Pandemics and Elections: Estimating the Net Effect of Pandemic Partisan Retrospection

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Abstract

Do voters reward or punish elected officials for pandemics? Recent research on natural disasters finds evidence for partisan retrospection, which maintains that voters' decisions to reward or punish incumbents following a disaster is influenced by whether or not the elected official is a co-partisan. We argue that the COVID-19 pandemic similarly affected voters' response to reward or punish incumbents. We contend with increasing COVID-19 infection rates and deaths, voters supported incumbents who were co-partisan and opposed incumbents who were not co-partisan. We look for evidence of pandemic partisan retrospection by estimating the net effects of the COVID-19 pandemic on the 2020 U.S. presidential and Senate elections. We find that voters were more likely to punish incumbents who were not co-partisan and more likely to reward incumbents who were co-partisan in counties with higher pandemic infection and death rates. Our results support pandemic partisan retrospection and suggest that, in the aggregate, the pandemic had an overall impact on voter choice similar to what occurs after natural disasters.

Keywords

pandemics, partisanship, COVID-19, elections, retrospective voting

Introduction

In the study of electoral behavior, dominant theoretical explanations center on demography, party identification, and retrospective voting, while voting preference models that focus on natural disasters and crises are still developing. Bisbee and Honig (2021) argued that in the presence of anxiety-inducing exogenous shocks like the COVID-19 pandemic, voters display "flight to safety" behavior by choosing safe candidates. Moreover, research on natural disasters finds evidence for partisan retrospection, in which voters' decisions to reward or punish incumbents following a disaster are influenced by whether or not the elected official is a co-partisan (Heersink et al., 2020). In this paper, we build on this vein of existing research by connecting pandemics to traditional party identification and partisanship models. External and extraordinary crises like pandemics offer an opportune setting to consider changes in the intensity of voters' preference for the status quo. We propose that voters responded to the COVID-19 pandemic with partisan retrospection, meaning that voters supported incumbents and candidates who were co-partisan and opposed those who were not co-partisan. Estimating net effects in the 2020 U.S. presidential and Senate elections, we find that voters punished incumbents and candidates who were not co-partisan and rewarded those who were co-partisan in counties where pandemic infections and death levels were higher, lending support to our pandemic partisan retrospection framework.

We use innovative empirical methods to investigate whether pandemic partisan retrospection influenced voter behavior. Our approach involves analyzing the net impact of the pandemic on elections. To accomplish this, we first estimate the intensity of the pandemic rather than typical cumulative measures that sum up cases or deaths over a period of time. Estimating pandemic intensity from daily data on COVID-19 infections and deaths allows us to look at changes in pandemic cases and deaths at the local county level at different points leading up to election day. We used county-level data instead of the state or national level because of the local variation in cases and deaths, public health policy enforcement, and news media. Unlike the typical approach of using cumulative sums, our measure captures the timing of the most intense phase of the pandemic in a county in terms of cases and deaths, relative to election day. By identifying and using country level COVID-19 case and death peaks, we can better address the differential impacts of COVID-19 on voters when they vote.

Our kernel based estimation procedures involve fitting a smoothing curve to each graph of pandemic statistics and identifying prominent features that are significantly associated with higher pandemic intensity. We refer to these features as "peak statistics" and show that they are informative indicators of aggregate-level pandemic intensity at the county level, allowing us to consider both temporal and spatial dimensions of intensity. More details on these specific methods are provided in the sub-section Explanatory Variables: Peak Statistics. While our study is limited to voter behavior at the county level due to the use of aggregate data, we believe that statistically significant and consistent voting patterns that correlate with the pandemic intensity are valuable contributions to the literature on retrospective voting and partisanship.

To better explain how people voted during the coronavirus pandemic, our pandemic partisan retrospection framework connects traditional voting models and partisanship. In the United States, the spread of COVID-19 triggered numerous unpopular government mandates and policies in 2020, followed by gradual vaccine rollouts in 2021. Following party identification and retrospective voting models, we would expect voters in the 2020 elections to punish incumbents and favor the opposition party and its candidates. However, the 2020 presidential election results seem to defy this expectation. In many U.S. counties that lost lives to COVID-19 at the highest rate, support for then-President Trump increased (McMinn and Stein, 2020). Similarly, adhering strictly to the flight to safety theory in Bisbee and Honig (2021), we would expect voters to choose safe establishment candidates regardless of the candidate's policy platforms, incumbency, or attributes. Again, the 2020 presidential election results seem to defy this expectation.

Recent electoral research on natural disasters and partisan retrospection finds that following a natural disaster, voters punish or reward incumbents depending on co-partisanship (Heersink et al., 2020). This work offers a path to reconcile competing theories and the 2020 election results. We argue that partisan retrospection is contextual, depending on the level of pandemic intensity at the county level. In counties that had a larger Republican vote share than Democratic in the previous 2016 Presidential election, we found evidence that in the aggregate, voters shifted their votes to their safe co-partisan candidate, a Republican, as the pandemic intensity level increased. Similarly, in counties that previously had a higher Democratic vote share then Republican in 2016, we looked for evidence that, in the aggregate, voters shifted their votes to their safe co-partisan candidate, a Democrat, when the COVID intensity level increased in their county. Even in counties where the prior 2016 presidential election results slightly favored one party but in which either Democratic or Republican candidates could have conceivably won a majority of the vote, we still expected that, in the aggregate, voters shifted their votes to their safe co-partisan candidate when COVID intensity levels increased in their county. While partisan retrospection, introduced by Heersink et al. (2020) includes the possibility of punishment and reward, their results focus mostly on punishment. Our findings for pandemic partisan retrospection represent a more complete and extreme version of partisan retrospection. As COVID-19 reached its peak in their county, not only were Democratic voters in Republican areas punishing Republican candidates, but Republican voters were also rewarding them at the aggregate level

This paper is organized as follows. First, in the following section, we explain our pandemic partisan retrospection framework by examining traditional voting models, existing research on natural disasters and voting behavior as well as previous research on pandemic voting and voting in times of crises. Then, in the first subsection of Research Design, we discuss the specific U.S. contexts that we use in our empirical analysis. Subsequently, in the second subsection of Research Design, data and measures for pandemic intensity and vote shares are used to examine the net effect of COVID intensity on partisanship. Next, in the third subsection of Research Design, we provide a brief overview of the methodological tools we use in this paper, starting with the "peak statistics," which is a set of summary statistics we develop for COVID-19 case and mortality progression curves, followed by kernel density estimation, and kernel regression. Finally, in the Results section, we provide empirical evidence in support of our choice for the measure with a discussion of our main finding in this paper on the heterogeneity in voting behavior between Democratic and Republican counties in periods of increasing pandemic intensity.

Pandemic Partisan Retrospection Framework

Taking a political psychology approach, the flight to safety theory imagines elections as a political marketplace where voter preference for the status quo increases in response to anxiety (Bisbee and Honig, 2021). By shifting the focus to the status quo, the flight to safety framework broadens the impact of anxiety on affected voters and candidates, with radical candidates on both ends of the ideological spectrum being penalized, while also accommodating well-established empirical work on incumbency advantage and risk aversion (Bisbee and Honig, 2021). The evidence presented for this flight to safety is promising, but it is based largely on the 2020 primary elections, avoiding questions of partisanship, which can be an influential voter heuristic (Heersink et al., 2020). In general elections, evaluations of establishment or safe candidates are not made in a vacuum but in the context of partisanship.

To address the context of partisanship, we also look to previous studies of elections in times of crisis, ranging from natural disasters, terrorism, and pandemics. We focus on crises, not just what Healy et al. (2010) call "irrelevant events", a catchall term for any event that an incumbent is not responsible for, which includes crises but also include sporting events (Busby and Druckman, 2018) or lottery results (Bagues and Esteve-Volart, 2016). Elected officials in crises are expected to create or enforce policies to address the crisis. While there is no consensus on how voters choose during times of crisis, this vein of research largely relies on testing retrospective voting models, whether or not voters reward or punish elected officials based on their performance or response. For the most part, the conclusions on whether voters at the polls respond retrospectively to crises are contradictory. Research on the 1918 flu pandemic found that the pandemic did not have a significant effect on election outcomes (Achen and Bartels, 2016) and the voter punishment for the incumbent's flu response was relatively minor in comparison (Abad and Maurer, 2020). The literature on terrorism and voting behavior has found that both incumbents can lose electoral support after terrorist attacks (Gassebner et al., 2008; Karol and Miguel, 2007) and incumbents are not punished for attacks (Koch and Tkach, 2012) or that such attacks do not have an impact on election outcomes (Baccini et al., 2021).

Accordingly, the research on natural disasters provides evidence for both blind retrospective voting, when voters punish incumbents for random events (Achen and Bartels, 2016), and attentive retrospective voting, when voters punish incumbents but also reward them for funding and aid (Gasper and Reeves, 2011). Achen and Bartels (2016) and Heersink et al. (2017) both found that voters did punish incumbent presidential candidates after a natural disaster. While Healy and Malhotra (2009, 2010), and Gasper and Reeves (2011) differ in whether voters punish incumbent presidential candidates after a natural disaster, voters reward candidates that provide relief aid or spending. The variety of mixed results in the research on elections in times of crisis suggests that retrospective voting models alone do not fully explain voter behavior and that the impact of crises on voter choice depends on additional contextual factors. Heersink et al. (2020) propose that partisanship acts as a screen in which voters interpret information and assign blame after natural disasters, instead of blind retrospection, meaning punishment for disaster damage or attentive retrospection, signifying rewards for government aid response.

