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# The COVID-19 Pandemic and the 2020 U.S. Presidential Election*

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**Abstract**

What is the effect of the COVID-19 pandemic on the 2020 U.S. presidential election? Guided by a pre-analysis plan, we estimate the effect of COVID-19 cases and deaths on the change in county-level voting for Donald Trump between 2016 and 2020. To account for potential confounders, we include a large number of COVID-19-related controls as well as demographic and socioeconomic variables. Moreover, we instrument the numbers of cases and deaths with the share of workers employed in meat-processing factories to sharpen our identification strategy. We find that COVID-19 cases negatively affected Trump's vote share. The estimated effect appears strongest in urban counties, in states without stay-at-home orders, in swing states, and in states that Trump won in 2016. A simple counterfactual analysis suggests that Trump would likely have won re-election if COVID-19 cases had been 5 percent lower. We also find some evidence that COVID-19 incidence had a positive effect on voters' mobilization, helping Biden win the presidency.

Keywords: COVID-19, pandemic, elections, political behavior, pre-analysis plan.

JEL classifications: D72, I18.

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The COVID-19 pandemic is among the most consequential global events since World War II, affecting virtually every country in the world. By the end of November 2020, more than 60 million people had contracted the virus and over one and a half million had died. In response to the pandemic, governments restricted citizens' movement to varying degrees through lockdown measures, with the objective of slowing the spread of the disease. The pandemic contributed to severe economic contractions in most countries, increasing unemployment and poverty around the world[1].

In the U.S., the COVID-19 pandemic struck during a presidential election year, shifting the political narrative and President Trump's re-election prospects. Prior to the pandemic, the U.S. economy was performing well, and Trump, while extremely polarizing, enjoyed strong support among Republican voters.[2] The virus changed the narrative and shaped the political campaign. As of the end of November 2020, the U.S. had suffered the largest numbers of cases (over 8 million) and deaths (over 220,000) in the world. Trump's pandemic response, which contrasted with those of many leaders in other Western democracies, was repeatedly criticized by epidemiologists and scientists.

In this paper, we explore the effect of the COVID-19 pandemic on the 2020 U.S. presidential election. We investigate whether Trump's electoral support fell in localities hit harder by the pandemic. Guided by a pre-analysis plan (PAP), which reduces concerns about data mining, we constructed a data set at the county-level, with the difference in vote share for President Trump between the 2020 and 2016 presidential elections as our dependent variable.[3] Our main independent variable is COVID-19 cases, which we gather from the data compiled by the Center for Systems Science and Engineering at Johns Hopkins University. In our estimates, we control for social distancing and four occupational measures: (1) exposure to disease or infection, (2) physical proximity, (3) essential worker designation, and (4) remote work. In addition, we account for demographic and socioeconomic variables and for changes in unemployment between August 2019 and August 2020. In placebo tests, we show that COVID-19 incidence is uncorrelated with changes in Republican candidates vote share in previous elections, e.g., votes for Trump in 2016 compared with votes for Romney in 2012.

In an attempt to sharpen our identification strategy, we instrument COVID-19

[1]See, for example, Chudik et al. (2020).

[2]https://www.rasmussenreports.com/public_content/politics/trump_administration/prez_track_dec04 [consulted on December 4 2020].

[3]The pre-analysis plan was posted and registered on October 30, 2020: https://osf.io/xvuzp/. See Appendix 5.1 for more details. We relied on a PAP to minimize issues of specification searching and p-hacking. A growing literature documents the extent of p-hacking in the social sciences, highlighting that the extent of p-hacking is larger for observational studies than for experimental studies (e.g., Brodeur, Cook and Heyes (2020)).

cases with the share of workers employed in meat-processing factories. We show that counties with a larger share of workers employed in meat-processing factories experienced a significantly larger number of cases than counties with a smaller share of workers employed in meat-processing factories. Our two-stage least squares estimates also control for the share of manufacturing workers and the share of food manufacturing workers in each county as well as for counties' vulnerability to Trump's trade policies in an effort to validate the exclusion restriction.

Our results indicate that COVID-19 cases had a significant negative effect on the Trump vote share in the 2020 presidential election (in comparison to 2016). This finding holds in both the reduced form analysis and the instrumental variable analysis. We also find potentially important heterogeneity in the effect of COVID-19. In particular, the negative impact of COVID-19 incidence on President Trump's support is stronger (1) in states without a formal stay-at-home order, (2) in states that Trump won in the 2016 presidential election, (3) in swing states, and (4) in urban counties. We find no evidence that the change in the unemployment rate is related to electoral support for President Trump. There is some evidence that COVID-19 cases affect voters' mobilization, measured as the number of votes cast in 2020 compared to 2016.

These effects not only are significant and robust to many robustness checks, but they are also quite sizable. A simple counterfactual exercise shows that, *ceteris paribus*, if the number of COVID-19 cases had been 5 percent lower, Trump would have won Arizona, Georgia, and Wisconsin—likely resulting in his re-election.

Our paper is related to several streams of the literature on political behavior and political economy.[4] First, our paper speaks to the literature on retrospective voting, which examines how citizens evaluate and vote based on their perceptions of the incumbent's performance (Fiorina 1981, Ferejohn 1986, Persson and Tabellini 1997, Fearon 1999, Canes-Wrone and Shotts 2001, Ashworth 2012). Our findings indicate that voters assess the competence of political leaders in the case of a pandemic and hold them accountable for rising numbers of cases and deaths. This is consistent with evidence in Herrera et al. (2020), who find in a sample of 35 countries that approval of incumbent politicians falls as COVID-19 cases grow, as well as Gutierrez et al. (2020), who find that voters punished the incumbent government following the H1N1 epidemic in Mexico.

Second, our paper is related to a literature that links shocks such as natural disasters to political behavior (Abney and Hill 1966, Chen 2012, Malhotra and Kuo 2008, Bechtel and Hainmueller 2011). The logic of this literature is similar to that of retrospective voting. Rational voters reward incumbents not only for delivering a positive economic performance in good times, but also for organizing prompt rescue

[4]For an excellent review of this literature, see Healy and Malhotra (2020).

and relief programs in bad times, such as in the aftermath of extreme weather events. Our findings indicate that incumbent governments are punished electorally for failing to provide effective mitigation and relief, even if the primary shock (in this case, a virus) is not directly attributable to them.

Third, our paper speaks to the literature on the effect of personally experiencing shocks (e.g., crises and wars) on political and social attitudes (Lau and Sears 1978, Kinder and Kiewiet 1981, Erikson and Stoker 2001, Mo and Conn 2018). Our findings are consistent with studies showing that negative economic shocks increase support for government intervention in the economy and redistributive policies as well as people's beliefs about the relative importance of luck versus effort (Margalit 2013, Giuliano and Spilimbergo 2014). These changes in voters' preferences and beliefs are consistent with increasing support for a Democratic candidate over an incumbent Republican president in the midst of a pandemic.

Finally, our paper also relates to a growing literature on the pandemic. For instance, Allcott et al. (2020) rely on smartphone data and provide evidence that areas with more Republicans engaged in less social distancing. Baccini and Brodeur (Forthcoming) show that Democratic governors and governors without a term limit are significantly faster (and more likely) to adopt stay-at-home orders than Republican governors and governors with a term limit. Warshaw et al. (2020) demonstrate that states and local areas with relatively more COVID-19 fatalities are less likely to support Republican House and Senate candidates. Other papers have explored related issues, such as policy responses and social distancing, in other countries such China and Italy (Qiu et al. 2020, Bonacini et al. 2021, Milani 2021).

## 1 The COVID-19 Pandemic and the U.S. Presidential Election

News of a novel coronavirus made global headlines beginning in January 2020. On January 9, 2020 the World Health Organization announced a coronavirus-type pneumonia outbreak in Wuhan, China. The U.S. Centers for Disease Control and Prevention began screening at three major U.S. airports on January 20, and the first U.S. coronavirus case was confirmed the following day. On January 23, China made the unprecedented move of quarantining Wuhan, a city of 11 million people. The White House announced on January 31 a travel ban on foreign nationals who had traveled to China within the past 14 days. The first U.S. death from the disease occurred on February 29 in Washington State.[5]

The WHO declared a pandemic on March 11. That same day the U.S. National Basketball Association suspended all games, and the actor Tom Hanks and his

[5] https://www.ajmc.com/view/a-timeline-of-covid19-developments-in-2020https://www.nbcnews.com/health/health-news/coronavirus-timeline-tracking-critical-moments\-covid-19-n1154341.

wife Rita Wilson announced they had tested positive for the virus in Australia. President Trump declared a national emergency on March 13, unlocking up to $50 billion dollars in federal funding to combat the spread of the disease, the same day on which several states announced school closures. On March 19, California became the first state to issue a "stay-at-home" order, with exceptions for work and shopping for essential needs. On March 26, Trump signed into law the CARES Act, which provided $2 trillion in aid to businesses, hospitals, and local governments.

While no country was unaffected, the COVID-19 pandemic hit the U.S. particularly hard. The U.S. COVID-19 death toll passed the grim mark of 100,000 on May 28; by September 22, 200,000 American lives had been lost. Measured on a per capita basis, only Brazil, Spain, and Mexico have recorded higher death rates among large countries.[6] Along with lost lives, the uncontrolled spread of COVID-19 in the U.S. exerted a profound economic impact. Increasing numbers of cases caused changes in consumer behavior, with large drops in consumption of services (Baker et al. Forthcoming, Chetty et al. 2020) leading to an unprecedented increase in unemployment (Chetty et al. 2020, Coibion et al. 2020). The economic downturn coincided with changing political attitudes about the role of government, with Rees-Jones et al. (2020a) finding deaths and infections associated with increased support for expanding the U.S. safety net.

In sharp contrast to most world leaders and to his opponent Joe Biden, Trump sought to downplay the threat of the virus, with limited political success. He began this tactic early in the crisis, and never veered from it. On February 10, Trump claimed, "a lot of people think that [coronavirus] goes away in April with the heat. . . " On February 26, as U.S. cases began to appear, he said, "when you have 15 people, and the 15 within a couple of days is going to be down to close to zero, that's a pretty good job we've done." Again, on April 3 he remarked, "It is going to go away. It is going away." He continued making similar comments throughout the summer, and in his first remarks after contracting the virus himself in October, he declared, "It's going to disappear. It is disappearing."[7] The tactic did little to help his standing with the electorate. According to Gallup, President Trump's approval rating fell from a 2020 high of 49% on March 22 to 38% on June 30.[8] Polls showed nearly 60% of Americans disapproved of Trump's response to the pandemic, with very little variation in the five months leading up to the election.[9]

There are several reasons to believe that the pandemic, and the Trump administration's response, were detrimental to Trump's reelection prospects. The strong

[6] https://coronavirus.jhu.edu/data/mortality.

[7] https://www.cnn.com/interactive/2020/10/politics/covid-disappearing-trump-\comment-tracker/.

[8] https://news.gallup.com/poll/203207/trump-job-approval-weekly.aspx.

[9] https://projects.fivethirtyeight.com/coronavirus-polls/

disapproval of the president's handling of the virus suggests that a majority of the public blamed the administration for its failure to curtail its spread. Most importantly, voters likely associate rising local cases and deaths with an increasing threat to the health and safety of themselves and their loved ones. In this context, we might expect that the greater the local exposure to risk, the more likely voters are to punish the president by voting for the challenger. Another channel through which COVID-19 may have lead to diminished Trump support is economic. Despite a big rebound in economic growth in the third quarter of 2020, the unemployment rate remains well above the historical average. Ominously, rising case numbers in the lead-up to the election portended another wave of hospitalizations and deaths—and the prospect of more localized lockdowns, business closures, and a double-dip recession. Both retrospective and prospective voting frameworks suggest that voters are likely to hold the president accountable for the toll of the virus. For these reasons, we examine whether more severe local outbreaks are associated with weaker support for Trump in 2020, compared to the 2016 presidential election.

