daily New Cases Per 100 K (2020-11-03)	−0.0418	0.022
#12	Cases Per 100 K (Max)	−0.0005	0
#13	Active Cases Per 100 K (Max)	−0.0024	0.001
#14	Daily New Cases Per 100 K (Max)	−0.0197	0.011
#15	Cases Per 100 K (2020-10-03 - 2020-11-03)	−0.0004	0
#16	Daily New Cases Per 100 K (2020-10-03 - 2020-11-03)	−0.0609 ***	0.024

5. Discussion and conclusions

Whether social, economic or demographic aspects are considered, COVID-19 had a profound impact on life in the United States. Its timing during an election year suggests that it might had an effect on politics as well, in the form of its effect on election outcomes. Thus, there may be simultaneity between political behavior and pandemics. Indeed, the relations between political behavior and epidemiology have become the object of major scientific interest (Parolin & Lee, 2021; Josephson et al., 2021; Druckman et al., 2021). The database we compiled for this project and the innovations in our theoretical framework—both capitalizing on geographical variance and characteristics—allow us to make better inferences, than those in the literature, on several key questions concerning the relations between politics and pandemics and the simultaneity between them (Bonaccorsi et al., 2020; Ferrante & Fearnside, 2020; Green et al., 2020; Holtz et al., 2020; Chiu et al., 2020; Rzymski & Nowicki, 2020; Wlliamson et al., 2020; Woolf, 2022; Yam et al., 2020).

To delve into this simultaneity, we took advantage of a research design that is a product of the COVID-19 pandemic of 2020 and the presidential elections that cooccurred that same year, and that the big-data for epidemiology and for voting is spatially organized with county as the geographical unit. The sequence of events unfolding in 2020 allowed us to test the effects of politics, in the form of voting patters in 2016, on the pandemic (the *politics-on-pandemics* effect). And then, examine the impact the pandemic had on politics.

Politics had a significant effect on the spread of COVID-19 at the outbreak. The politicized manner by which the pandemic was handled in the USA meant that above the economic, sociological and demographic variables that influenced its outburst, variables that are at the core of the political realm, such as partisanship, had their own distinct effect. With the politicization of a range of issues related to COVID-19 in the USA—including mask wearing and social distancing—partisanship's effect is distinct from other variables known to have an influence. Partisanship, however, does not have a direct effect on the pandemic, but only through mobility of particular types, specifically those that involve human interaction with close physical contact. The effect of partisanship on the pandemic, however, was limited in time and dependent on variables such as education. The effect of partisanship on growth rate, while initially substantial, subsided within a matter of weeks, never to regain its power. What is more, when controlling for education, the effect of partisanship on the growth rate of the pandemic was seriously mitigated. While it remained statistically significant, its substantive effect shrank considerably.

As for the opposite direction, the pandemic seems to have little effect on politics, at least as far as voting behavior in the presidential elections is concerned and when quantified as the vote margin in county-level elections returns. The pandemic did little, it seems, to sway the effects of political variables well documented in the literature—including partisanship and polarization (Green et al., 2020; Sommer et al., 2022)—on how elections are determined in the United States. President Donald Trump was an unusual president by many standards, not least by the fact that he failed to win reelection. As dramatic as COVID-19's impact on America was in the year 2020, it did little, our research suggests, to impact the outcomes of the presidential elections that year at least when measured by its effects at the local level. Analyses at that level suggest that the pandemic did not lead to the defeat of an incumbent president. In a polarized era, policy concerns took the backseat and, thus, did little to drive voting behavior.

In sum, our spatial analyses offer scant support for simultaneity in the relations between political behavior and COVID-19. The effect seems more directional than bidirectional and limited in time. The effect of political behavior on pandemics is significant and substantively meaningful but only at the outbreak of COVID-19 and through mobility. Conversely, if there is an effect of pandemics on politics, it is often insignificant and never of meaningful magnitude. Granted, it is possible that the relationship between politics and the pandemic is even more complicated. Future research will have to look into relationships, some of which feed back into each other. For instance, partisan elite cues likely affected individuals' perception of how big of a threat the pandemic posed, which will have affected their adoption of social norms relating to social distancing, mask wearing, etc. before public policies explicitly structured such behaviors (Woolf, 2022; Sommer & Rappel-Kroyzer, 2022b). Both voluntary and policy-based reductions in mobility patterns should be studied in the future, as they would have affected the spread of the pandemic. Lastly, the inherent differences in the approximately 3000 counties that constitute our datapoints, which differ with a meaningful statistical spread on each of the predictors, mean that the potential of ecological fallacy is small. The likelihood of ecological fallacy is further diminished as our database is large enough to select subsamples of smaller counties based on homogeneity in partisanship or education, and single out the effects of those predictors with a better ability to draw inferences.

We use mobility as the only measure of politics on the pandemic, which means that our models test a single channel through which partisanship might influence the pandemic. Yet, others also exist. Government orders, masking behavior and employer policies, potentially impact reproduction rates and are impacted by partisanship. We examine a single channel of influence in each direction, not the universe of possible influences of politics on the pandemic and vice versa. Yet, at the level of mass behavior, mobility is the only type of behavior for which we have valid and reliable bigdata at the level of the nation as a whole. To the best of our knowledge, the ways to empirically test other channels, such as masking behavior, cannot be based on the same type of sound empirical work made possible by the unique behavioral data we were able to assemble. In sum, testing the simultaneous effects between politics and pandemics via the only channel where comprehensive bigdata at the level of the nation could be compiled—that is, mobility—we find scant evidence for simultaneous relations.

COVID-19 was the first major pandemic in a hundred years. Yet, its relations to politics are of utmost importance, in case such a global epidemic happens again. What is more, even if there are 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 how such extreme circumstances of emergency situations due to a natural cause interact with human behavior, and in particular its political facets, may be useful. Such understanding is likely to be useful in times of such a natural emergency. Insights from this study may be particularly valuable then and its spatial analysis based on county as territorial unit doubly useful.

Declaration of competing interest

The authors declare no conflict of interests.

Data availability

Data will be made available on request.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.polgeo.2023.102939.

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