The partisan retrospection model posits that following a natural disaster, voters punish and reward incumbent conditionally, based on pre-existing partisanship. Heersink et al. (2020) argue that in the wake of natural disasters, voters rely on a key heuristic shortcut, shared partisanship with elected officials. Voters will support candidates of their own party (Campbell, 1960) and partisanship shapes how information is processed by voters (Jones and Brewer, 2019). Similarly, we focus on the role of partisanship screening to explain pandemic voting outcomes. Research on how voters experience and react to a pandemic, which differs from natural disasters and terrorism in its geographical scope and duration, is sparse and offers mixed findings. While pandemics, natural disasters, and terrorism, all involve the loss of life, the key impacts of natural disasters and terrorism center on housing and infrastructure damage. In contrast, pandemics contribute to an overall economic recession and longer term stresses on healthcare systems and local and national governments. As a result, we do not know much about why some voters might choose co-partisan candidates or why some voters may punish incumbent candidates in pandemic elections.

However, COVID-19 has been called the pandemic of blame for the widespread discourse on who to blame for the rise and spread of the pandemic (Flinders, 2020; Hardy et al., 2021; Bouguettaya et al., 2022). In pandemics, local and state governments are fully operational, in addition to federal level leadership and technical assistance. Some studies have shown support for the public blaming the actions and response of their governments in causing coronavirus conditions and its later impacts (Lee, 2020; Porumbescu et al., 2023; Matthews and Heesambee, 2024). Considering the diffuse economic and social impacts of pandemics and the role of government responses in the pandemic, rational voters, who do not use a partisanship lens, should punish elected officials for the pandemic when they fail to act or act ineffectively to address pandemic deaths and impacts, especially when deaths and impacts are perceived as preventable. However, Graham and Singh (2024) find that in the first six week of the pandemic, Democrats increasingly blamed then President Donald Trump for the pandemic, while Republicans did not. Furthermore, they also found that after viewing positive developments about the pandemic, the president's co-partisans attributed more responsibility to the president, while seeing negative developments, led to ascribing less responsibility to president (Graham and Singh, 2024).

Bringing in the context of partisanship, we propose a pandemic partisan retrospection framework to understand how voters behave during times of heightened pandemic intensity levels. If voters do rely on pandemic partisan retrospection across counties with increasing pandemic intensity, in the aggregate, voter responses should diverge along partisan lines, with previously Democratic counties shifting more Democratic and similarly Republican counties shifting more Republican. We should see this net effect even in counties where previous election results slightly favored one party but in which either Democratic or Republican candidates could have conceivably won a majority of the vote.

Research Design

In this section, we first discuss the 2020 U.S. presidential and Senate elections as the context for our investigation of the effect of pandemic intensity on aggregate voter behavior. Second, we introduce our regression model, starting with the dependent variable defined as the county-level change in party vote shares. Then, we describe our measure for time-varying aggregate COVID-19 intensity levels based on certain features of time series plots of daily COVID-19 cases and deaths. We conclude with a discussion of the county-level demographic and socioeconomic covariates that are included as controls for our regression analysis.

Electoral and Pandemic Contexts

Does a pandemic influence whether voters are likely to re-assess their prior vote choice? To answer this question, we evaluate our pandemic partisan retrospection framework by testing whether the relationship between rising COVID intensity levels and aggregate voter choice of their safe candidate depends on the preexisting partisanship of a county. Specifically, using two important cases, COVID-19 and the 2020 presidential election and the 2020 Senate elections, we study the association between pandemic intensity levels and aggregate voter choice in majority Democratic and majority Republican counties, and investigate whether the direction and magnitude of these relationships showcase pandemic partisan retrospection.

U.S. federal elections during the COVID-19 pandemic provide a compelling empirical setting to test our pandemic partisan retrospection framework. On March 11, 2020, the World Health Organization declared COVID-19 a worldwide pandemic, and two days later, then-President Donald Trump declared a national emergency. Super Tuesday, when about a third of states hold their primaries, occurred on March 3, 2020. Twenty-five states had already held their Democratic primaries, and twenty-two states had previously held their Republican primaries or conventions by March 10, 2020. As a result, instead of considering the remaining primaries, we chose to examine the November general election. As the virus continued to spread across the U.S., COVID-19 continued to be a salient topic, influencing the campaigns of Joe Biden, the Democratic nominee, and then-President Trump, the Republican nominee, as well as Democratic and Republican candidates in 33 Senate races (Medina and Russonello, 2020; Mervosh and Smith, 2020; Bosman et al., 2020).

By focusing on general elections in the U.S., we can use the lens of partisanship to determine safe candidates for voters. Drawing on partisanship offers a natural approach to determining safe candidates that is not automatically based on incumbency from retrospective models. We also avoid categorizing specific candidates that we perceive as mainstream or status quo for voters, which is necessary for primary elections. It is also important to note that since the 2020 election was held during the pandemic, voters had to contend with the possibility of COVID-19 exposure. At the same time, all states allowed some form of mail in voting, with some states being more accessible than others. In 34 states, voters could cite the coronavirus as a reason to vote absentee or they can cast absentee ballots without specifying a reason (Stewart III, 2021). In nine states and Washington, D.C., every registered voter was mailed a ballot ahead of the election or voters were automatically mailed an application to request an absentee ballot (Stewart III, 2021). Although there was a partisan divide on perception of mail-in voting (Lockhart et al., 2020; Atkeson et al., 2022) and the use of mail-in voting, with 58% of Democrats voted by mail, compared to 29% of Republicans (Stewart III, 2021), voting by mail had little overall impact on partisan turnout and vote share in 2020 (Thompson et al., 2020; Yoder et al., 2021), with some models showing a tilt in favor of Republicans (McGhee et al., 2022). Mendoza Aviña and Sevi (2021) also found that exposure to COVID-19 had a negligible impact on the choice of vote in the 2020 presidential election. Subsequently, we do not include controls for pandemic turnout in our analysis.

While the use of aggregate data limits the analyses of causal mechanisms, we do find correlational support for a net effect of pandemic intensity on voters at the county level. Our assessments are not able to determine whether these partisan shifts are based on affective and/or ideological factors in different counties. Yet, aligning with Heersink et al. (2020), our findings suggest that voters were not consistent in holding elected officials accountable during the pandemic as traditional blind or attentive retrospective voting would predict. Rather, there is evidence of a pandemic partisan retrospection, in which voters consider shared partisanship when choosing their preferred candidates in the context of heightened pandemic intensity.

Data and Measures: COVID and 2020 U.S. Elections

Our analysis of the impact of COVID intensity on the party vote shares at the county level in the U.S. uses several data sources on public health (National Center Health Statistics, 2022; New York Times, 2022; Yu Group UC Berkeley Statistics, 2022), demographics (Economic Research Service, 2013; MIT Election Data and Science Lab, 2020), and elections (MIT Election Data and Science Lab, 2020). In the following sections, we discuss the response, explanatory, and various control variables that will be used in our regression model, which we formally present at the end of this section.

Explanatory Variables

Peak Statistics To test our pandemic partisan retrospection argument, we constructed summary statistics as a surrogate measure for the intensity of the pandemic at the county level based on daily progressions of confirmed COVID-19 cases and deaths. We then used a regression model to measure the effects of heterogeneous voting behavior that emerged from the 2020 U.S. Presidential and Senate elections amid varying levels of COVID-19 intensity. We found that in counties where the 2016 election results showed a majority Democratic vote share, voters, in the aggregate, shifted their votes to Joe Biden or the Democratic Senate candidates when the COVID intensity level increased in their county. Then, in contrast, in the counties in which Donald Trump held the largest vote share in 2016, voters, in the aggregate, shifted their votes to Trump or the Republican Senate candidates in 2020 as the pandemic intensity level increased. The estimated net effect size we find ranged from: (1) a 0.008% increase in the majority party's vote share per each day closer to the nearest peak in COVID-related cases to the election day for Democratic counties to (2) a 0.005% increase per each day closer to the nearest peak in COVID-related deaths to the election day for Republican counties. Overall, across both U.S. Presidential and Senate elections, we find consistent correlational evidence of pandemic partisan retrospective voting in areas of higher pandemic intensity. These correlational results are important in assessing the net effect of pandemic intensity on voter choice. Moreover, if pandemics are associated with higher incumbent candidate or party support in counties that are co-partisan and lower in contra-partisan counties, this suggests that co-partisan voters reward their respective incumbents and parties for the pandemic, calling into question voters' ability to determine incumbent performance through the traditional retrospective voting lens. We propose a novel measure of county-level pandemic intensity that reflects pandemic intensity levels at the state level with statistical significance. Our proposed measure of pandemic intensity uses specific summary statistics, which we call "peak statistics", to gauge the pandemic intensity experienced by voters in each county, taking into account the recency and severity of the temporal progression of the pandemic. This approach allows for a more nuanced measure of pandemic levels at the county level. Based on COVID-19 infection and death counts, we used kernel based estimators to model peaks, meaning high points for infection and death levels for each county over time. Daily case and death counts for all states and counties in the U.S. were taken from *The New York Times* COVID-19 data repository (New York Times, 2022). The county-level case and death counts considered in this paper are up to date as of March 2, 2022. We also used data regarding the relevant covariates from the COVID-19 Severity Prediction Project repository (Yu Group UC Berkeley Statistics, 2022).

To model the progression of the COVID-19 case counts and the death counts in each county, we smoothed out the unavoidable noise in the reported data by taking the seven-day moving average of the corresponding count data. We used seven days to nullify any weekly periodic effects to obtain smoothed time series data. Next, we computed the associated kernel density estimation (KDE) and kernel regression curves for all counties.[1]

First, to create KDE curves, the time series data for each county were transformed into frequencies for density estimation by date. Then, seven-day moving averages were computed as frequency data. On this denoised and smoothed data, the probability density for each data point was approximated using KDE. One potential issue with using KDE at the county-level data is that while KDE reasonably captures the general trends, the bias of the high-density portions can be quite high around the regions where the curvature is the highest. This is especially common for counties since their daily progression counts can be highly variable. This is a known shortcoming of KDEs (Friedman et al., 2001).