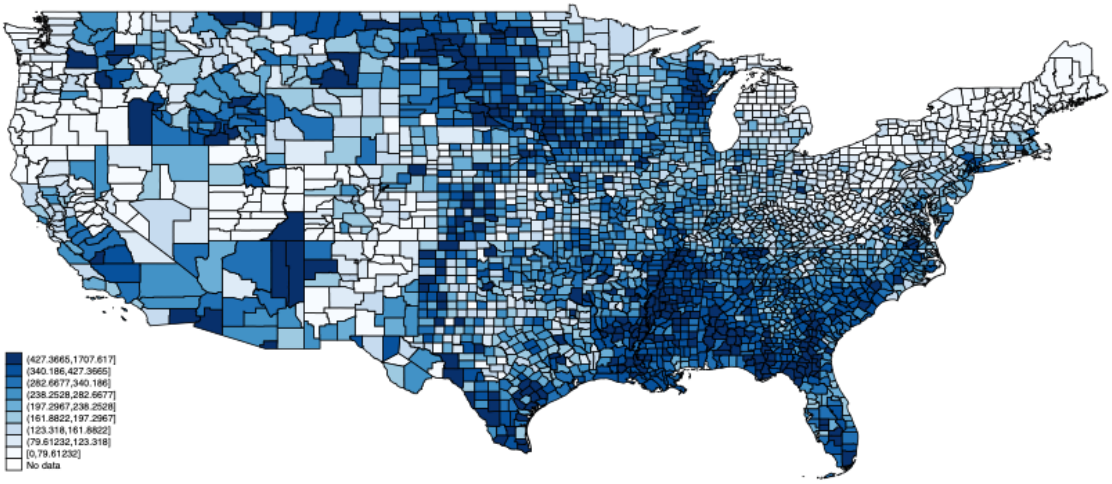
There is, however, a counter-argument to be made. A possible interpretation of Trump's strategy in responding to the pandemic is that it was in line with the preferences of his core constituents. Survey data reveal a striking difference in attitudes towards the pandemic between Democratic and Republican voters. According to Gallup, only 25% of Republican respondents are "worried about getting the coronavirus," whereas this percentage climbs to almost 80% among Democratic respondents.[10] Similarly, about 60% of Republican respondents are "ready to return to normal activities right now," whereas a mere 3% of Democratic respondents are ready to resume a normal lifestyle. We see similar differences for questions related to practicing social distancing, wearing masks, and avoiding large crowds. While ideology influences attitudes toward the pandemic in other countries as well, the differences between Democratic and Republican voters in the U.S. are uniquely large. In short, given the polarization of U.S. politics, voters seem to be experiencing the very same event in very different ways based on their partisan identities. If this is the case, even a global pandemic responsible for hundreds of thousands of deaths may not meaningfully reduce support for President Trump, especially among his base.

## 2 Data and Empirical Strategy

We describe all the data that we use in our analysis below.

[10] https://news.gallup.com/opinion/gallup/321698/covid-responses-men-women.aspx [consulted on November 4, 2020].

Figure 1: Cumulative Number of COVID-19 Cases per 10,000




Notes: This figure illustrates the the cumulative number of COVID-19 cases per 10,000 as of October 22, 2020.

### 2.1 COVID-19 Data

Our analysis relies on known COVID-19 cases and deaths, recorded at the county-level. We use the COVID-19 incidence data compiled by the Center for Systems Science and Engineering at Johns Hopkins University. The data and data sources at the state and county levels can be accessed here: https://github.com/CSSEGISandData/COVID-19. The cumulative totals of COVID-19 cases and deaths correspond to October 22, 2020. In our sample, the mean for the cumulative number of COVID-19 cases per 10,000 is 247 (std. dev. 157), while the cumulative number of COVID-19 deaths per 100,000 is 53 (std. dev. 56). Figure 1 and Appendix Figure A1 illustrate the distribution of cases and deaths in the U.S., respectively.

We also gather data on the following COVID-19 policies: stay-at-home orders, mandatory face mask policies, day care closures, freezes on evictions, and mandated quarantine for individuals arriving from another state. Data on policy duration are drawn from Raifman et al. (2020). See our discussion paper for more details about these policies (Baccini et al. (2020)).

We draw social distancing data from Google's COVID-19 Community Mobility Reports. This data set captures visits to a location relative to a baseline day using data from users who have enabled "location history" in their Google account. The baseline day is the median value for the 5-week period from January 3 to February 6, 2020. We rely on workplace as the location of interest as of April 1, 2020, i.e., the midpoint of the first COVID-19 wave. We also rely on mobility change as of August 1st as a robustness check, i.e., the midpoint of the second wave.[11]

[11] See Brodeur, Gray, Islam and Bhuiyan (2020) for a review of studies using cellphone data to measure mobility during the pandemic.

### 2.2 Election Data

We merge variables capturing COVID-19 incidence by county with data on county-level election results from Dave Leip's Atlas of U.S. Presidential Elections.[12] We compute the difference of vote shares of President Trump between the 2020 and 2016 U.S. presidential elections. Specifically, we compute shares dividing the total number of votes for Trump by the total number of votes in each county.

Table 1 provides summary statistics, and Figure 2 illustrates changes in voting share from 2016 to 2020. The map shows that Trump's support fell in parts of the Rust Belt and the Sun Belt in 2020 compared with the 2016 presidential election.[13]

Table 1: Descriptive Statistics

| | Mean | S. D. | Max | Min | $n$ |
|---|---|---|---|---|---|
| *Election Outcomes* | | | | | |
| Trump Voting (2020) | 63.4 | 15.7 | 90.9 | 8.8 | 2,689 |
| Change in Trump Voting (2020–2016) | 1.72 | 2.64 | 28.11 | -7.12 | 2,689 |
| Change in Total Votes (2020–2016) | 7,334 | 28,149 | 824,800 | -220,281 | 2,689 |
| *COVID-19 Incidence* | | | | | |
| Cum. COVID-19 Cases | 3,020 | 10,724 | 290,486 | 0 | 2,689 |
| Cum. COVID-19 Cases per 10,000 | 247 | 157 | 1,708 | 0.0 | 2,689 |
| Cum. COVID-19 Deaths | 81 | 362 | 7,374 | 0 | 2,689 |
| Cum. COVID-19 Deaths per 100,000 | 53 | 56 | 524 | 0.0 | 2,689 |
| *Labor Outcomes* | | | | | |
| Share Emp. Meat Factories | 0.014 | 0.054 | 0.585 | 0.0 | 2,689 |
| Unemployment Rate Change | 2.90 | 1.85 | 18.6 | -5.0 | 2,689 |

Notes: Authors' calculations. Election results from Dave Leip's Atlas of U.S. Presidential Elections. Electoral outcomes are not weighted (by the number of registered voters). Changes in Trump Voting (2020–2016) and Trump voting (2020) are in percentages. Cumulative COVID-19 cases, cases per 10,000 people, deaths, and deaths per 100,000 people are the cumulative totals corresponding to October 22, 2020. Share of employment in meat-processing factories is computed using data from the County Business Patterns. Monthly unemployment data comes from the Bureau of Labor Statistics' Local Area Unemployment Statistics.

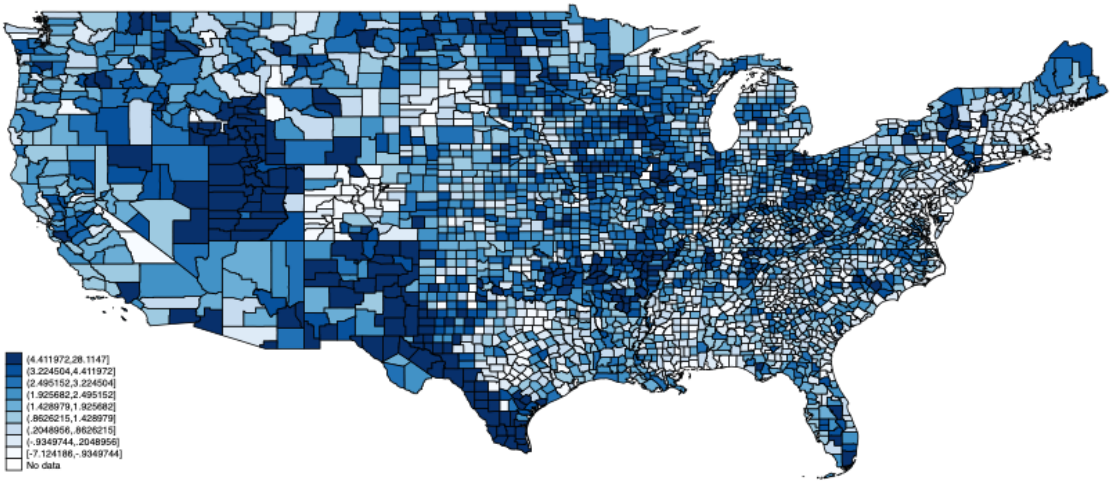
### 2.3 Economic Data

**2.3.1 Employment Data** We rely on the County Business Patterns (CBP) to compute the share of employment in meat-processing factories. Of note, there are

[12] Data can be purchased from https://uselectionatlas.org/BOTTOM/store_data.php.

[13] Of note, Trump won relatively more sparsely populated counties while Biden won relatively more densely populated counties. This explains that the mean of the variable "Trump Voting (2020)" is 63%. Note that our variables and estimates are unweighted throughout. We show that our results are robust to different weighting schemes in Baccini et al. (2020).

Figure 2: Changes in Share of Votes for Donald Trump from 2016 to 2020




Notes: This figure illustrates the differential in vote shares for Trump in 2020 and 2016.

jobs in this industry for about 52% of counties. The CBP provides annual data for establishments with paid employees within the U.S. This data set provides annual employment data at the county-level for the week of March 12 and annual payroll data. Note that the CBP does not include employment for most establishments with government employees and the following NAICS industries: crop and animal production; rail transportation; Postal Service; pension, health, welfare, and vacation funds; trusts, estates, and agency accounts; office of notaries; private households; and public administration. See https://www.census.gov/programs-surveys/cbp/about.html for more details.

Last, we get monthly unemployment rates at the county-level from the U.S. Bureau of Labor Statistics' Local Area Unemployment Statistics. In our sample, the mean change in the unemployment rate from August 2019 to August 2020 was an increase of 2.87.[14]

### 2.4 Occupational Measures

We rely on four occupational indexes as control variables: (1) exposure to disease or infection, (2) physical proximity, (3) essential worker designation, and (4) remote work. The first three indexes were built in Beland et al. (2020), while the remote work index comes from Dingel and Neiman (2020). These indexes serve as covariates in our analysis since they have been shown to be related to the severity of job losses in the U.S. and could be related to voting behavior and COVID-19 incidence.

[14]The increase in the unemployment rate was much larger during the months of April and May 2020. Also note that the increase in unemployment does not include workers who are currently employed but are not working due to lockdowns. See Beland et al. (2020) for a discussion.

## 3 Empirical Strategy

In this section, we describe the empirical strategy that was pre-specified in a PAP. We first present our OLS model and provide evidence that our model is more appropriate than a naïve model relating COVID-19 incidence and Trump vote share. We then describe the IV specification, in which we instrument COVID-19 incidence with the share of employment in meat-processing plants.

### 3.1 COVID-19 Incidence: OLS

As stated in our PAP, we first rely on the following model:

$$\Delta Y_c = \alpha + \beta COVIDIncidence_c + X_c'\gamma + \theta_s + \varepsilon_c, \tag{1}$$

where $Y_c$ is the differential in Trump's vote share in 2020 and 2016 for county $c$. $COVID\ Incidence_c$ is the cumulative number of confirmed COVID-19 cases per 10,000 inhabitants or COVID-19 deaths per 100,000 inhabitants as of October 22, 2020.[15] We report standard errors clustered at the state-level.

We include in the model $X_c$, which is a vector of county-level variables. We include the following demographic and socioeconomic variables: population, share of female population, share of foreign-born population, share of population with a college degree, share of non-Hispanic Black population, share of non-Hispanic White population, share of population by age group (9 dummies), social mobility index, and four occupational indexes. Moreover, we compute employment changes due to the pandemic at the county-level by taking the unemployment rate as of September 2020 minus the unemployment rate as of September 2019.[16] The inclusion of these variables is key to our identification assumption that no omitted variables are related to COVID-19 incidence and the change in voting behavior from the 2016 to the 2020 presidential election. Finally, $\theta_s$ represents state fixed effects. This set of fixed effects allows us to further control for county-level characteristics that are common to counties within the same state.

Our estimation is thus at the county-level and we effectively test whether counties with relatively more COVID-19 cases or deaths differentially voted for the Trump in 2020 compared with the previous presidential election. We use this model instead of a model relating COVID-19 incidence to vote share in 2020 alone to better capture trends in voting behavior. In other words, we compare how voting behav-

[15] We follow our PAP in using October 22, 2020 for calculating the number of COVID-19 cases. Nonetheless, we check the robustness of our results using other dates for calculating the number of COVID-19 cases. See the Results section for more details.