To address this issue, we next considered a non-parametric local regression technique known as kernel regression. Using kernel regression to fit the shape of each county's progression of case and death counts, we computed the peaks or high points. We then extracted the locations of the most prominent peaks from each of the smoothed curves, one for confirmed cases and another for deaths, as measures of pandemic intensity or "peak statistics" for each county.[2]

County-level figures on cases and mortality were commonly tracked and widely available by the summer of 2020 throughout the U.S. They formed the basis for various social-distancing measures adopted at the county levels. We hypothesize that the more recent and intense the peaks are in daily progressions of *local* cases and deaths due to COVID-19 relative to the election date (i.e., the larger the "peak", i.e., the closer the "peak" is to the election date), the higher the pandemic intensity level experienced by the general public *in the locality*.

Control Variables To control the potential confounding of the association, we incorporate a set of variables that are believed to be associated with county-level election outcomes along with other suspected factors (Campbell, 1960; Igielnik et al., 2021) into our model. We consider various demographic, socioeconomic, and healthcare indicators at the county and state levels. We summarize these for the U.S. presidential and Senate election case studies in Table 1 below.

Table 1. The U.S. Control Covariates

Demographic and Socioeconomic	**Health Conditions**
% White	% smokers
% Male	% mortality due to heart disease
% Medicare-eligible	% mortality due to respiratory disease
% population Black	
% Single-parent households	
% of population in age groups 20-29	
% of population in age groups 30-39	
% of population over the age of 65	
Rural-Urban Continuum Code[3]	
Median age	

Source: MIT Election Data and Science Lab (2020).

The Response Variable Since our focus is on the differential responses to the pandemic in the presence of partisanship, the response variable that we consider is the county-level change in vote share for the winning party from 2016 to the 2020 elections. We focus on the county level because all states have Democratic and Republican voters. State-level vote shares can mask important local-level variations. So, county-level vote shares offer a more detailed picture of the composition of Democratic and Republican voters than at the state level.

Using the county-level election data (MIT Election Data and Science Lab, 2020), we consider 2016 as the base year for comparing the 2020 election. Starting with the presidential elections, to isolate the *change* in voters' behavior in the aggregate in response to COVID intensity as an exogenous shock, we compute the difference in the county-level percentage shares of votes for Donald Trump, the nominee of the Republican Party, in 2016 and 2020 presidential elections. Table 1 summarizes and

Figure 2 depicts the distribution of this measure across the counties belonging to the U.S.'s four major geographical regions, namely Northeast, Midwest, West, and South.

To quantify the change in the voting behavior in the form of a shift in aggregate vote shares in favor of one party over the other, the response variable associated with a county is taken to be the difference between the change in the aggregate vote shares from 2016 to 2020 for the Republican candidates and that for the Democratic candidates for that county. More precisely, the response variable Δ_C associated with county C is given by

$$\Delta_C := \text{Vote.Share.Party}_{C,2020} - \text{Vote.Share.Party}_{C,2016} \quad (1)$$

where Vote.Share.Party$_{C,2016}$ denotes the vote share of the party that received the majority of votes in county C in the 2016 election, and Vote.Share.Party$_{C,2020}$ refers to the vote share for that party in the 2020 election in county C. Instead of relying on a strict percentage threshold to determine whether a county is a majority Democratic or Republican, we use a plurality rule. Democratic counties are those with a larger Democratic vote share than Republican vote share and Republican counties are those with a higher Republican vote share than a Democratic vote share.

We perform an exploratory data analysis of the response variable defined above. We examine and find that the response variable described in Equation (1) is aligned with some of the well-known regional polarization patterns. For instance, the Republican party traditionally gets greater vote shares in the South and Midwest regions compared to other regions (Gelman, 2009; Feller et al., 2013; Shin and Webber, 2014), and our response variables follow a similar pattern (see Figure 1). In addition, we also find comparatively greater aggregate vote shares for the Republican party in the rural areas, which are coded 4-6 in Figure 2, following the rural-urban polarization patterns (Scala and Johnson, 2017; Johnston et al., 2020).

We categorize the counties in three different ways, namely (a) geographical region, (b) vote share in the 2016 election, and (c) rural/urban status given by the Rural-Urban Continuum Code,[4] and obtain the distributions of our response variable across the counties belonging to each of these groups. Figure 2 shows the box plots associated with the above distributions.

Along with the observations involving some state-level features mentioned above, there are variations among the counties for many of the relevant covariates. We control for these sources of heterogeneity, along with a comprehensive list of common county-level demographic characteristics that can influence the voting outcomes, including

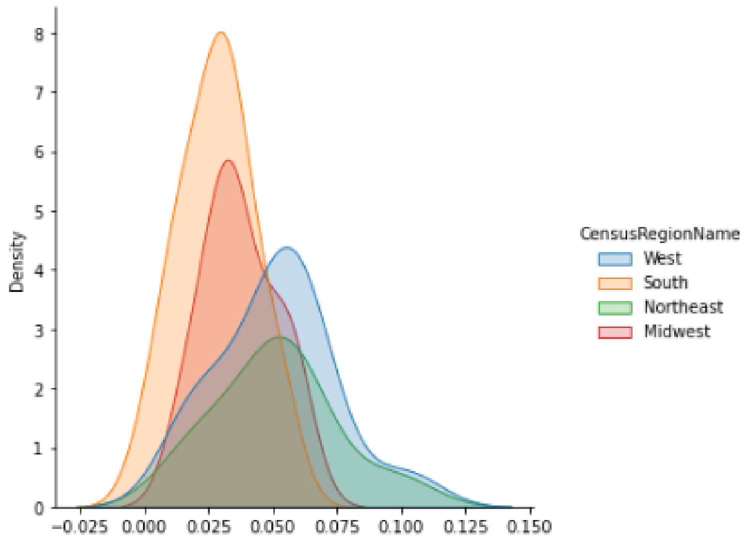

Figure 1. Democrats' state-level vote share change in 2016-2020 aggregated to the census region. The X-axis is the change in Democrats' vote shares in the presidential elections of 2016 to 2020. The Y-axis is the density. See Equation 1.
Source: MIT Election Data and Science Lab (2020).

Table 2. Descriptive statistics for state level vote share change for 2020 Democratic Presidential candidates

Census Region	**Count**	**Mean**	**Std.Err.**
West	13	0.051	0.023
Midwest	12	0.037	0.014
South[a]	17	0.028	0.015
Northeast	9	0.051	0.023

[a] Includes the District of Columbia.
Source: MIT Election Data and Science Lab (2020).

population, percentage of the people that are female, the portion of the population in their 20s, 30s, and older than 65 years, percentage of the population living in poverty, and percentage of the population eligible for Medicaid.

In some states, aggregate vote shares for both parties increased due to the proportional decrease in independent parties' shares in those states. For instance, in Utah, the Republicans' aggregate vote share increased from 45.5% to 58.1%, and that for

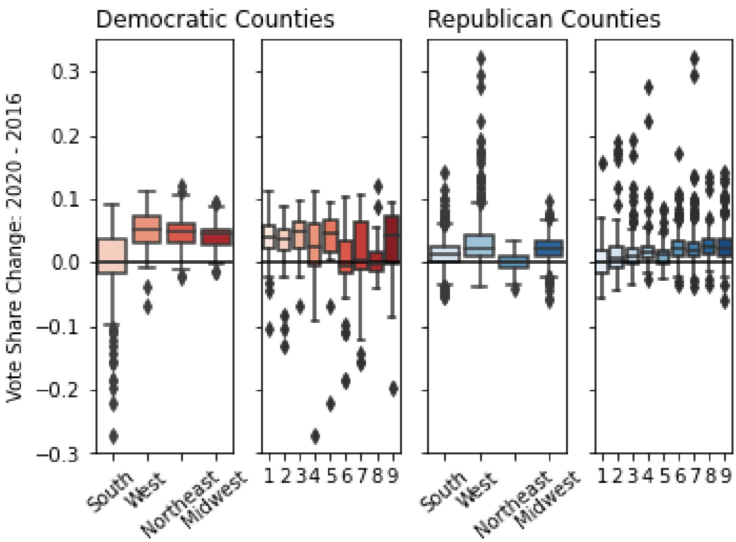

Figure 2. On the y-axis, Δ_C is computed as defined in Equation 1. The first and third charts from left depict Δ_C by geographical region, while the second and fourth charts show Δ_C by the Rural-Urban Continuum Codes of counties. The party affiliation is based on the 2016 election results.
Source: MIT Election Data and Science Lab (2020) and Economic Research Service (2013).

Democrats increased from 27.5% to 37.6%. These gains in aggregate vote shares for the two parties came at the expense of the independent candidates, whose shares decreased from 27.0% to 4.2%. Figure 3 shows that the reduction of the vote shares for the independent party candidates in 2020 compared to that in 2016 was a uniform phenomenon for all states. As with the two major parties, there is a clear geographical variation by census region. The states in the West region show the largest decrease in independents' aggregate vote share, while those in the South had the least. Similar patterns are observed at the county level, as shown in Figure 4. Lastly, elections for 33 class 2 seats of the U.S. Senate were held in 2020. A multivariate regression model (See Equation (2)) involving Δ_{RC} and Δ_{DC} analogously defined for the Senate candidates is fitted.

Methods

We perform the following county-level multivariate regression analysis, where the response variable is the difference in vote share for the winning party between the 2016

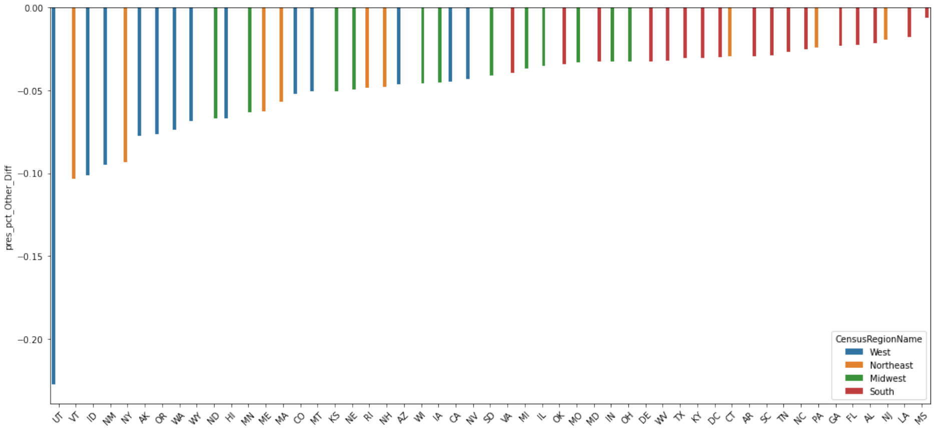

Figure 3. Change in state-level independent parties' vote shares from 2016 to 2020. Y-axis: County level (% Vote Share in 2020) - (% Vote Share in 2016). X-axis: The 50 states and the District of Columbia. The strong support for independent candidates in Utah in 2016 was due to the popularity of the Utah native Evan McMullin, who received 21.3% of the votes in 2016 but did not run in 2020.
Source: MIT Election Data and Science Lab (2020).