[16] Relying on different months for the before and during COVID-19 periods has no effect on our conclusion that job losses are not related to differential voting behavior from the 2016 to the 2020 elections.

ior changed pre- and post-COVID-19 rather than simply analyzing voting behavior post-COVID-19. We believe this is crucial in this context given the increasing political polarization in the U.S. Moreover, we think that the inclusion of state fixed effects and controlling for social distancing and a large set of demographic variables helps account for differential (changes in) behavior and preferences across counties. This is also crucial because a growing literature has shown, for instance, that individuals identifying as Republicans are less likely to comply with social distancing orders than those identifying as Democrats (e.g., Allcott et al. (2020); Gollwitzer et al. (2020)).

### 3.2 COVID-19 Incidence: IV

We complement the reduced form analysis with an instrumental variable approach. The concern we attempt to address is that COVID-19 cases and COVID-19 deaths do not occur at random, but rather they correlate with individuals' behavior, which may be different between those who vote for the Democratic Party and those who vote for the Republican Party. For instance, it may be that voters living in "red" (i.e., Republican-leaning) counties are less likely to observe social distancing or to wear masks. If this is the case, this type of behavior would be likely to increase the number of COVID-19 cases (and in turn COVID-19 deaths) and we would observe a larger share of votes for Trump than for Biden in the same counties. While we control for social distancing in the previous analysis, we may have missed some other confounders in our analysis.

To attempt to achieve exogenous variation of COVID-19 cases and deaths at the county-level, we instrument COVID-19 cases and deaths with the share of employment in meat-processing factories in each county. More specifically, we use the average number of workers in the NAICS industry code 3116, "Animal Slaughtering and Processing," in each county between 2012 and 2015, i.e., before Trump's presidency. We divide this number by the average number of total workers in each country during the same time frame, i.e., 2012–2015. Data come from the CBP and measure raw employment.

The rationale for the instrument is that there is evidence of meat-processing plants becoming COVID-19 hotbeds due to their cold, humid environment and difficulties with workplace physical distancing.[17] According to a CDC report on July 10, among 23 states reporting COVID-19 outbreaks in meat and poultry facilities, 16,233 cases in 239 facilities occurred, including 86 (0.5%) COVID-19 related deaths.[18] Based on cases reported by Johns Hopkins University, as of May 6, coun-

[17] https://www.cnn.com/2020/06/27/health/meat-processing-plants-coronavirus-intl/index.html [consulted on October 5, 2020].

[18] https://www.cdc.gov/mmwr/volumes/69/wr/mm6927e2.htm [consulted on October 5 2020].

ties containing or within 15 miles of one or more meatpacking plants reported 373 COVID-19 cases per 10,000 residents.[19] That is roughly double the U.S. average of 199 cases per 100,000 in all counties with reported cases.[20] The severity of the incidence of COVID-19 cases in meat-processing facilities prompted research on how to control the spread of the virus in these plants.[21]

Armed with this instrument, we estimate:

$$\begin{cases} COVID_c = \rho + \phi \cdot MEAT_c + X_c'\psi + \theta_s + \nu_c \\ \Delta Y_c = \alpha + \delta \hat{COVID}_c + X_c'\gamma + \theta_s + \varepsilon_c, \end{cases} \tag{2}$$

where $MEAT_c$ is the share of workers in meat-processing plants. We run a first stage in which we regress this variable on the cumulative number of COVID-19 cases per 10,000 inhabitants or deaths per 100,000 inhabitants at the county level, including all controls and state fixed effects as in equation 1. Then we plug in the predicted values of this first stage and estimate the second stage of the 2SLS.

For our instrument to be valid two conditions have to hold. First, our instrument has to be a strong predictor of the number of COVID-19 cases and deaths. Figure 3 illustrates the relationship between the cumulative number of COVID-19 cases and the share of employment in meat-processing factories since the beginning of the pandemic for the (1) top 1% of counties with the highest share of employment in meat-processing factories, (2) top 5% of counties with the highest share of employment in meat-processing factories, (3) counties with at least one job in meat-processing factories, and (4) counties without any jobs in meat-processing factories.

This figure provides direct evidence that counties with a higher share of employment in meat-processing factories had a higher incidence of COVID-19 during the entire pandemic. COVID-19 case (and death) incidence is much larger for counties with a relatively high share of employment in meat-processing factories and much smaller for counties with no employment or positive employment share. This result suggests our first stage is strong and that the relationship between the share of employment in meat-processing factories and COVID-19 incidence is non-linear.

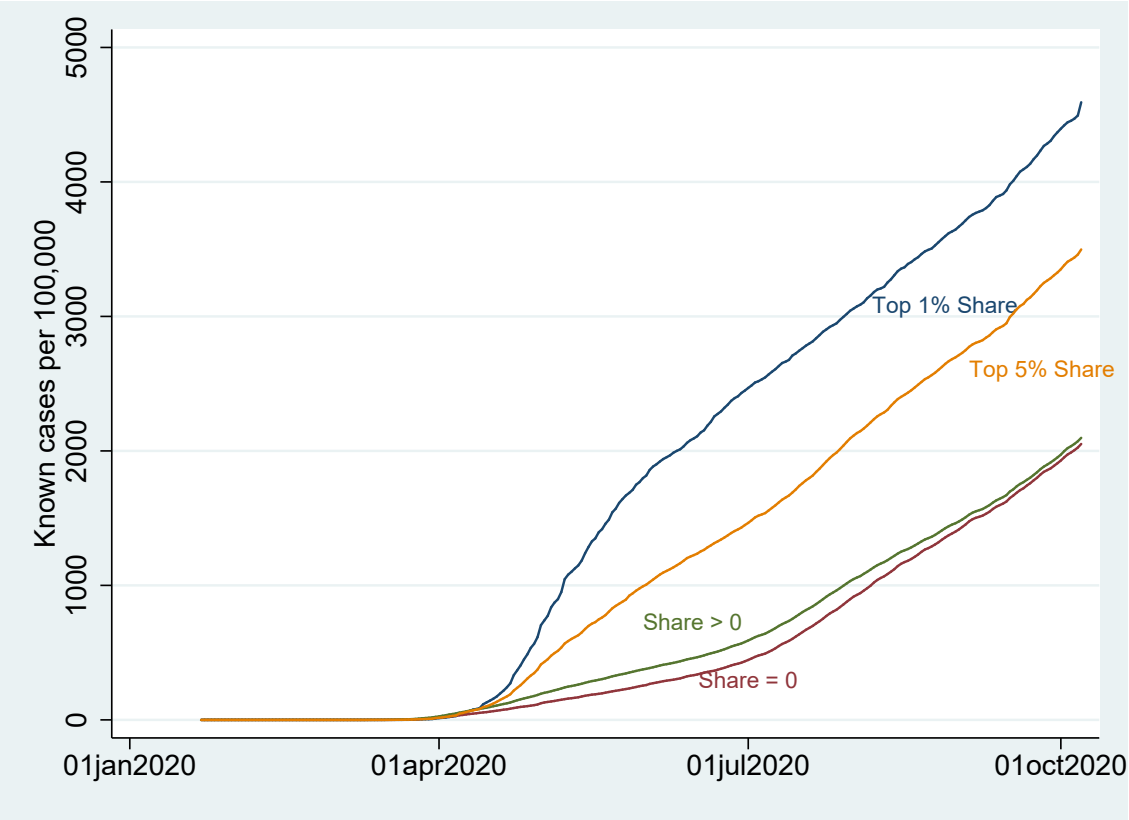
Note also that the raw correlation between COVID-19 cases and deaths and our instrument is 0.3 and 0.1, respectively. The correlation between COVID-19 cases and deaths and our instrument conditional on controls and state fixed effect is much

[19] News about these cases are distributed by the media across counties and have therefore a general effect, although these news may have more weights in counties with a large share of workers employed in meat-processing plants.

[20] https://www.ewg.org/news-and-analysis/2020/05/ewg-map-counties-meatpacking-\plants-report-twice-national-average-rate [consulted on October 5 2020].

[21] https://www.thepigsite.com/news/2020/09/new-research-to-mitigate-covid-19-in\-us-meat-and-poultry-processing-facilities [consulted on October 5, 2020].

Figure 3: COVID-19 Cases and the Share of Employment in Meat-Processing Factories




Notes: This figure illustrates the cumulative number of number of COVID-19 cases and the share of employment in meat-processing factories for the (1) top 1% of counties with highest share of employment in meat-processing factories, (2) top 5% of counties with highest share of employment in meat-processing factories, (3) counties with at least one job in meat-processing factories, and (4) counties without any jobs in meat-processing factories. Employment data is from the County Business Patterns.

higher, i.e., above 0.5 for cases and 0.3 for deaths.

Second, the identifying variance is the industrial composition of each county, specifically the presence of meat-processing factories. In order for our instrument to allow a causal interpretation, employment in meat-processing factories must only affect the change in voting behavior from 2016 to 2020 through its effect on COVID-19 cases and deaths, i.e., the exogeneity assumption. While there is no test to assess the validity of this assumption, we discuss other possible channels through which our instrument can affect the outcome variable and explain how we account for these channels. While we control for a host of variables that could potentially affect the exclusion restriction, we discuss here two main possible violations of the exogeneity assumption.

First, we control for the share of manufacturing employment. We do so because it may be that counties with a large share of workers in manufacturing voted against Trump in 2020 due to job losses for which he was now held accountable as the incumbent president. It may also be that trade unions were more actively campaigning against Trump in 2020 than they were in 2016, since he was the incumbent Republican president. In an effort to isolate the effect of our instrument on COVID-19 cases, we also include the share of workers in food manufacturing, i.e., NAICS industry code 311, to which "Animal Slaughtering and Processing" belongs. Including this variable implies that every possible violation of the exclusion restriction has to be specific to the meat-processing industry.

In the same spirit, we are concern that Trump policies – both those related and those unrelated to trade – did not specifically affect meat packaging industry. We thus include the China trade shock variable, which captures the vulnerability of U.S. manufacturing counties to foreign competition especially from China.[22] Autor et al. (2020) shows that the China trade shock increased Trump's vote in 2016 and, in the same vein, it could have decreased his electoral support in 2020 as the incumbent president.

Second, it may be that President Trump's trade policies have negatively affected meat sales, and in turn this could have led to a loss of support among workers in this industry and in surrounding communities. Kim and Margalit (Forthcoming) provide evidence of that. For addressing this concern, we include variables capturing the potential impact of Chinese tariffs and U.S. tariffs on the workforce in each county.[23]

[22]The *China shock* variable is a Bartik measure capturing rising Chinese imports to the United States in each industry $i$, weighted by baseline share of workers in the same industry $i$ in each county. This variable varies both across counties and over time. The over-time variation is given by the difference in imports from China to the U.S. between 2000 (i.e., pre-accession to the WTO) to the period 2016-2019 (i.e., average value over this four-year window).

[23]These variables are built by matching the list of targeted commodities (by China and the U.S.) to industry classifications and constructing an original measure of the county-level share of employment targeted in each round of retaliatory tariffs. Data come from Kim and Margalit

Note also that the correlation between our instrument and the share of manufacturing employment and share of employment in food manufacturing is 0.3 and 0.4 respectively, whereas the correlation between our instrument and the other controls is never higher than 0.1.[24]

### 3.3 Placebo Analyses

In Appendix Table A1, we provide empirical evidence that COVID-19 incidence is significantly related to votes for Trump in 2016 and 2020. We then provide evidence that COVID-19 incidence in our models is not successfully predicting changes in voting behavior for previous presidential elections. The variables of interest are the cumulative number of COVID-19 cases per 10,000 (columns 1–3) and COVID-19 deaths per 100,000 (columns 4–6). In Panel A (B), the dependent variable is the vote share for Trump in the 2020 (2016) presidential election, whereas the dependent variable in Panel C is the change in votes for Trump from 2012 to 2016. Columns 1 and 4 include only state fixed effects and our demographic controls, while columns 2 and 3 sequentially add socioeconomic controls and our social distancing indicator.

The estimates in Panels A and B are positive and significant, suggesting that counties with more Trump's supporters had larger numbers of COVID-19 cases. The fact that both estimates are positive and significant for both the 2016 and the 2020 presidential elections suggest that this model is misspecified and that a naïve estimation would conclude that COVID-19 incidence helped Trump during the 2020 presidential election.[25] In contrast, the estimates are imprecisely estimated and statistically insignificant in all columns in Panel C, suggesting that using the differential in voting is more appropriate than using the vote share for the current elections.

We also provide placebo evidence that our IV method leads to null findings for previous presidential elections. The estimates are presented in Panels D, E and F. The dependent variables are respectively the differential in vote share for the Republican Party for the elections in 2016 and 2012 (Panel D), in 2012 and 2008 (Panel E), and in 2008 and 2004 (Panel F). The point estimates for COVID-19 cases are all statistically insignificant and much smaller than our 2SLS estimates for 2016–2020. These results provide evidence that our empirical models are properly

(Forthcoming).

[24]We also implemented the plausibly exogenous test as suggested by Conley et al. (2012). The result of the test, which is available upon request, shows that our instrument is plausibly exogenous with $p < 0.1$. In other words, the effect of the instrumented variable, i.e., cases, remains negative with a 90% confidence interval.

[25]Press analyses indicate a positive correlation between COVID-19 cases and Trump's support. See for instance, "Counties with worst virus surges overwhelmingly voted Trump" by AP news, available at https://apnews.com/article/counties-worst-virus-surges-voted-trump-d671a483534024b5486715da6edb6ebf.

specified.

**Results**

### 3.4 OLS and 2SLS Estimates

In this section we estimate the effect of COVID-19 incidence on voting behavior using OLS and 2SLS. We focus on COVID-19 cases in the main analysis. We note again that our analysis and choice of control variables was fully detailed in our pre-analysis plan. Table 2 contains OLS estimates of equation (1) (columns 1–3). The sample size is 2,689 observations (i.e., counties).[26] The dependent variable is the differential in vote for Donald Trump in 2020 and 2016. A positive value indicates that Trump received more votes in 2020 than in 2016. We report standard errors clustered at the state-level. The variables of interest are the cumulative numbers of COVID-19 cases per 100,000 inhabitants.

What clearly emerges is that COVID-19 cases are negatively related to votes for Trump during the 2020 presidential election in comparison to the 2016 election. In column 1, we include state fixed effects and our set of demographic and socioeconomic controls. We find that a county with 100 more COVID cases per 10,000 people (as compared to others in the same state) reduced its Trump vote share from 2016 to 2020 by an additional 0.12 percentage points on average. The point estimate is statistically significant at about the 10% level.

In column 2, we add to the model our indicator of social distancing, i.e., time spent at workplaces in April 2020. Column 3 is our most extensive model specification. We saturate our model with all the previous controls and state fixed effects. In addition, we add to the model the unemployment change from before to during COVID-19. The magnitude of the estimates and statistical significance remain the same.

In column 4, we add to the model a quadratic term of COVID-19 cases. The quadratic term of COVID-19 cases is positive and statistically significant at the 5% level, but very small in magnitude (6.10e-08). In contrast, the magnitude and sign of the coefficient of our variable of interest, Cumulative COVID-19 Cases per 10,000, remains the same. This result suggests that the negative effect of additional COVID-19 cases on Trump's 2020 vote share becomes slightly smaller as the number of cases increases.

Of note, the coefficient of unemployment change (August 2019 to August 2020) is small and statistically insignificant.[27] Our results thus suggest that job losses during

[26] We lose about 400 observations (i.e., counties) because of lack of data for our social distancing indicator. Excluding this control variable and doing the analysis on the full set of counties has no effect on our main conclusions.

[27] Using the change in unemployment for different dates does not affect our conclusions. For

Table 2: The Impact of COVID-19 Cases: OLS and 2SLS Estimates

Panel A: **First Stage**

| | | | | | **Cumulative COVID Cases** | | |
|---|---|---|---|---|---|---|---|
| | | | | | (5) | (6) | (7) |
| Share Workers | | | | | 300.24 | 63.31 | 258.01 |
| Meat Plants | | | | | (78.27) | (78.91) | (74.74) |

Panel B: **OLS and 2SLS**

| | | | **Change in Trump Vote** from 2016 to 2020 | | | | |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| Cumulative COVID | -0.0012 | -0.0011 | -0.0011 | -0.0012 | -0.0120 | -0.0135 | -0.0137 |
| Cases per 10,000 | (0.0007) | (0.0007) | (0.0007) | (0.0007) | (0.0040) | (0.0045) | (0.0043) |
| Cumulative COVID Cases | | | | 6.10e-08 | | | |
| Squared per 10,000 | | | | (2.62e-08) | | | |
| Unemp. Change | | | 0.0210 | 0.0223 | | -0.0245 | |
| | | | (0.0803) | (0.0812) | | (0.0580) | |
| State FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| IV Controls | | | | | Yes | Yes | Yes |
| Demo. Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Socioecon. Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Social Distancing | | Yes | Yes | Yes | | Yes | Yes |
| Observations | 2,689 | 2,689 | 2,689 | 2,689 | 2,689 | 2,689 | 2,689 |
| F-Statistics | | | | | 49.23 | 37.38 | 35.49 |

Notes: Election data from Dave Leip's Atlas of US Presidential Elections. An observation is a county. Robust standard errors are in parentheses, adjusted for clustering by state. We present OLS estimates in columns 1–4 of specification 1. We present the first stage (Panel A) and the 2SLS estimates (Panel B) of specification (2) in columns 5–7 in which we instrument COVID-19 incidence in a first stage by the share of employment in meat-processing factories. In Panel A, the dependent variable is the cumulative number of COVID-19 cases per 10,000 (columns 5–7). In Panel B, the dependent variable is the difference in vote for Trump in 2020 and 2016. Demographic controls include: population, female population share, foreign-born population, non-Hispanic Black population, non-Hispanic White population and the share of the population by age group. Socioeconomic controls include: share of the population with a college degree and four occupational indexes. IV controls include variables for the share of employment in manufacturing and in food manufacturing. The unemployment change variable is the unemployment rate in September 2020 minus the unemployment rate in September 2019.

the pandemic are not significantly related to voting behavior and that increases in the unemployment rate does not seem to be a major factor behind the negative effect of COVID-19 on the share of votes for Trump. A possible explanation is that job losses are triggered by policies, e.g., lockdowns, implemented by the states, which Trump opposed or at the very least for which Trump cannot be held directly responsible.

The coefficients for some of the other control variables are worth discussing (not shown for space consideration). We find that the share of women is strongly negatively correlated to the change in vote share for Trump. Similarly, Trump seems to have lost vote share in counties with a high share of adults aged 25–54.

Our OLS results provide suggestive evidence that the pandemic affected the 2020 presidential election. The main concern with our OLS estimates is that omitted variables could be related to both COVID-19 incidence and differential voting behavior in the 2016 and 2020 presidential elections. We now turn to our instrumental variable strategy.

In Table 2 (columns 5–7), we present the first stage (Panel A) and the two-stage estimates (Panel B) of specification (2) in which we instrument COVID-19 incidence in the first stage by the share of employment in meat-processing factories. We control for our usual set of fixed effects and control variables. As shown in Figure 3, we find that the share of employment in meat-processing factories is strongly positively correlated with COVID-19 incidence. The coefficient is always significant and the F-statistics indicate no concern of a weak instrument.

Our second-stage estimates are presented in the bottom panel (columns 4–6). We find that counties with more COVID-19 cases substantially decreased their vote share for Trump in 2020. The 2SLS estimates are larger than the OLS estimates, and suggest that a county with 100 more COVID cases per 10,000 people (as compared to others in the same state) reduced its Trump vote share from 2016 to 2020 by an additional 1.2 percentage point on average.[28] The point estimates are statistically significant at the 1% level and robust to the inclusion of our large set of controls and the share of manufacturing employment as well as the share of employment in food manufacturing.

So far, our analysis has underscored an important finding: the COVID-19 pan-

instance, measuring unemployment during the first wave of COVID-19 (i.e., April 2020) instead of the month of August 2020 leads to similar estimates and has no effect on the magnitude or significance of the COVID-19 cases variable.

[28]There are many plausible explanations for why our 2SLS estimates are larger than our OLS estimates. First, there is a great deal of measurement error in our estimation. Second, we are estimating a local average treatment effect (LATE) with our IV estimation. Voting behavior in counties with relatively more employment in meat-processing factories may be differently affected by the pandemic than counties with no or a small share of employment in this industry. For instance, counties with employment in meat-processing factories are significantly more populous than counties without any jobs in this industry.

demic costs President Trump votes. But is this effect large enough to have changed the outcome of the 2020 presidential election? To answer this question, we conduct a simple counterfactual exercise to determine the magnitude of the effect by exploring how the composition of votes in a number of closely contested states would have differed if there had been fewer COVID-19 cases. The computation of the counterfactual is based on the coefficient estimate in column 1 of Table 2. For each county, we compute the fraction of total votes that Trump would have received if the number of COVID-19 cases had been X% smaller as -0.0012 $\times COVID_c \times$ X% – i.e., the point estimate of the effect of $COVID_c$ on Trump's vote share from the OLS estimates, the size of each county's measured COVID-19 cases, and the scaling factor X%. We next multiply this product by the number of total votes in a county to calculate the number of additional votes that Trump would have received in the counterfactual scenario. We then aggregate these county-level votes into state totals. To allow for the margin of error in our counterfactual calculations, we use the lower and upper bounds of our estimate (i.e., 0.0012), using the 90% confidence interval. We report these bounds in parenthesis.

Table 3 presents the results of this counterfactual analysis. Column 1 shows the actual vote margin in favor of Biden in the 2020 election for a set of closely contested states. The three subsequent columns show counterfactual outcomes had COVID-19 cases been 5% or 10% or 20% fewer. Since we find that the COVID incidence decreased Trump's vote share, the counterfactual analyses for fewer COVID-19 cases correspondingly increase Trump's counterfactual vote totals. The results in Table 3 show that, *ceteris paribus*, Trump would have won Michigan in a counterfactual scenario with 20% fewer cases. He would have added Pennsylvania to his list with 10% fewer COVID-19 cases. He would have won Arizona, Georgia, and Wisconsin, with 5% fewer COVID-19 cases. Under this last counterfactual, Trump would have been reelected. Even if we consider the lower bound calculations, which are very conservative, Trump would have kept the presidency with 21% fewer cases.

### 3.5 Effect Heterogeneity

We investigate heterogeneous effects of COVID-19 on voting in Table 4. In columns 1 and 2, we first investigate whether the effect of COVID-19 incidence is larger/smaller for states that have implemented a stay-at-home order than for states that did not implement such a policy during the pandemic. Data on stay-at-home order comes from Raifman et al. (2020) and only include directives/orders for the entire state, i.e., did not include guidance or recommendations. Of note, all states without a stay-at-home order are states that Trump won in 2016. Our 2SLS estimates suggest that COVID-19 had a larger effect in states that did not implement a stay-at-home

Table 3: Counterfactual Outcomes in Closely Contested States Won by Biden

| | | COVID-19 Cases | | |
|---|---|---|---|---|
| State | Trump's Gap | 5% Smaller | 10% Smaller | 20% Smaller |
| Arizona | -10,457 | 64,505 | 129,011 | |
| | | (5,375; 118,260) | (10,750; 236,519) | |
| Georgia | -12,670 | 18,169 | 36,339 | |
| | | (7,571; 30,282) | (15,141; 60,564) | |
| Michigan | -154,188 | 53,175 | 106,350 | 212,701 |
| | | (4,431; 88,625) | (8,863; 177,251) | (17,726; 354,501) |
| Pennsylvania | -81,701 | 61,450 | 122,900 | 245,800 |
| | | (5,121; 102,417) | (10,242; 204,833) | (20,484; 409,667) |
| Wisconsin | -20,682 | 61,337 | 122,675 | 245,349 |
| | | (5,111; 102,229) | (10,223; 204,458) | (20,446; 408,916) |

Note: The computation of the counterfactual is based on the estimate from the OLS model. An increase in per COVID-19 cases reduces Trump's share of vote by 0.0012 percentage points (see column 3 in Table 2). The actual outcome in column 2 reports the margin in favor of Biden in each state. Negative values indicate that Biden won the state in 2020. The reported values in columns 3 and 4 are estimated margins in favor of Trump in the counterfactual scenario of fewer COVID-19 cases. The numbers in parenthesis are the lower and upper bound on these calculations, using the 90% confidence intervals of our OLS estimate. A positive value in columns 3 or 4 larger than the negative value in column 2 implies that Trump would have won the state.

order during the pandemic. This result seems to suggest that if Trump had taken the pandemic more seriously and had placed more emphasis on health and safety issues, he would have lost less electorally and he would have had higher chances to get re-elected.