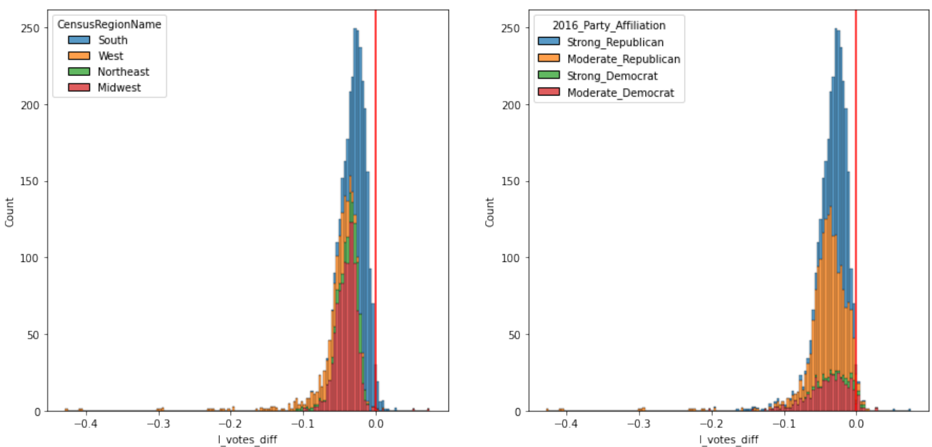

Figure 4. Change in county-level independent parties' vote shares from 2016 to 2020. X-axis: County level (% Vote Share in 2020) - (% Vote Share in 2016). "Moderate" denotes counties where the winning party received less than 70% of total votes.
Source: MIT Election Data and Science Lab (2020).

and 2020 presidential elections, and the predictors are (a) the peak statistics associated with both the case-count and death-count data, and (b) the control variables that are listed in Table 1. More precisely, we fit the following regression model:

$$\begin{aligned}\Delta_C =& \alpha_0 + \alpha_1 t + S_C + \bar{\alpha}_2 \cdot \text{Controls}_c \\ &+ \beta_1 \text{Peak.C}_C + \beta_2 \text{Peak.D}_C + \epsilon_c\end{aligned} \tag{2}$$

Here t is the time (in days) between January 22, 2020, and the election day, Δ_C denotes the change in the vote share between the 2016 and 2020 elections for the 2016-winning party in county C, S_C denotes fixed effects for the state where county C is located, Peak.C_C denotes the number of days between January 22, 2020, and the peak in the kernel regression curve fitted to the count data corresponding to daily confirmed COVID cases for county C until the election day. Similarly, Peak.D_C denotes the number of days between January 22, 2020, and the peak in the kernel regression curve fitted to the death count data corresponding to daily death count data for county C until election day. Controls_C is a $K \times 1$ vector of covariates to incorporate heterogeneity due to various demographic and socioeconomic characteristics and population health conditions across the counties. These control variables are listed in Table 1. ϵ_C is the idiosyncratic error term associated with county C.

The main hypotheses that we consider are given below.

$$H_0: \quad \beta_1 = \beta_2 = 0 \tag{3}$$

$$H_A: \quad \beta_1 \text{ or } \beta_2 > 0 \tag{4}$$

Our main interest is to see whether there is any empirical evidence that voters respond to periods of increased COVID-19 intensity by co-partisan voting in co-partisan areas. Coefficients β_1 and β_2 capture the effects of the intensity of the pandemic in co-partisan and contra-partisan counties. We do not make predictions regarding the magnitude or direction of the effects of the pandemic intensity in either type of county. The null hypothesis says that after accounting for the fixed effects of states and county-specific control variables listed in Table 1, the effect of COVID intensity on the extent of partisan voting is nil. *This null hypothesis implies that, in counties affected to a similar degree by the pandemic, vote share for a co-partisan candidate will be larger in co-partisan counties than in contra-partisan counties.*

Results

For the 2020 US presidential and Senate elections, our results show that voters in co-partisan counties favored co-partisan incumbents candidates and parties. Most importantly, the correlational findings indicate that voters rewarded those who were co-partisan in counties where pandemic infections and death levels were higher as well as punished incumbent candidates and parties who were not co-partisan. Partisan retrospection research has for the most part shown evidence for the punishment aspect, but our findings illustrate both punishment and reward. This analysis lends support to our pandemic partisan retrospection framework, in which partisanship is the filter through which voters assess candidates and parties as the pandemic intensity increases.

The 2020 U.S. Presidential Election

The results of our analysis of the 2020 pandemic Presidential elections appear in Table 3. We classify the counties as either Democratic or Republican depending on the vote shares of each party in the 2016 general election and conduct statistical tests on the significance of the peak statistics in explaining the changes in aggregate vote shares in the counties within each group. Our analysis shows a geographic concentration of Democratic votes that aligns with the demographic research findings of Desilver (2016) and Frey (2021), which shows that the Democrats dominated the most populous counties in the US although there are fewer Democratic counties than Republican counties. In Table 5, our analysis considers 484 of these Democratic counties and 2,621 Republican counties. We provide summaries of regression model diagnostics in Supplemental Materials: Appendix D.

Our analysis of the regression model presented in Equation (2) reveals a key finding: in Republican counties, the percentage aggregate vote share of then-President Trump increased in the 2020 election compared to 2016, while the Democratic candidates saw a smaller increase in support. A similar pattern emerged in Democratic counties where the Democratic candidates had higher support compared to Republican candidates. This confirms our intuition that, in the aggregate, voters in co-partisan counties favor co-partisan candidates.

In Democratic counties, the nearest peak in COVID-related cases occurring a day closer to the election day was associated with a 0.0077% increase at 5% significance and 0.0028% increase at 10% significance in Δ_C after accounting for the state fixed effects and county-specific control covariates. In Republican counties, the nearest peak

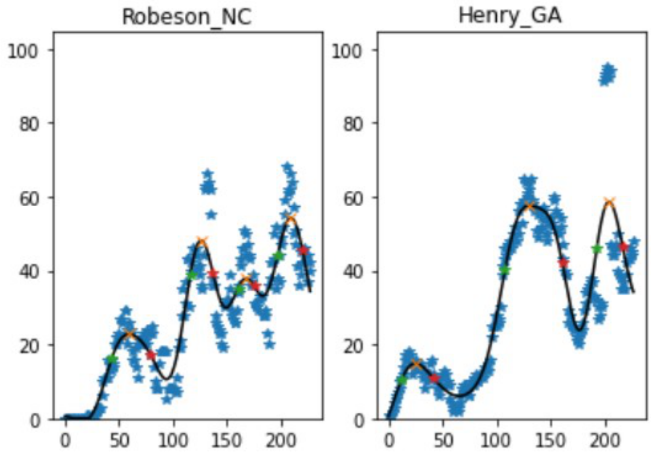

Figure 5. Peaks in the daily count of confirmed cases. X-axis: The number of days from January 21, 2020, and ending on November 3, 2020; Y-axis: daily count of confirmed cases of COVID-19 in the county. In Robeson County, the nearest peak is on October 9. In Henry County, the nearest peak occurred on October 5 .

in COVID-related deaths occurring a day closer to the election day was associated with a 0.005% increase in Δ_C. This offers some support for our expectation that, in the aggregate, voters in co-partisan counties favor co-partisan candidates in both types of counties.

To illustrate the intuition for these results, we briefly look at Robeson County, North Carolina, in which candidate Trump increased his aggregate vote share by 8.1% from 50.8% in 2016 versus a 6.2% decrease for the Democrats despite heightened pandemic intensity levels with the nearest of 5 peaks in confirmed cases occurring three weeks before the election (see Figure 5). In Henry County, Georgia, candidate Biden received 59.7% of the votes, an increase of 9.0% from 2016, although the nearest of four peaks in confirmed cases occurred less than four weeks before the election date. In comparison, the Republicans' aggregate vote share decreased by 7.0%.

The 2020 U.S. Senate Elections

A summary of the analysis of the 2020 U.S. Senate elections for 33 class 2 seats is presented in Table 4. Our analysis of the 2020 pandemic Senate elections in Democratic counties corroborates our findings about the 2020 pandemic presidential elections described in the section above. Similarly, we conducted tests using peak statistics

Table 3. Results from 2020 U.S. President Election OLS Output of Pandemic Intensity and Party Vote Shares (Equation 2)

Covariate	Democrat[a]	Republican[b]
Peak[c], Cases	7.7e-5**	2.8e-5 †
	(3.7e-5)	(1.8e-5)
Peak[c], Deaths	-1.5e-5	5.0e-5**
	(5.3e-5)	(2.5e-5)
Number of Observations	484	2621
R-squared	0.795	0.533

Note: ***, **, *, † indicate significance at 1%, 5%, and 10% respectively.
[a]Counties where the Democratic Party's vote share in 2016 was greater than the Republican Party's.
[b]Counties where the Republican Party's vote share in 2016 was greater than the Democratic Party's.
[c]Number of days from the date of the first reported case of COVID-19 in the U.S. (January 22, 2020) to the date of the 2020 General Election.

as covariates and vote share as the outcome variable, separated into Democrat and Republican counties.

In Democratic counties, the nearest peak in COVID-related cases occurring a day closer to the election day was associated with a 0.023% increase in Δ_C after accounting for the state fixed effects and county-specific control covariates. This offers some support for our expectation that, in the aggregate, voters in co-partisan counties favor co-partisan candidates in Democratic counties.

To show some details at the county level, we first look at Iowa. Joni Ernst, the Republican candidate, was re-elected by a larger margin than expected, given her decreasing popularity after a well-publicized debate stumble against her Democratic rival, Theresa Greenfield, who ran a strong campaign (Beauchamp, 2020; Pfannenstiel, 2020). However, in Linn County, Theresa Greenfield, the Democratic candidate, received 54.7% of the votes, an increase of 13.5% from 2016, although the nearest of four peaks in confirmed cases occurred just a week before the election date. In comparison, the Republicans' aggregate vote share decreased by 12.2%.

In Colorado, the incumbent Republican Senator Cory Gardner lost his bid for re-election. While on the surface, this seems like a case of retrospective voting, we see evidence for our pandemic partisan retrospection framework and Democratic domination of larger urban counties. In Yuma County, Colorado, Republican Cory Gardner increased his aggregate vote share by 14.8% from 71.1% in 2016 versus a 13.1% increase for the Democrats led by candidate John Hickenlooper. This occurred despite heightened pandemic intensity levels, with the nearest of five peaks in confirmed cases occurring three weeks before the election (see Figure 6).

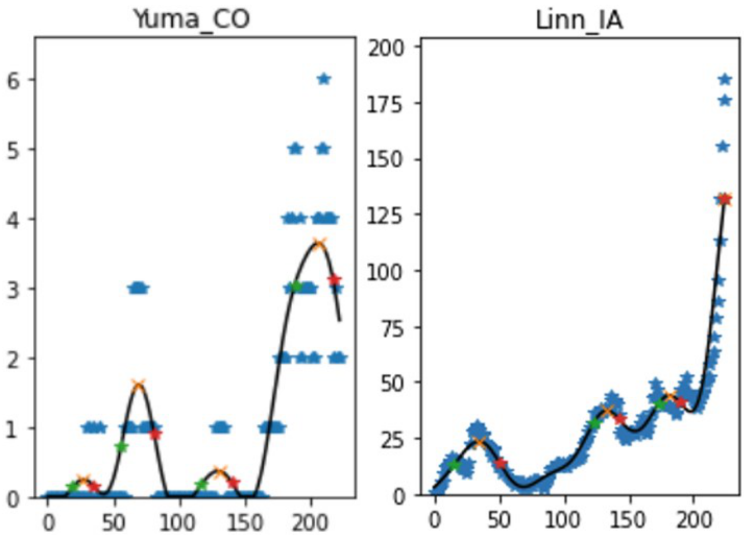

Figure 6. Peaks in the daily count of confirmed cases. X-axis: The number of days from January 21, 2020, and ending on November 3, 2020; Y-axis: daily count of confirmed cases of COVID-19 in the county. In Yuma County, the nearest peak is on October 7, and its corresponding area consists of 60 cases. In Linn County, the nearest peak occurred on October 26 .

Conclusion

Drawing from several strains of election literature on partisanship during natural disasters and other external crises, we developed a framework to understand how voters behave in the context of pandemic intensity. In this paper, we estimate whether voters in areas more heavily impacted by the COVID pandemic as a whole, favor incumbents candidates and parties who were co-partisan and opposed those who were not co-partisan. We argue that shocks like those experienced during the COVID-19 pandemic generally favored co-partisan candidates at the aggregate county level. From our pandemic partisan retrospection framework, in pandemic elections, we expect that increasing pandemic intensity to be associated with an increased aggregate Democratic vote share in previously Democratic majority counties. Similarly, heightened pandemic intensity is

Table 4. Results from 2020 U.S. Senate Elections OLS Output of Pandemic Intensity and Party Vote Share (Equation 2)

Covariate	**Democrat**[a]	**Republican**[b]
Peak[c], Cases	2.3e-4†	-6.7e-5
	(1.5e-4)	(9.9e-5)
Peak[c], Deaths	-4.2e-4†	-6.8e-5
	(2.6e-4)	(1.3e-4)
Number of Observations	132	849
R-squared	0.917	0.734

Note: ***, **, *, † indicate significance at 1%, 5%, 10%, and 15% respectively. Dependent Variable: Δ Party Vote Share - Δ Opposition Vote Share.
[a]Counties where the Democratic Party's vote share in 2016 was greater than the Republican Party's.
[b]Counties where the Republican Party's vote share in 2016 was greater than the Democratic Party's.
[c]The number of days from the date of the first reported case of COVID-19 in the U.S. (January 22, 2020) to the date of the 2020 General Election.

predicted to be correlated with an increase in the aggregate Republican vote share in counties that had prior Republican majorities in 2016.

We conducted two analyses of U.S. elections held during the 2020 pandemic. Specifically, pandemic partisan retrospection can be observed in both U.S. presidential and Senate elections. Our findings also represent a more complete and extreme version partisan retrospection by including results not just for punishment but also reward. We also introduced a novel method of measuring the pandemic at the local level, using peak statistics. By modeling pandemic intensity at the local county level, we were able to consider both geographic and time dimensions of the pandemic.

The magnitude of the net effects we discovered shows the potential impact of pandemic intensity on election outcomes. The estimated net effect size we found ranged from: (1) 0.2% increase in majority party vote share per 1% increase in deaths in the nearest peak for moderate Democratic counties to (2) 0.06% increase per one unit increase in the number of peaks in cases for strong Republican counties. Our results suggest that the impact of the pandemic on vote choice does depend on partisanship. Previous research on the persuasive impact of political campaigns on vote shares estimates an average effect of zero in general elections but non-zero in primary elections (Kalla, 2018). Bisbee and Honig (2021) in their study of pandemic effects on primary elections, find effect sizes ranging from 2 to 15 percentage points, which they present as non-trivial in comparison to campaign effect sizes. Similarly, while the magnitude of our results can vary depending on pandemic intensity, we capture the non-zero impacts of the pandemic intensity in the general elections.

Additionally, research using retrospective approaches to look at the impact of external crises like pandemics on elections has come to varying conclusions, from very little change in outcomes to changing levels of support for incumbents. In a retrospective study of voting in the 1918 pandemic, Abad and Maurer (2020) found a small swing against incumbent candidates in gubernatorial elections and the Democrats in congressional elections; however, it was small, ranging from 0.6 to 1.0 percentage points when local excess mortality increased twofold. This shift was not enough to change election outcomes (Abad and Maurer, 2020). In relation to this research, despite different theoretical explanations and cases, our results similarly show that pandemic intensity influenced aggregate vote shares. Our pandemic partisan retrospection framework operates even in counties where party majorities were not large but slim and in elections where traditional retrospective voting models do not explain voter choice. Consequently, these findings can inform political responses to the next pandemic in democracies and question how well voters can accurately judge an incumbent's performance.

Our results also question the function of electoral accountability during times of heightened pandemic intensity. Pandemic partisan retrospection may mean that candidates will not be judged solely on their performance but rather on co-partisanship or contra-partisanship. In addition, our results also suggest the possibility of pandemic intensity levels as a contributing factor in the polarization of the electorate. While our findings did not support blind or attentive retrospection, emerging local data on pandemic aid would clarify the role of government response on the election results.

Moreover, partisan retrospection frameworks do not include details on the underlying mechanisms that produce the described results. A candidate's performance in an election in comparison to a previous election could be the result of higher turnout among their co-partisan voters, lower turnout among their opponent's voters, voters persuaded to change their vote from a previous election, and any combination of all three mechanisms. One possible channel through which pandemic intensity levels can affect election outcomes is through voter anxiety and depression. Hassell and Settle (2017) describe the differential effects of stress on voter turnout, depending on previous political participation. Anxiety can increase political engagement (Albertson and Gadarian, 2015), while depression has been linked to lower voter turnout (Landwehr and Ojeda, 2021; Ojeda, 2015). Bisbee and Honig (2021) also include the role of anxiety in explaining COVID-induced changes in the voter preference for the status quo in the 2020 Democratic primary. One way to test the impact of anxiety and depression symptoms on voters is to demonstrate the association between peak statistics and the intensity of voter anxiety and depression. Studying the role of anxiety and depression on voters in the pandemic context can also potentially offer insights into the role of anxiety and depression on partisanship and affective polarization.

Based on the methods we introduced in this paper, avenues for further research include: the impacts of pandemic intensity on voter turnout and possible interaction effects of mail-in voting, examining the long-term effects of pandemics, the role of pandemic assistance, the adoption of intensity measures for other pandemics and external crises, and determining possible causal links between pandemic intensity and voter behavior, as well as the role of anxiety and depression.

Notes

1. For more detailed descriptions of both the kernel density estimation and kernel regression methodologies, see Section on Data and Measures "Explanatory Variables" and Supporting Materials: Appendices B and C for a more detailed treatment.
2. See Supplemental Materials: Appendix Section A for illustrative plots and detailed discussions of the peak statistics.
3. Economic Research Service (2013).
4. The United States Department of Agriculture classifies counties based on the population using the following codes: 1. Counties in metro areas of 1 million population or more; 2. Counties in metro areas of 250,000 to 1 million population; 3. Counties in metro areas of fewer than 250,000 population; 4. Urban population of 20,000 or more, adjacent to a metro area; 5. Urban population of 20,000 or more, not adjacent to a metro area; 6. Urban population of 2,500 to 19,999, adjacent to a metro area; 7. Urban population of 2,500 to 19,999, not adjacent to a metro area; 8. Completely rural or less than 2,500 urban population, adjacent to a metro area; 9. Completely rural or less than 2,500 urban population, not adjacent to a metro area (Economic Research Service, 2013).