Columns 3 and 4, we document the relationship between COVID-19 incidence and the differential in vote for Trump in 2020 and 2016, for Trump's and his opponent Hillary Clinton's states separately. We define states as Trump's or Clinton's using the electoral votes for the 2016 U.S. presidential election.[29] We find that the negative effect of COVID-19 cases on Trump's vote is driven by those states that he won in the 2016 presidential election. The magnitude of the coefficient is about 50% larger than the magnitude of the coefficient in the entire sample.[30] In contrast, the coefficient of COVID-19 cases is small, positive, and not significant in those states that Clinton won in the 2016 presidential election (column 2).[31]

Columns 5 and 6 restrict the sample to swing and non-swing states.[32] Our results

[29]We classify Maine as a blue state. This has no effect on our conclusions.

[30]The cumulative number of COVID-19 cases per 10,000 inhabitants varies across Trump's states (271) and Clinton's states (166).

[31]We also tested the relationship between COVID-19 incidence and the differential in vote for Trump in red states, for states with and without stay-at-home order. Our 2SLS estimates suggest a large negative effect of COVID-19 cases on Trump's vote for both sets of red states, but that the effect is larger for states without stay-at-home orders.

[32]We classify states as swing or non-swing using the NYT classification available at https://www.nytimes.com/interactive/2020/us/elections/electoral-college-battleground-states.html, consulted on November 2, 2020. We consider swing states as states categorized as tossup and leaning Democratic: Arizona, Florida,

indicate that the negative effect of COVID-19 cases on Trump's vote is almost twice as large in swing states as it is in non-swing states.

Columns 7 and 8 restrict the sample to urban and rural counties, respectively. We define a county as "urban" ("rural") if over (below) 50% of its population was living in an urban area in 2010 (U.S. Census). Our results show that urban counties drive the negative effect of COVID-19 cases on Trump's vote. Indeed, the effect is negative and significant in the urban sample, whereas it is smaller and statistically insignificant in rural counties.

In Table 5, we investigate heterogeneity by county demographic characteristics. We find that negative effect of COVID-19 cases is stronger for countries below the median percentage of residents aged 65 than for counties above the median percentage of residents aged 65. Our estimates also indicate that the negative effect of COVID-19 cases is stronger in more racially diverse counties (i.e., those with white population shares below the median). Furthermore, our findings show that the negative effect of COVID-19 cases on Trump's vote is driven by less educated counties (i.e., those with a below-median share of residents with college degrees), which may help explain Biden's victory in the Rust Belt.

**3.5.1 COVID-19 Deaths** We now check whether our results are robust to the use of COVID-19 deaths instead of cases. Table 6 shows our estimates. We do not find any evidence that COVID-19 deaths are related to changes in voting behavior from the 2016 to the 2020 presidential election with our OLS model. The estimates are all statistically insignificant. For our 2SLS estimates, our first stage is weaker than for cases, with F-statistics ranging from 2 in the less parsimonious model to 6 in our model with the full set of controls. The 2SLS estimates are all negative and of similar magnitude as our 2SLS estimates for cases, but more imprecise with only the estimate in column 6 being statistically significant at conventional levels.

The fact that our 2SLS estimates are of about the same magnitude for cases and deaths suggests that our conclusions are similar when using deaths instead of cases. Nonetheless, two differences are worth mentioning. First, our instrumental variable is only weakly related to COVID-19 deaths.[33] The probability that a COVID-19 infection results in death rises dramatically with age, and we expect that this and other factors such as healthcare coverage may contribute to the divergence in estimated effects. Second, it is plausible that voters are less aware or less likely to know someone who has died of COVID-19 than to know someone who has tested

Georgia, Iowa, Maine, Michigan, Minnesota, Nebraska, New Hampshire, Nevada, North Carolina, Ohio, Pennsylvania, Texas, and Wisconsin.

[33]There is a very small differences in death per capita since mid-September 2020 for counties with and without employment in meat-processing factories.

Table 4: The Impacts of COVID-19 Cases (2SLS): Heterogeneity Analyses by State and County Characteristics

Panel A: **First Stage**

| | **Cumulative COVID Cases** | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Share Workers Meat Plants | 186.41 | 456.19 | 225.62 | 492.81 | 351.35 | 204.58 | 768.25 | 111.61 |
| | (87.96) | (126.43) | (85.01) | (239.63) | (131.29) | (83.87) | (121.21) | (62.74) |

Panel B: **2SLS**

| | **Change in Trump Vote** from 2016 to 2020 | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | States With Lockdown | States Without Lockdown | Trump 2016 States | Clinton 2016 States | Swing States | Not Swing States | Urban Counties | Rural Counties |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Cumulative COVID Cases per 10,000 | -0.0067 | -0.0237 | -0.0200 | 0.0022 | -0.0156 | -0.0100 | -0.0128 | -0.0024 |
| | (0.0045) | (0.0034) | (0.0052) | (0.0036) | (0.0050) | (0.0047) | (0.0040) | (0.0046) |
| State FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| IV Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Demo. Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Socioecon. Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Social Distancing | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 2,017 | 668 | 2,007 | 682 | 1,079 | 1,610 | 1,209 | 1,480 |
| F-Statistics | 13.86 | 27.65 | 20.72 | 27.12 | 26.35 | 13.61 | 73.35 | 5.11 |

Notes: Election data from Dave Leip's Atlas of US Presidential Elections. An observation is a county. Robust standard errors are in parentheses, adjusted for clustering by state. In Panel A, the dependent variable is the cumulative number of COVID-19 cases per 10,000. In Panel B, the dependent variable is the differential in vote for Trump in 2020 and 2016. We report the second stage estimates of our 2SLS (equation 2). In columns 1 and 2, we restrict the sample to counties in states that implemented a stay-at-home order during the pandemic and counties in states that did not implement a stay-at-home order, respectively. In columns 3 and 4 we document the relationship between COVID-19 cases and the difference in vote for Trump in 2020 and 2016 for states that Trump and Clinton won, respectively. Columns 5 and 6 restrict the sample to swing and non-swing states. Columns 7 and 8 restrict the sample to urban and rural counties, respectively. The variables of interest are the cumulative number of COVID-19 cases per 10,000 (Panel A) and COVID-19 deaths per 100,000 (Panel B), respectively. Demographic controls include: population, female population share, foreign-born population, non-Hispanic Black population, non-Hispanic White population and the share of the population by age groups. Socioeconomic controls include: share of the population with a college degree and four occupational indexes. IV controls include variables for the share of employment in manufacturing and in food manufacturing.

Table 5: The Impacts of COVID-19 Cases (2SLS): Heterogeneity Analyses by Demographic Characteristics

Panel A: **First Stage**

| | Cumulative COVID Cases | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Share Workers Meat Plants | 255.85 | 232.76 | 264.55 | 15.21 | 274.12 | 159.79 |
| | (109.05) | (92.00) | (96.92) | (72.59) | (95.60) | (57.43) |

Panel B: **2SLS**

| | Change in Republican Vote from 2016 to 2020 | | | | | |
|---|---|---|---|---|---|---|
| | Below Median 65 Years | Above Median 65 Years | Below Median White non-Hisp. | Above Median White non-Hisp. | Below Median College | Above Median College |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Cumulative COVID Cases per 10,000 | -0.0181 | -0.0033 | -0.0142 | -0.0628 | -0.0136 | 0.0004 |
| | (0.0060) | (0.0042) | (0.0047) | (0.3040) | (0.0042) | (0.0070) |
| State FE | Yes | Yes | Yes | Yes | Yes | Yes |
| IV Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Demo. Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Socioecon. Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Social Distancing | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 1,467 | 1,222 | 1,383 | 1,306 | 1,400 | 1,289 |
| F-Statistics | 1 | 166.10.90 | 20.28 | 0.04 | 23.66 | 4.67 |

Notes: Election data from Dave Leip's Atlas of US Presidential Elections. An observation is a county. Robust standard errors are in parentheses, adjusted for clustering by state. In Panel A, the dependent variable is the cumulative number of COVID-19 cases per 10,000. In Panel B, the dependent variable is the differential in vote for the Republican Party in 2020 and 2016. We report the second stage estimates of our 2SLS (equation 2). We restrict the sample to counties: below (column 1) and above (column 2) the median percentage of residents aged 65; below (column 3) and above (column 4) the median percentage of white (non Hispanic) residents; and below (column 5) and above (column 6) the median percentage of residents who attended college. The variable of interest is the cumulative number of COVID-19 cases per 10,000. Demographic controls include: population, female population share, foreign-born population, Non-Hispanic Black population, Non-Hispanic White population and the share of the population by age groups. Socioeconomic controls include: share of the population with a college degree and four occupational indexes. IV controls include variables for the share of employment in manufacturing and in food manufacturing.

positive for COVID-19.

**3.5.2 Voters' Mobilization** One of the defining outcomes of the 2020 presidential election was the record-high turnout. Both presidential candidates would had won any previous elections, given their number of votes at the national-level. We use differences in total votes between the 2016 and 2020 presidential elections as a rough proxy of turnout. We run the same model specification as in equations 1 and 2. We show the results in Table 7.

We find no evidence that COVID-19 cases affected voters' mobilization in the

Table 6: The Impacts of COVID-19 Deaths: OLS and 2SLS Estimates

Panel A: **First Stage**

| | | | | | **Cumulative COVID Deaths** | | |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| Share Workers Meat Plants | | | | | 26.17 | 39.36 | 42.49 |
| | | | | | (22.36) | (23.05) | (21.587) |

Panel B: **OLS and 2SLS**

| | | | | **Change in Trump Vote** from 2016 to 2020 | | | |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| Cumulative COVID Deaths per 100,000 | 0.0017 | 0.0015 | 0.0015 | 0.0004 | -0.1380 | -0.0901 | -0.0831 |
| | (0.0017) | (0.0016) | (0.0016) | (0.0016) | (0.1260) | (0.588) | (0.0486) |
| Cumulative COVID Deaths Squared per 10,000 | | | | 3.03e-06 | | | |
| | | | | (9.99e-07) | | | |
| Unemp. Change | | | 0.0245 | 0.0639 | | | 0.1100 |
| | | | (0.0832) | (0.0852) | | | (0.1370) |
| State FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| IV Controls | | | | | Yes | Yes | Yes |
| Demo. Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Socioecon. Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Social Distancing | | Yes | Yes | Yes | | Yes | Yes |
| Observations | 2,689 | 2,689 | 2,689 | 2,689 | 2,689 | 2,689 | 2,689 |
| F-Statistics | | | | | 2.32 | 5.16 | 5.95 |

Notes: Election data from Dave Leip's Atlas of US Presidential Elections. An observation is a county. Robust standard errors are in parentheses, adjusted for clustering by state. We present OLS estimates in columns 1–4 of specification 1. We present the first stage (Panel A) and the 2SLS estimates (Panel B) of specification (2) in columns 5–7 in which we instrument COVID-19 incidence in a first stage by the share of employment in meat-processing factories. In Panel A, the dependent variable is the cumulative number of COVID-19 cases per 10,000 (columns 5–7). In Panel B, the dependent variable is the differential in vote for Trump in 2020 and 2016. Demographic controls include: population, female population share, foreign-born population, Non-Hispanic Black population, Non-Hispanic White population and the share of the population by age groups. Socioeconomic controls include: share of the population with a college degree and four occupational indexes. The unemployment change variable is the unemployment rate in September 2020 minus the unemployment rate in September 2019. IV controls include variables for the share of employment in manufacturing and in food manufacturing.

Table 7: The Impact of COVID-19 Cases on Total Votes: OLS and 2SLS Estimates

Panel A: **First Stage**

| | | | | **Cumulative COVID Cases** | | |
|---|---|---|---|---|---|---|
| | | | | (4) | (5) | (6) |
| Share Workers | | | | 300.24 | 263.31 | 258.01 |
| Meat Plants | | | | (78.27) | (78.91) | (74.73) |

Panel B: **OLS and 2SLS**

| | | | **Change in Total Votes** from 2016 to 2020 | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Cumulative COVID | -1.371 | -2.430 | -2.934 | 42.69 | 40.67 | 33.15 |
| Cases per 10,000 | (3.227) | (3.473) | (3.698) | (22.81) | (21.13) | (17.95) |
| Unemp. Change | | | -947 | | | -797 |
| | | | (621) | | | (575) |
| State FE | Yes | Yes | Yes | Yes | Yes | Yes |
| IV Controls | | | | Yes | Yes | Yes |
| Demo. Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Socioecon. Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Social Distancing | | Yes | Yes | | Yes | Yes |
| Observations | 2,689 | 2,689 | 2,689 | 2,689 | 2,689 | 2,689 |
| F-Statistics | | | | 49.23 | 37.38 | 35.49 |

Notes: Election data from Dave Leip's Atlas of US Presidential Elections. An observation is a county. Robust standard errors are in parentheses, adjusted for clustering by state. We present OLS estimates in columns 1–3 of specification 1. We present the first stage (Panel A) and the 2SLS estimates (Panel B) of specification (2) in columns 4–6 in which we instrument COVID-19 incidence in a first stage by the share of employment in meat-processing factories. In Panel A, the dependent variable is the cumulative number of COVID-19 cases per 10,000 (columns 4–6). In Panel B, the dependent variable is the differential in total votes from 2016 to 2020. Demographic controls include: population, female population share, foreign-born population, non-Hispanic Black population, non-Hispanic White population and the share of the population by age group. Socioeconomic controls include: share of the population with a college degree and four occupational indexes. The unemployment change variable is the unemployment rate in September 2020 minus the unemployment rate in September 2019. IV controls include variables for the share of employment in manufacturing and in food manufacturing.