Supplemental material

- Appendices: (A) Peak Statistics, (B) Overview of Kernel Density Estimation, (C) Overview of Kernel Regression, and (D) Regression Model Diagnostics
- Availability of data and materials: The data and materials required to verify the computational reproducibility of the results, procedures, and analyses in this article are available at https://github.com/CompSocSciences/Pandemics_Elections.git

- Code availability: All of the code to verify the computational reproducibility of the results, procedures, and analyses in this article are available at https://github.com/CompSocSciences/Pandemics_Elections.git

Appendix A: Peak Statistics

We derive salient features from the curves depicting progressions of the COVID-19 infection rate and mortality in counties leading up to November 3, 2020. We use kernel based estimators to create curves for infection and death data for each county, which allow us to give different weights to observations with a different distance, here time. Kernel based estimators are used to smooth noisy data, detect outliers, classify and cluster data based on the similarity of the data points, and visualize data. We consider two different kernel based estimators, the kernel density estimation (KDE) and kernel regression. Appendix B details the KDE method and Appendix C explains the kernel regression method.

For each curve, we propose several summary statistics to describe each county's daily count data N_S, which we call "peak statistics." We compute the location of the most prominent peak for each curve. We define a peak to be any point that is higher than its immediate neighbors, that is, any $t \in [T]$ such that $\hat{N}_t > \hat{N}_{t-1}$ and $\hat{N}_t > \hat{N}_{t+1}$, where $\hat{N}$ is an estimator of N_t, i.e., a case or death count at time t for a county. For each peak p, we compute its height by $\hat{N}_p$ and its width by $t_i - t_j$, where t_i is the midpoint between the peak and the left-most point that hill-climbs to the peak. t_j is likewise defined.

For each state and county, we compile summary statistics $\big($**(peak-1,.., peak-p)**$\big)$ in non-increasing order, with the index 1 corresponding to the tuple whose peak has the maximum height down to the smallest. p corresponds to the number of peaks in a county with the maximum number of peaks and for those counties with $q < p$ peaks, we assign **peak-i** $\leftarrow$ **0** for all $i \in (q, p]$. We perform this procedure for both confirmed infections and deaths, with each suffixed by either c (for a reported case of COVID-19 infection) or d (death). For example, $\{\text{peak-ic}\}_{i\in[p]}$ for the infection curve.

Each state and county is represented as a vector consisting of the peak statistics and population characteristics. The peak statistics are computed for seven peaks for both deaths and confirmed cases in each jurisdiction. The feature space is summarized in the table below with $i \in [7]$:

Table 5. Peak Statistics Feature Space

Feature	Description
LocalMax_i	i^{th} peak
Peak_c^i	the location of the nearest peak in cases to the election day
Peak_d^i	the location of the nearest peak in deaths to the election day

In Figure 7, one can see that kernel regression for N_c of New York approximates the scatterplot reasonably well. Further, we see that there are two peaks and the widths appear reasonable and that there are two peaks as summary statistics that we use for clustering.

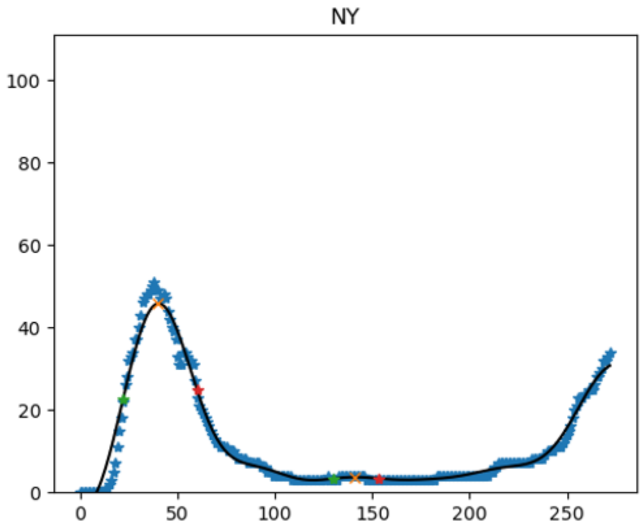

Figure 7. $\mathbf{N}_c$ (scatterplot) and $\hat{\mathbf{N}}_c$ (line) for New York. The peaks are notated by yellow x and the left and right endpoints of the widths are notated by green and red points.

Similarly, Figure 8 depicts scatterplots and fitted kernel regression plots for Kentucky and Missouri, respectively. Unlike the New York plot in Figure 7, Figure 8 shows more peaks and the corresponding widths and heights due to the more rugged nature of their progressions and the estimator $\hat{\mathbf{N}}$.

Appendix B: Kernel Density Estimation

We present an overview of the density estimation tool known as kernel density estimation (KDE) and its role in our analyses. First, we smooth out each of the count data by

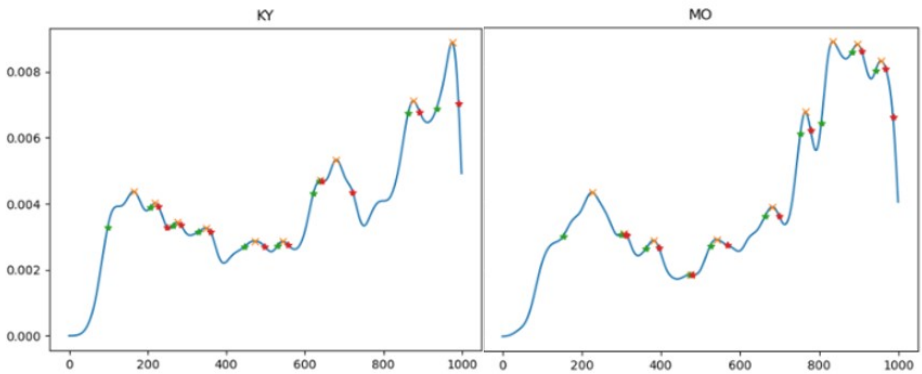

Figure 8. $\mathbf{N}_c$ (scatterplot) and $\hat{\mathbf{N}}_c$ (line) for Kentucky (left) and Missouri (right). The peaks are notated by yellow x and the left and right endpoints of the widths are notated by green and red points. Missouri also has a much higher **no-peaks** than Kentucky at 9.

applying a seven-day moving average procedure. Then, we approximate each of the smoothed data using a procedure based on the Gaussian radial basis function (RBF).*

We then cluster states based on the curves fitted to their daily counts of confirmed COVID cases through the 2020 election day.† One insightful pattern that we observe is that the patterns of the curves that describe the daily progressions of COVID-19 in different localities are highly correlated with the geographical locations of those localities. In Figure 9 below, the KDE curves associated with daily COVID case counts for all states are projected onto the top two principal components for visualization‡ Remarkably, the plot resembles the geographical map of the U.S. because the input data is based only on the case count data and no other covariates.

This shows that for at least for some states, the shapes of their KDE density curve estimates provide sufficient information to classify their constituent counties (see Figure

*Other popular choices for the kernel in the literature include Epanechnikov and Box. Later in this Appendix B: "Kernel Density Estimation", we offer a detailed technical discussion and rationale for this choice of RBF kernel.

†We opted to use K-means clustering due to its simplicity and widespread use in various applications. The clustering was computed using vector representations of daily case counts for each state. Interested readers can refer to Hastie et al. (2009) for a more detailed explanation of the methodology, including its strengths and limitations.

‡Principal components (PCs) are convex combinations of variables that capture the maximum amount of variation in the data. PCs are then ranked in the order of the amount of variation they capture and are mutually orthogonal, i.e., there is no overlap in the variation captured by each PC. For a more detailed discussion, readers are referred to Hastie et al. (2009).

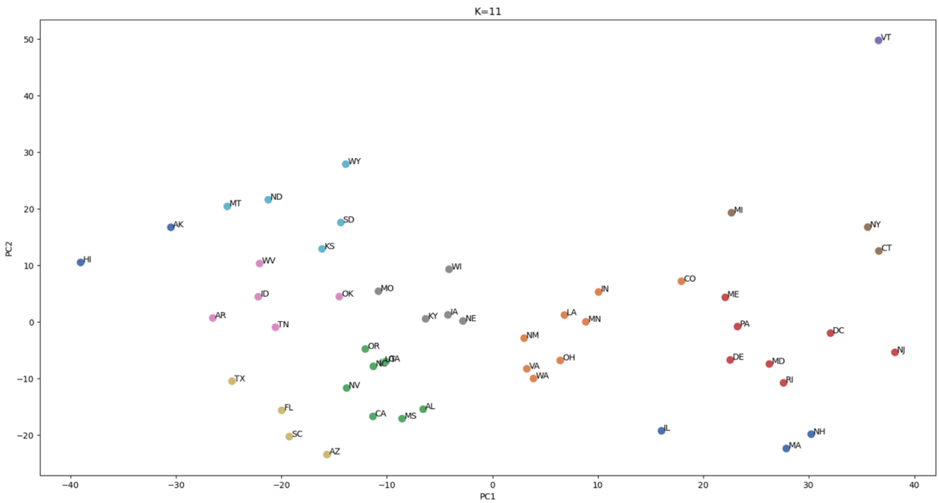

Figure 9. KDEs of all states plotted against two principal components. Colors show clustering based on K-$means$ algorithm with $K = 11$.

10), although, for other states, there is significant variability at the county level (see Figure 14). For this reason, we include "states" as a categorical control covariate in our regression model framed for measuring the effect of pandemic intensity on voter behavior.

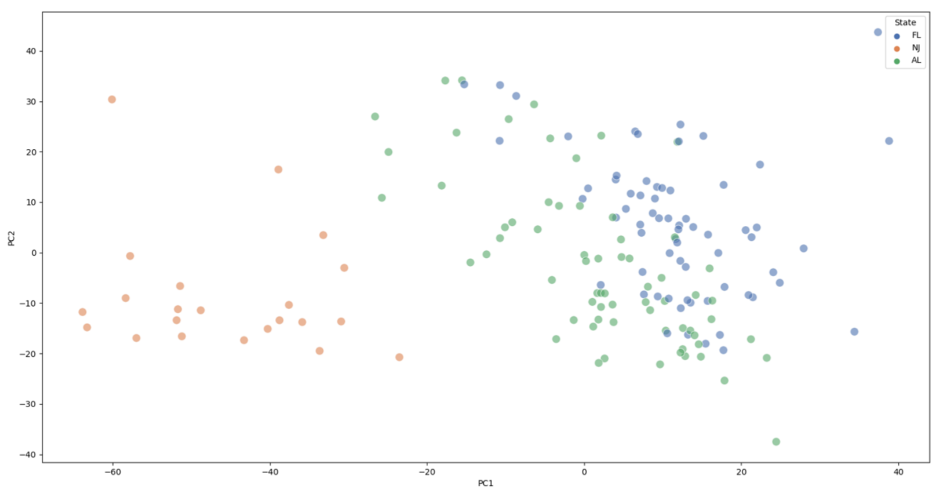

Figure 10. KDEs of all counties in Florida, New Jersey, and Alabama, clustered with $K = 11$.

Despite the informativeness of the COVID curves, there is significant variability among states and more so among counties. For this reason, we investigate the effect of extracting summary features from each curve that capture its essential geometric features, referred to as "peak statistics".

First, the time series data for each county and state were transformed into frequencies for density estimation by date. Then, seven-day moving averages were computed as frequency data. On this denoised and smoothed data, the probability density for each data point was approximated using KDE using various choices for the key parameter, the bandwidth. Changing the bandwidth changes the shape of the kernel.

Recall that given a bandwidth λ to define the width of the local support, a discrete first-order estimate defined by the counting process N and over the support for the input domain of T days has the following expression:

$$\hat{f}_X(N_t) = \frac{|i : t_i \in (t \pm \lambda)|}{T\lambda} \tag{5}$$

To make this metric more continuous and smooth, we can replace the counting process N over the local support with a symmetric similarity measure called as kernel K and obtain the KDE, also known as the Parzen estimate, as follows:

$$\hat{f}_X(t) = \frac{K_\lambda(N_t - N_i)}{T\lambda} \tag{6}$$

There are several choices for the kernel K that have been used in the literature, such as Gaussian, Epanechnikov, and Box. Regardless of the choice, K assigns weights to each observation in determining the estimated density for a given point $t \in [T]$. It has been noted that the particular choice of K is not material to the resulting estimate of density Friedman et al. (2001). In this paper, we use the Gaussian radial basis (RBF) kernel that yields the following KDE form:

$$\hat{f}_X(t) = \frac{1}{T(2\lambda^2\pi)^{1/2}} \sum_{t=1}^{T} \exp(-\frac{1}{2}(\|N_{t_i} - N_t\|/\lambda)^2 \tag{7}$$

More important than the choice of K is the bandwidth λ as it controls the degree of granularity of the details of the progression captured in the estimate. To determine a value for λ, we use the "median trick" commonly used in the literature, which has the following form:

$$\hat{\lambda} := h \cdot Med_{i,j}|t_i - t_j| \tag{8}$$

where $h \in (0, 1)$ is a hyperparameter and $i, j \in [T]$.

As an illustration, Figure 11 shows the scatterplot of $\mathbf{N}_c$ and KDE of $\mathbf{N}_c$ in Oregon.

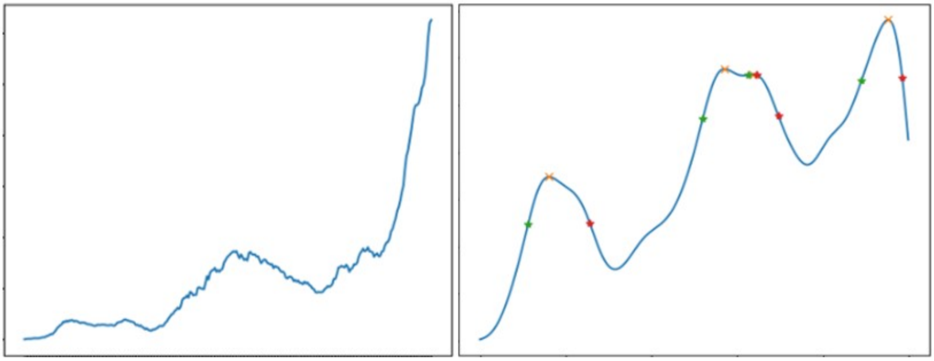

Figure 11. Daily Case Counts (left) and the KDE of Case Counts (right) in Oregon.

We then performed K-Means clustering on the KDEs for $\mathbf{N}$ for all states based on the daily counts of confirmed cases through November 2, 2020. One insightful pattern is that the variation in the shapes of daily progressions of COVID-19 appears to be highly correlated with localities' geographical location. In Figure 12 below, KDEs of all states' daily case counts $\mathbf{N}_c$ are projected onto the top two principal components. Notably, the plot resembles the geographical map of the U.S. because the input data is based only on the case count data, and no other covariates were used that may contain information about its geographical location or its neighbors. We applied K-Means clustering to the full vectors of KDEs with $K = 11$.

It is apparent that clustering is largely based on the geographical proximity of states. For instance, the states in the Mountain region are in the same cluster, namely Montana, North, and South Dakota, and Wyoming. Another example is the Mid-Atlantic states in the same cluster, namely Pennsylvania, New Jersey, Maryland, Delaware, and the District of Columbia. Another cluster is comprised of West Coast states, namely California, Oregon, Nevada, and Southern states seem to constitute another. This implies that while states have implemented a number of non-pharmaceutical intervention policies, the severity and the progression of the disease in each state were primarily

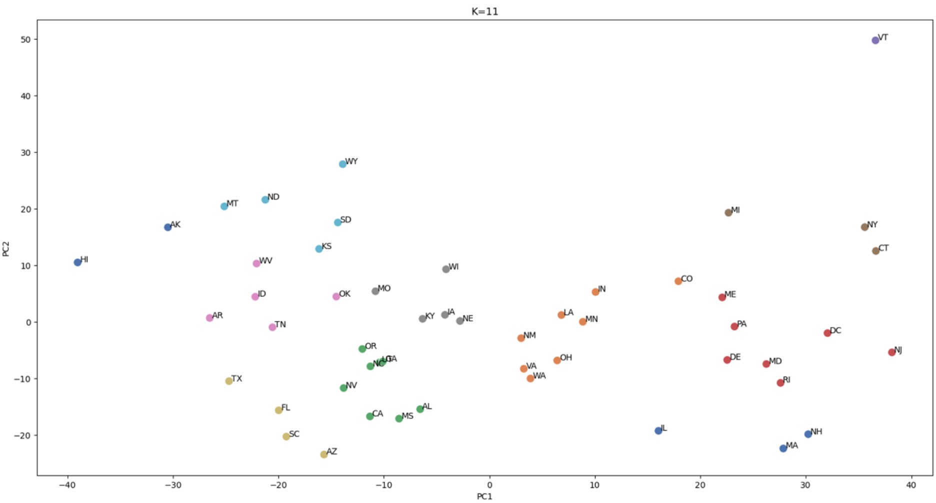

Figure 12. KDEs of all states plotted against two principal components. Colors show clustering based on K-$means$ algorithm with $K = 11$.

driven by their geographical location and their neighboring states.

For some groups of states, this clustering based on KDEs is sufficient to enable state-membership estimation for their constituent counties. In Figure 13 below, one can readily see that counties are “soft” linearly separable.

On the other hand, Figure 14 below shows that the counties of Florida are not linearly separable from those in Louisiana and Michigan. This indicates that for at least for some states, the shapes of their KDE density curve estimates provide sufficient information to classify their constituent counties, although, for other states, there is significant variability at the county level. Hence, we control for states when we construct our model to investigate the county-level heterogeneity in voting behavior. One potential issue with using KDE at the county-level data is that while KDE reasonably captures the general trends, the bias of the high-density portions can be quite high around the regions where the curvature is the highest, i.e., where the first derivative is a large positive or negative. This is especially common for counties since their daily progression counts can be highly variable. This is a known shortcoming of KDEs (Friedman et al., 2001). For this reason, for the county-level data, we propose to use kernel regression which addresses this weakness of KDEs.

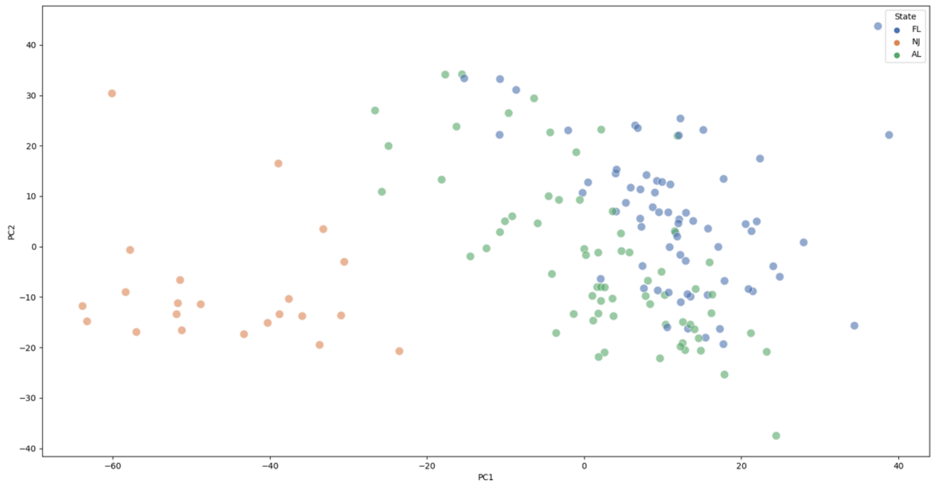

Figure 13. KDEs of all counties in Florida, New Jersey, and Alabama, clustered with $K = 11$.