OLS estimates.[34] On the contrary, there is some evidence that the incidence of COVID-19 boosts turnout in the 2SLS. These conflicting results on the effect of the pandemic on mobilization are also found in previous studies that explore this topic in different electoral contexts (Giommoni and Loumeau 2020, Fernández-Navia et al. 2020).[35]

[34] We also find no evidence that the the quadratic terms for COVID-19 deaths is related to Trump vote share in 2020 in comparison to 2016.

[35] We also investigate the impact of COVID-19 cases on the number of votes for Trump and the Democratic Party separately. The estimates are presented in Baccini et al. (2020). We do not find evidence that COVID-19 is related to the number of votes for Trump in 2020 in comparison to 2016 in our OLS and 2SLS models. But we do find some evidence that COVID-19 cases are positively and significantly related to total votes for the Democratic Party in 2020 in comparison to 2016 in our 2SLS models.

**3.5.3 Robustness Checks** We provide many robustness checks for our 2SLS results in Baccini et al. (2020). For instance, we add to the models well-known predictors of voting behavior or COVID-19 incidence. We show that our results are robust to controlling for the *China shock* variable (Autor et al. (2020)) and two variables capturing Chinese tariffs and protection by U.S. tariffs at the county-level from Kim and Margalit (Forthcoming). The rationale for including these variables has been explained in the previous section.

We also show that our estimates are robust to the inclusion of weather controls such as precipitation and air pollution (i.e., PM2.5 and precipitation for the first months of the pandemic),[36] the share of employment in nursing care facilities,[37] county-to-county (in and out) migration, and the duration (in days) of the following statewide non-pharmaceutical interventions: stay-at-home orders, mandatory face mask policies, day care closures, freezes on evictions, and mandated quarantine for out-of-state individuals.[38] Overall, the inclusion of one or all of these control variables has no effect on the magnitude and significance of our 2SLS estimates.

We also check whether our OLS and 2SLS point estimates vary if we change the date for the moment in which we calculate the cumulative number of COVID-19 cases. As stated in our pre-analysis plan, we rely on October 22nd for our main analysis. In a set of robustness checks, we instead rely on July 1st, August 1st, September 1st, and August 1st. The estimates for the OLS are all larger and more significant than for our baseline, i.e., cases as of October 22nd, suggesting that we are very conservative in estimating the relationship between COVID-19 cases and the differential in votes for Trump. For the 2SLS, the point estimates all range from -0.011 to -0.013 and are statistically significant at the 1% level. Similarly, changing the start period to April or May, i.e., excluding cases that occurred early on in the pandemic, has no impact on our conclusions.

Last, we show that our conclusions are robust to using a different geographical level for the analysis. In Baccini et al. (2020), we replicate our main analysis using commuting zones as our unit of analysis. Commuting zones are significantly larger than counties, which provides the advantage that the distribution of employment in the meat-processing industry is less limited geographically, since many commuting zones have at least one meat-processing factory.[39]

[36] A number of studies provide suggestive evidence that air pollution may be associated with an increased risk of COVID-19 death (Wu et al. (2020)).

[37] http://jedkolko.com/2020/10/18/the-geography-of-the-covid19-third-wave/ [consulted on November 2, 2020].

[38] Note that we only have data for statewide non-pharmaceutical interventions. One exception is for stay-at-home orders, which have been implemented by some cities and counties prior to statewide orders. Typically, the city or county order precedes the statewide order by few days.

[39] Our first stage F-statistics at the commuting zone-level are smaller than at the county-level, ranging around 10. The magnitude of the first stage coefficients is larger at the commuting zone-level than at the county-level, suggesting that COVID infections spread to neighboring counties.

## 4 Conclusion

This paper explores the effect of the COVID-19 pandemic on the 2020 U.S. presidential election using both a reduced form and IV approach. Our key finding is that COVID-19 cases decreased electoral support for Trump. A simple counterfactual exercise shows that, *ceteris paribus*, if COVID-19 cases had been 5 percent lower, Trump would have been reelected. We find that the negative impact of COVID-19 incidence on Trump's support is stronger (1) in states without a stay-at-home order, (2) in states that Trump won in the 2016 presidential elections, (3) in swing states, and (4) in urban counties. We find no evidence that worsening economic conditions reduced electoral support for Trump. The 2SLS estimates show evidence that COVID-19 cases affect positively voters' mobilization, helping Biden win the presidency.

At least two explanations are consistent with these findings. First, voters may have electorally sanctioned President Trump for how he handled the pandemic, which was at odds with most major countries, and widely criticized. This explanation is consistent with a retrospective voting approach (Fiorina 1981, Fearon 1999, Norpoth 2001), in which voters sanction incumbents for their handling of negative shocks. Second, some voters may have switched from Trump to Biden due to changes in preferences triggered by the pandemic and the recession. In particular, a severe public health threat and major economic losses may have shifted preferences in favor of an expansion of the social safety net, including healthcare and unemployment insurance programs (Rees-Jones et al. 2020b). Since the Democratic Party is more likely to champion these policies, Biden benefited from this switch in voters' preferences. This explanation is in line with studies claiming that political preferences are shaped by personal experience. If it is true that these changes in preferences are long lasting (Giuliano and Spilimbergo 2014), the Democratic Party may be able to capitalize electorally in future elections.

Our empirical analysis is unable to tease out which of these two channels is operative; this remains an important task for future research. Future studies should also explore how turnout, which was quite high for the 2020 presidential election but for which granular data is not yet available, influenced the results reported in this paper. Finally, when individual-level survey data become available, it will be important to explore how voter heterogeneity in race, age, and other characteristics conditions voters' responses to the pandemic.

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Conflict of Interest: The authors declare that they have no conflict of interest.

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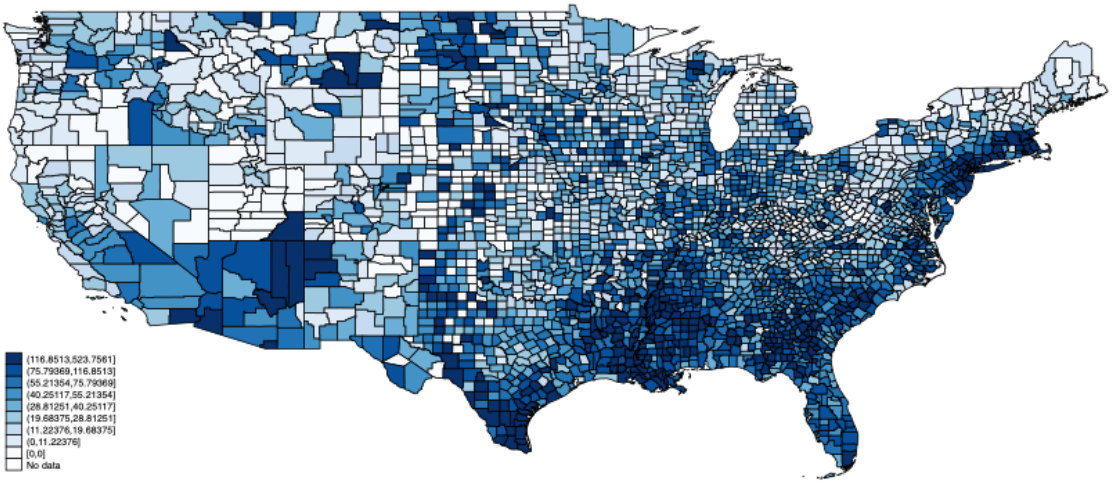
# 5 Appendix

## 5.1 Pre-Analysis Plan

For the empirical analysis, we follow the specifications and test the hypotheses detailed in our pre-analysis plan (PAP). Our PAP was archived on October 30th, 2020, at https://osf.io/xvuzp/, four days prior to the Presidential Elections. We relied on a PAP to minimize issues of specification searching and p-hacking. Another advantage of relying on a PAP is that it allowed us to think carefully about the analyses to be conducted prior to the outcome of the Presidential Elections. This is potentially important given the growing concerns that social science researchers may be politically biased.

We aimed to follow the PAP to the greatest extent possible, but made some modifications following suggestions from other researchers and reviewers, and gaining access to the voting data. We try to be as transparent as possible and list all the modifications made to the pre-analysis plan and supplementary analyses not included in the PAP in Baccini et al. (2020).

Figure A1: Cumulative Number of COVID-19 Deaths per 100,000




Notes: This figure illustrates the the cumulative number of COVID-19 deaths per 100,000 as of October22, 2020.

Table A1: Placebo Analysis Using Previous Presidential Elections

| | Impact of COVID-19 Cases | | | Impact of COVID-19 Deaths | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| **Panel A: OLS** | | | | | | |
| Trump Vote | 0.0078 | 0.0076 | 0.0057 | 0.0065 | 0.00529 | 0.0086 |
| Share 2020 | (0.0021) | (0.0021) | (0.0021) | (0.0042) | (0.0040) | (0.0040) |
| **Panel B: OLS** | | | | | | |
| Republican Vote | 0.0088 | 0.0087 | 0.0068 | 0.0038 | 0.0034 | 0.0062 |
| Share 2016 | (0.0025) | (0.0025) | (0.0025) | (0.0049) | (0.0045) | (0.0043) |
| **Panel C: OLS** | | | | | | |
| Change Republican | -0.0013 | -0.0013 | -0.0013 | 0.0013 | 0.0013 | 0.0011 |
| Vote from 2012 to 2016 | (0.0009) | (0.0009) | (0.0010) | (0.0012) | (0.0012) | (0.0012) |
| **Panel D: 2SLS** | | | | | | |
| Change Republican | -0.0035 | -0.0031 | -0.0026 | -0.0614 | -0.0315 | -0.0225 |
| Vote from 2012 to 2016 | (0.0023) | (0.0026) | (0.0027) | (0.0666) | (0.0319) | (0.0252) |
| **Panel E: 2SLS** | | | | | | |
| Change Republican | 0.0006 | -5.69e-05 | 0.0002 | 0.0098 | -0.0006 | 0.0019 |
| Vote from 2008 to 2012 | (0.0015) | (0.0020) | (0.0018) | (0.0269) | (0.0204) | (0.0161) |
| **Panel F: 2SLS** | | | | | | |
| Change Republican | 0.0019 | 0.0013 | 0.0036 | 0.0332 | 0.0126 | 0.0311 |
| Vote from 2004 to 2008 | (0.0034) | (0.0036) | (0.0041) | (0.0535) | (0.0339) | (0.0334) |
| State FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Demographic Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Socioeconomic Controls | | Yes | Yes | | Yes | Yes |
| Social Distancing | | | Yes | | | Yes |
| Observations | 2,732 | 2,732 | 2,732 | 2,732 | 2,732 | 2,732 |
| F-Statistics (Panel D) | 87.26 | 67.54 | 62.50 | 1.69 | 4.05 | 5.01 |

Notes: Election data from Dave Leip's Atlas of US Presidential Elections. An observation is a county. Each point estimate is from a different regression. Robust standard errors are in parentheses, adjusted for clustering by state. In Panel A, the dependent variable is the vote share for the Republican Party in 2020 (OLS). In Panel B, the dependent variable is the vote share for the Republican Party in 2016 (OLS). In Panel C, the dependent variable is the difference in vote for the Republican Party in 2016 and 2012 (OLS). In Panel D, the dependent variable is the difference in vote for the Republican Party in 2016 and 2012 (2SLS). In Panel E, the dependent variable is the difference in vote for the Republican Party in 2012 and 2008 (2SLS). In Panel F, the dependent variable is the difference in vote for the Republican Party in 2008 and 2004 (2SLS). The variables of interest are the cumulative number of COVID-19 cases per 10,000 (columns 1–3) and COVID-19 deaths per 100,000 (columns 4–6). Demographic controls include: population, female population share, foreign-born population, Non-Hispanic Black population, Non-Hispanic White population and the share of the population by age groups. Socioeconomic controls include: share of the population with a college degree and four occupational indexes.