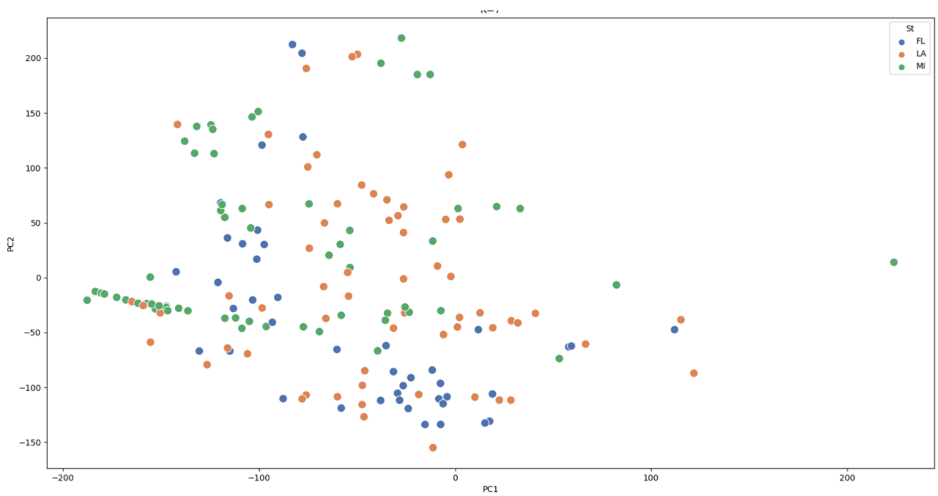

Figure 14. KDEs of all counties in Florida, Louisiana, and Michigan, clustered with $K = 11$.

Appendix C: Kernel Regression

Unlike linear regression models, Kernel regression allows one to model nonlinear functional forms of input variables using nonlinear basis functions as follows:

$$\hat{f}_X(t) = \Theta^T \Phi(t) \tag{9}$$

where $\Theta = [\theta_1, ..., \theta_T]$ is a vector of the model coefficients, one for each of the nonlinear basis functions ϕ_i capturing the nonlinear relationships of interest comprising $\Phi(t) = [\phi_1(t), ..., \phi_T(t)]$. As with KDEs, we use the Gaussian RBF for Φ such that we have $\Phi(t) = [k(N_t, N_{t_1}), ..., k(N_t, N_{t_T})]^T$, where N_{T_i} for $i \in [T]$ are fixed observations used for inference on some random point of interest N_t. Hence, incorporating this Gaussian RBF, we obtain the following Kernel regression model form:

$$\hat{f}_X(t) = \sum_{t=1}^{T} \theta_t k(N_t, N_{t_i}) \tag{10}$$

The parameter Θ is estimated by minimizing the following empirical loss below:

$$L(\Theta) := \|\mathbf{N} - \hat{\mathbf{N}}\|^2 \tag{11}$$

where $\hat{\mathbf{N}} := \mathbf{K}\Theta, \mathbf{N} := [N_1, ..., N_T]^T \in \mathbb{R}^{T\times 1}$ and $\mathbf{K} := [k_1, ..., k_T]^T \in \mathbb{R}^{T\times T}$. Plots of $\hat{\mathbf{N}}$ along with the scatterplots of $\mathbf{N}$ that underlie $\hat{\mathbf{N}}$ for select counties are shown in the next section. We identify the peaks and their other statistics on the estimator of $\mathbf{N}$, namely $\hat{\mathbf{N}} = \mathbf{K}\Theta$, on which we perform K-Means clustering, as was done in the KDE section above in Appendix B.

Appendix D: Regression Model Diagnostics

Homoscedasticity

Below are plots of residuals vs. fitted values to assess the appropriateness of homoscedasticity assumption of residuals. Overall, the residuals appear homosceastic for the Senate-Democratic model. However, there is some heteroscedasticity in Senate-Republican, albeit limited to a relatively few observations.

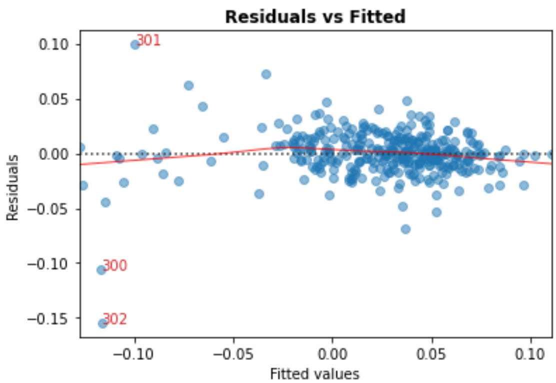

Figure 15. Presidential-Democratic

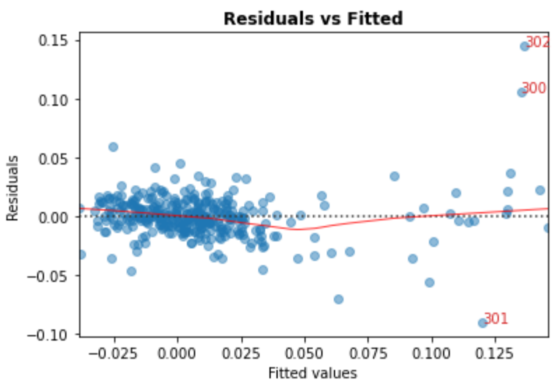

Figure 16. Presidential-Republican

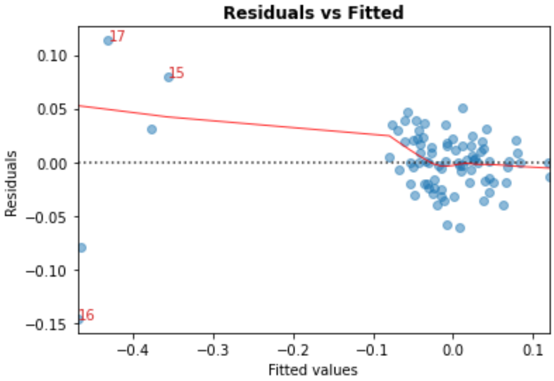

Figure 17. Senate-Democratic

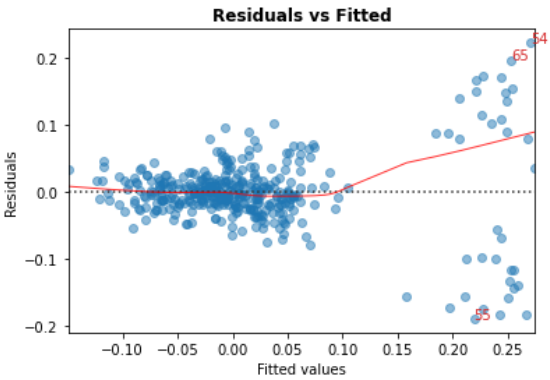

Figure 18. Senate-Republican

Normal distribution of residuals

Below are quantile-quantile plots of standardized residuals versus theoretical quantiles to assess the appropriateness of normality assumption of residuals. Overall, the residuals appear normally distributed.

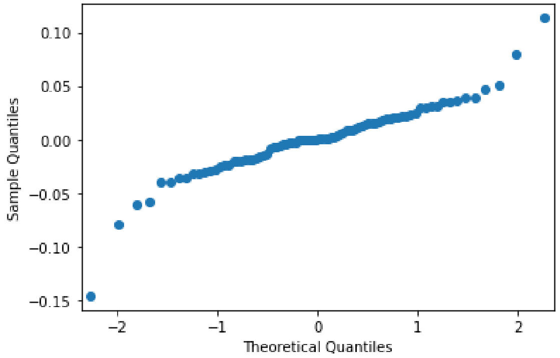

Figure 19. Q-Q Plot for Presidential-Democratic

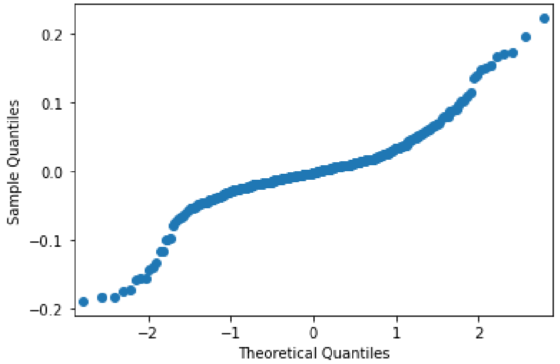

Figure 20. Q-Q Plot for Presidential-Republican

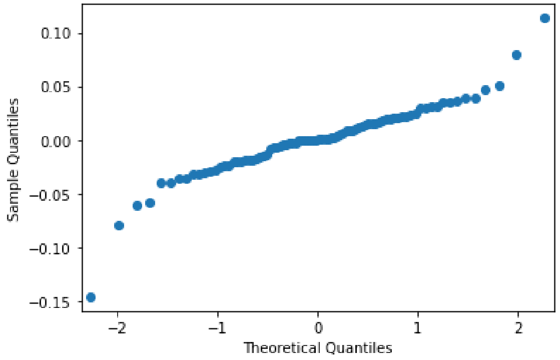

Figure 21. Q-Q Plot for Democratic-Senate.

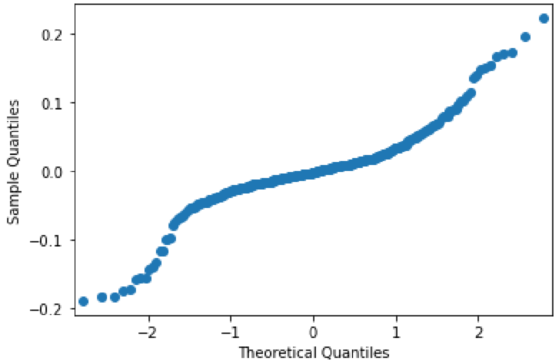

Figure 22. Q-Q Plot for Republican-Senate.

Outliers

Model	**Bonferroni p-value** < 0.05	**Number of Observations**
Democratic, Presidential	3	484
Republican, Presidential	3	2621
Democratic, Senate	2	84
Republican, Senate	2	849

Multicollinearity

There was no multicollinearity for our variables of interest, namely peak_cases and peak_deaths, as they had VIF values of less than the tolerance of 5 in all of the models.

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