# 1 Updated GLO Working Paper Appendix (NOT TO BE INCLUDED IN JOURNAL ARTICLE)

## 1.1 Modifications to the Pre-Analysis Plan:

While we follow the PAP for the choice of control variables for our main specifications, we added control variables as a robustness check in Appendix Table A4. The additional control variables are only included in this table and have no effect on the conclusions of this paper.

Another modification that was made to the PAP was to exclude the analysis on the impacts of non-pharmaceutical interventions. We instead include these statewide policy variables as controls in Appendix Table A4. Our decision to not conduct this analysis is based on the fact that our model includes state fixed effects and that we have access to county-level policy changes only for stay-at-home orders. Furthermore, stay-at-home orders implemented by cities or counties typically preceded statewide orders by only a few days. There is thus not enough variation to conduct this analysis with state fixed effects. We do provide an analysis splitting the sample for states with and without stay-at-home orders, respectively. This analysis was added following a suggestion by the editor.

We also added one outcome variable to the analysis: differences in total votes between the 2016 and 2020 presidential elections. We rely on the same (OLS and 2SLS) specifications and control variables as for the analyzes for the differential voting share for Trump from 2016 to 2020. We added this variable because of the record-high turnout.

The last modification we have made to the PAP is to change the list of states considered "Swing". In this paper, we classify states as swing or non-swing states using the NYT classification available at https://www.nytimes.com/interactive/2020/us/elections/electoral-college-battleground-states.html, while we write in the PAP that "We classify states as swing or non-swing states using election polls compiled by Dave Leip's Atlas of U.S. Presidential Elections. We rely on the latest three polls as of October 25th, 2020 and consider swing states as states in which the spread is 5 or less: Arizona, North Carolina, Florida, Georgia, Iowa, Ohio, Texas and Alaska. We also add the following three states which have been labeled as swing states in the media and included in Dave Leip's report on closest states: Michigan, Wisconsin and Pennsylvania."

In practice, we add the following states as swing states in the paper: Minnesota, Nevada, New Hampshire, Maine and Nebraska. We show in Appendix Table A7 that using the states stated in the PAP leads to similar conclusions.

## 1.2 Occupational Measures

The exposure to disease or infection and physical proximity indexes were developed using the Occupational Information Network (O*NET) survey data. O*NET is an online database that gathers occupational data and develops applications to help the workforce better understand the U.S. labor market. More precisely, the index of exposure to disease is taken from a survey question asking, "How often does this job require exposure to disease/infections?" The physical proximity index is built using answers to the question "How often does this job require exposure to disease/infections?" The answers to these two questions include five possible answers: (1) Never, (2) Once a year or more but not every month, (3) Once a month or more but not every week, (4) Once a week or more but not every day, and (5) Every day. Occupations such as dental hygienist score 100 (the maximum) in both indexes.

Our third index captures the likelihood that a worker in a given occupation is designated an essential worker. Essential worker designations are based on the LMI Institute index.[40] Our last index is measuring feasibility of remote work at the occupation level. Using this index, Dingel and Neiman (2020) argue that 34% of U.S. jobs can plausibly be performed at home. The indexes were built using data collected prior to the pandemic. It is thus plausible that they are changing over time in response to the pandemic.

### 1.3 Non-Pharmaceutical Interventions

We also gather data on the following COVID-19 policies: stay-at-home order, mandatory face mask policies, day care closures, freezes on eviction, and mandated quarantine for individuals arriving from another state. Data on policy duration are drawn from Raifman et al. (2020).

**Stay-at-home order**: "The date a state's stay at home/shelter in place order went into effect. Only included directives/orders. Did not include guidance or recommendations. Order must apply to entire state."

**Day care closure**: "The date a state closed daycares statewide. Only included directives/orders. Did not include guidance or recommendations. Order must apply to entire state."

**Face masks**: "The date a state mandated face mask use in public spaces by all individuals statewide. The order does not have to apply to all public spaces, but must apply state wide. Only included directives/orders. Did not include guidance or recommendations. Order must apply to entire state."

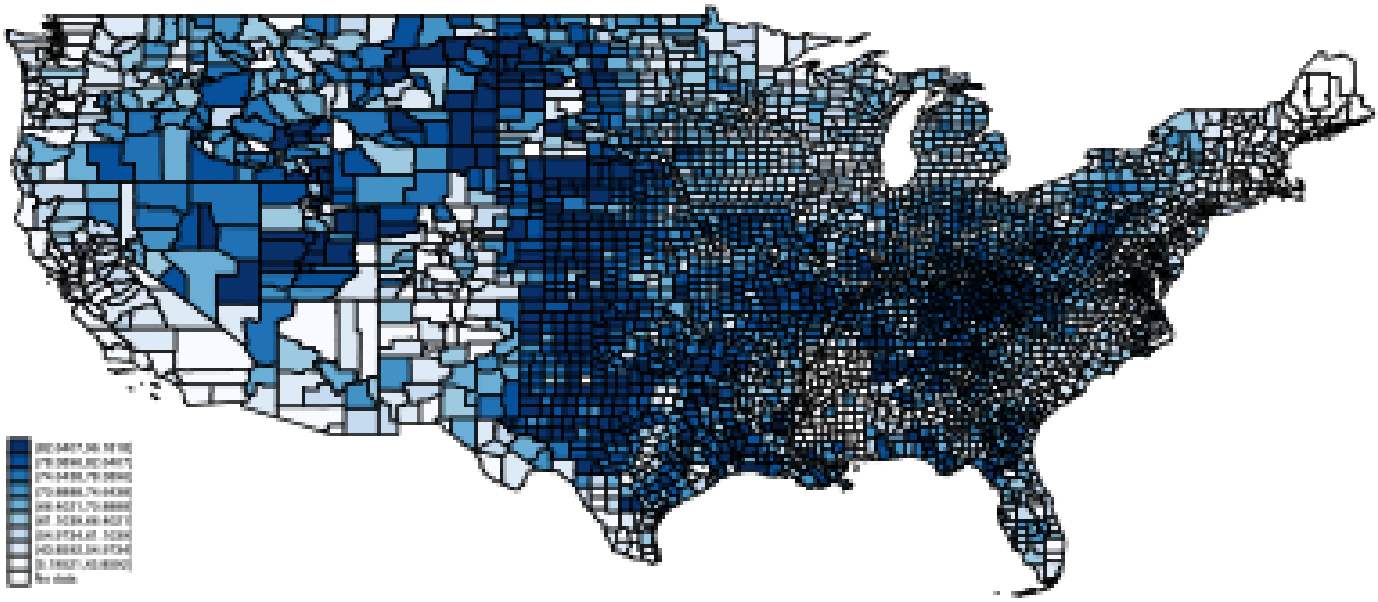
**Freezes on evictions**: "The date a state stopped the initiation of evictions (overall or due to COVID-19 related issues) statewide. This could be mandated from governors or though the state court system. Did not include guidance or recommendations. Order must apply to entire state."

**Quarantine**: "The date a state first mandated that individuals arriving in their state from any state must undergo quarantine. Did not include guidance or recommendations. Order must apply to entire state. Quarantine order must apply to visitors using all forms of transportation to enter the state (not just air travel)."

### 1.4 Additional Figures for GLO WP

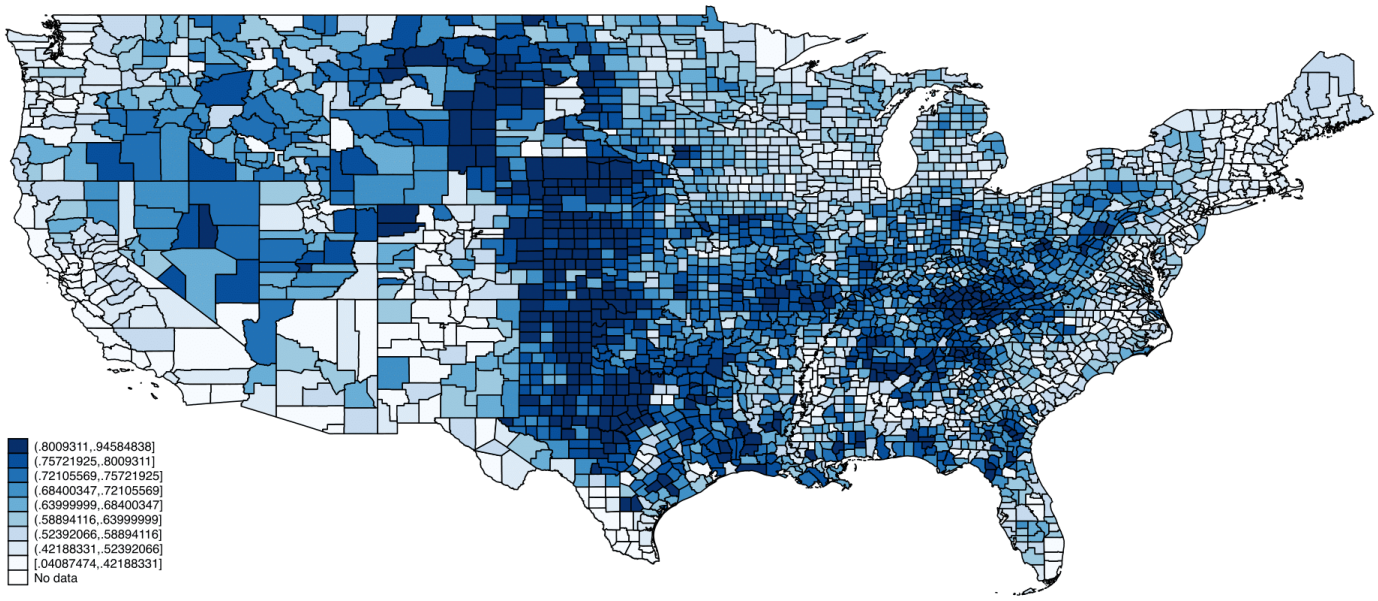
[40] See https://www.lmiontheweb.org/ for more details [consulted on October 25, 2020].

Figure A2: Share of Votes for the Republican Party in 2020



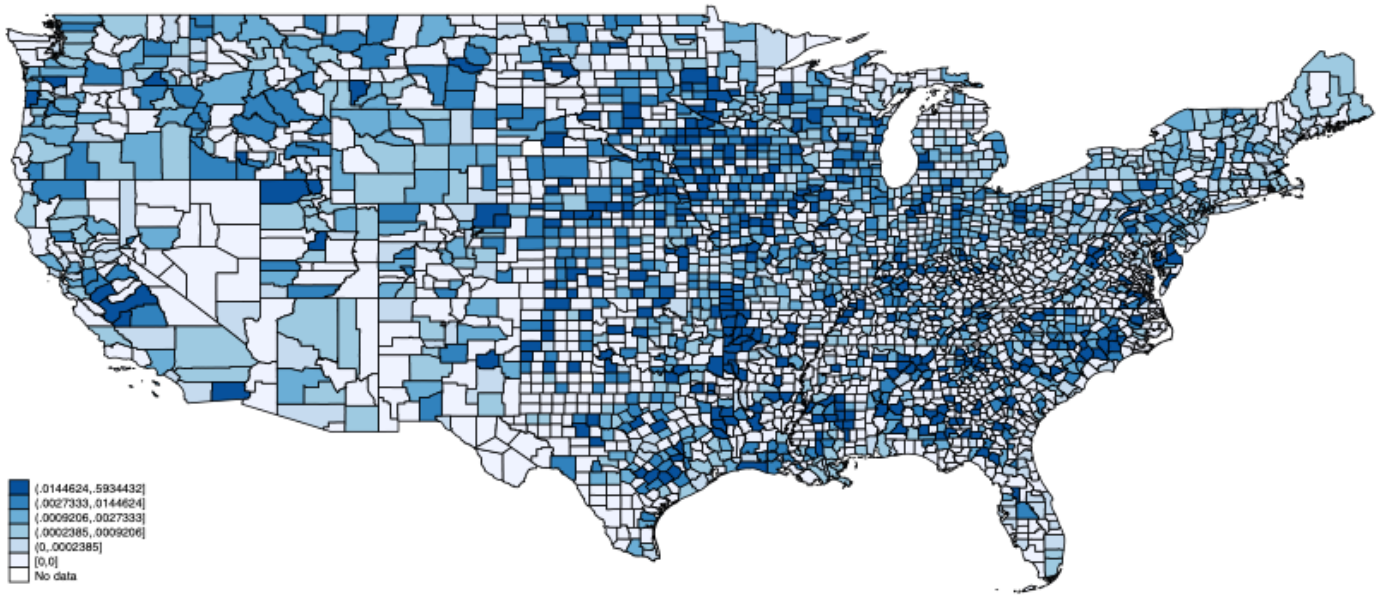
Notes: This figure illustrates the share of votes for the Republican Party during the 2020 Presidential Elections.

Figure A3: Share of Votes for the Republican Party in 2016



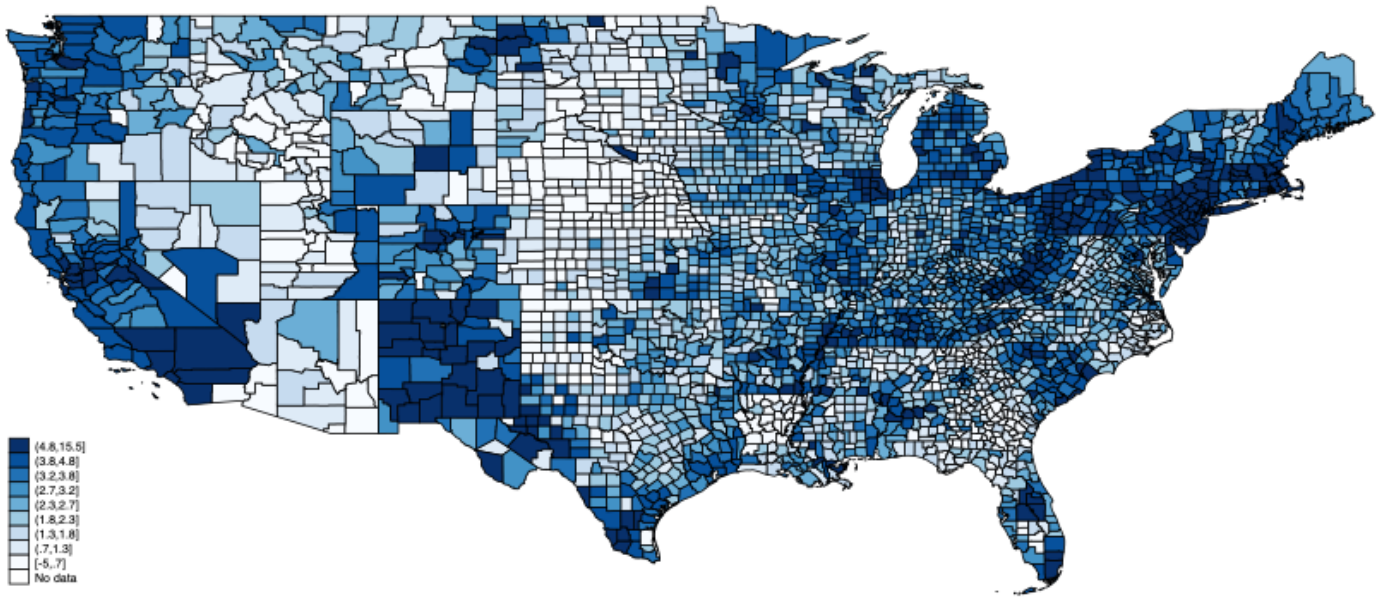

Notes: This figure illustrates the share of votes for the Republican Party during the 2016 Presidential Elections.

Figure A4: Share of Employment in Processing Meat Factories




Notes: This figure illustrates the share of employment in processing meat factories. Data is from the County Business Patterns.

Figure A5: Change in Unemployment from before to During COVID-19




Notes: This figure illustrates the change in the unemployment rate from August 2019 to August 2020. Data from the U.S. Bureau of Labor Statistics' Local Area Unemployment Statistics.

## 1.5 Additional Tables for GLO WP

Table A2: The Impact of COVID-19 Cases on Total Votes for Trump

Panel A: **First Stage**

| | | | | **Cumulative COVID Cases** | | |
|---|---|---|---|---|---|---|
| | | | | (4) | (5) | (6) |
| Share Workers | | | | 300.24 | 263.31 | 258.01 |
| Meat Plants | | | | (78.27) | (78.91) | (74.74) |

Panel B: **OLS and 2SLS**

| | | | **Change in Trump Vote** from 2016 to 2020 | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Cumulative COVID | 32.85 | 16.01 | 10.92 | 596.21 | 543.7 | 477.6 |
| Cases per 10,000 | (178.3) | (185.3) | (185.9) | (832.9) | (853.8) | (813.7) |
| State FE | Yes | Yes | Yes | Yes | Yes | Yes |
| IV Controls | | | | Yes | Yes | Yes |
| Demo. Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Socioecon. Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Social Distancing | | Yes | Yes | | Yes | Yes |
| Observations | 2,689 | 2,689 | 2,689 | 2,689 | 2,689 | 2,689 |
| F-Statistics | | | | 49.23 | 37.38 | 35.49 |

Notes: Election data from Dave Leip's Atlas of US Presidential Elections. An observation is a county. Robust standard errors are in parentheses, adjusted for clustering by state. We present OLS estimates in columns 1–3 of specification 1. We present the first stage (Panel A) and the 2-stage estimates (Panel B) of specification (2) in columns 4–6 in which we instrument COVID-19 incidence in a first stage by the share of employment in processing meat factories. In Panel A, the dependent variable is the cumulative number of COVID-19 cases per 10,000 (columns 4–6). In Panel B, the dependent variable is the differential in total votes for Trump in 2020 and 2016. Demographic controls include population, female population share, foreign-born population, non-Hispanic Black population, non-Hispanic White population and the share of the population by age group. Socioeconomic controls include: share of the population with a college degree and four occupational indexes. The unemployment change variable is the unemployment rate as of September 2020 minus the unemployment rate as of September 2019. IV controls include variables for the share of employment in manufacturing and in food manufacturing.

Table A3: The Impact of COVID-19 Cases on Total Votes for Democratic Party

Panel A: **First Stage**

| | | | | **Cumulative COVID Cases** | | |
|---|---|---|---|---|---|---|
| | | | | (4) | (5) | (6) |
| Share Workers | | | | 300.24 | 263.31 | 258.01 |
| Meat Plants | | | | (78.27) | (78.91) | (74.74) |

Panel B: **OLS and 2SLS**

| | | | **Change in Trump Vote** from 2016 to 2020 | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Cumulative COVID | -42.38 | -125.3 | -174.2 | 4,222 | 4,199 | 3,469 |
| Cases per 10,000 | (242.8) | (261.8) | (280.8) | (2,089) | (2,045) | (1,790) |
| State FE | Yes | Yes | Yes | Yes | Yes | Yes |
| IV Controls | | | | Yes | Yes | Yes |
| Demo. Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Socioecon. Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Social Distancing | | Yes | Yes | | Yes | Yes |
| Observations | 2,689 | 2,689 | 2,689 | 2,689 | 2,689 | 2,689 |
| F-Statistics | | | | 49.23 | 37.38 | 35.49 |

Notes: Election data from Dave Leip's Atlas of US Presidential Elections. An observation is a county. Robust standard errors are in parentheses, adjusted for clustering by state. We present OLS estimates in columns 1–3 of specification 1. We present the first stage (Panel A) and the 2-stage estimates (Panel B) of specification (2) in columns 4–6 in which we instrument COVID-19 incidence in a first stage by the share of employment in processing meat factories. In Panel A, the dependent variable is the cumulative number of COVID-19 cases per 10,000 (columns 4–6). In Panel B, the dependent variable is the differential in total number of votes for the Democratic Party in 2020 and 2016. Demographic controls include population, female population share, foreign-born population, non-Hispanic Black population, non-Hispanic White population and the share of the population by age group. Socioeconomic controls include: share of the population with a college degree and four occupational indexes. The unemployment change variable is the unemployment rate as of September 2020 minus the unemployment rate as of September 2019. IV controls include variables for the share of employment in manufacturing and in food manufacturing.

Table A4: 2SLS Estimates: Robustness Checks

| Panel A: **First Stage** | | | | | | |
|---|---|---|---|---|---|---|
| | | | **Cumulative COVID Cases** | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Share Workers Meat | 263.31 | 258.98 | 262.08 | 264.27 | 262.53 | 257.12 |
| Processing Plants | (78.91) | (77.92) | (78.02) | (78.30) | (78.84) | (76.27) |
| Panel B: **2SLS** | | | | | | |
| | | | **Change in Trump Vote** from 2016 to 2020 | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Cumulative COVID | -0.0135 | -0.0122 | -0.0133 | -0.0133 | -0.0135 | -0.0118 |
| Cases per 10,000 | (0.0045) | (0.0039) | (0.0044) | (0.0045) | (0.0046) | (0.0038) |
| State FE | Yes | Yes | Yes | Yes | Yes | Yes |
| IV Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Demographic Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Socioeconomic Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Social Distancing | Yes | Yes | Yes | Yes | Yes | Yes |
| Tariff Controls | | Yes | | | | Yes |
| China Shock | | Yes | | | | Yes |
| Pollution & Precip. | | | Yes | | | Yes |
| Share Nursing Employment | | | | Yes | | Yes |
| Migration | | | | Yes | | Yes |
| Statewide Interventions | | | | | Yes | Yes |
| Observations | 2,689 | 2,673 | 2,689 | 2,688 | 2,685 | 2,671 |
| F-Statistics | 37.38 | 35.25 | 50.39 | 37.13 | 37.12 | 35.06 |

Notes: Election data from Dave Leip's Atlas of US Presidential Elections. An observation is a county. Robust standard errors are in parentheses, adjusted for clustering by state. We present the first stage (Panel A) and the 2-stage estimates (Panel B) of specification (2) in which we instrument COVID-19 incidence in a first stage by the share of employment in processing meat factories. In Panel A, the dependent variable is the cumulative number of COVID-19 cases per 10,000. In Panel B, the dependent variable is the differential in vote for Trump in 2020 and 2016. Demographic controls include population, female population share, foreign-born population, Non-Hispanic Black population, Non-Hispanic White population and the share of the population by age groups. Socioeconomic controls include: share of the population with a college degree and four occupational indexes. IV controls include variables for the share of employment in manufacturing and in food manufacturing. In column 2, we add to the model the *China shock* variable and two controls from Kim and Margalit (Forthcoming) for targeted tariffs (China) and protection by U.S. tariffs. Column 3 adds to the model precipitation and air pollution controls. In column 4, we control for the share of employment in nursing care facilities and two variables for county-to-county migration flows. Column 5, we control for the duration (in days) of the following statewide non-pharmaceutical interventions: stay-at-home order, mandatory face mask policies, day care closures, freezes on eviction, and mandated quarantine for out of state individuals.

Table A5: OLS Estimates: Date for Cumulative COVID-19 Cases

| | | | **Change in Trump Vote** from 2016 to 2020 | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Cumulative Cases per 10,000 July 1st | -0.0034 | | | | | |
| | (0.0020) | | | | | |
| Cumulative Cases per 10,000 August 1st | | -0.0030 | | | | |
| | | (0.0014) | | | | |
| Cumulative Cases per 10,000 September 1st | | | -0.0018 | | | |
| | | | (0.0009) | | | |
| Cumulative Cases per 10,000 October 1st | | | | -0.0014 | | |
| | | | | (0.0008) | | |
| Cumulative Cases per 10,000 (April-October) | | | | | -0.0015 | |
| | | | | | (0.0008) | |
| Cumulative Cases per 10,000 (May-October) | | | | | | -0.0016 |
| | | | | | | (0.0007) |
| State FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Share Manufacturing | Yes | Yes | Yes | Yes | Yes | Yes |
| Demographic Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Socioeconomic Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Social Distancing | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 2,689 | 2,689 | 2,689 | 2,689 | 2,689 | 2,689 |

Notes: Election data from Dave Leip's Atlas of US Presidential Elections. An observation is a county. Robust standard errors are in parentheses, adjusted for clustering by state. We present OLS estimates of specification (1). The dependent variable is the differential in vote for Trump in 2020 and 2016. The main independent variable is the cumulative number of COVID-19 cases per 10,000. We rely on different dates to calculate the cumulative number of cases. For instance, column 1 reports the estimates for the cumulative number of cases as of July 1st. Demographic controls include population, female population share, foreign-born population, Non-Hispanic Black population, Non-Hispanic White population and the share of the population by age groups. Socioeconomic controls include: share of the population with a college degree and four occupational indexes.

Table A6: 2SLS Estimates: Date for Cumulative COVID-19 Cases

Panel A: **First Stage**

| | **Cumulative COVID Cases** | | | | | |
|---|---|---|---|---|---|---|
| | July 1 | Aug. 1 | Sept. 1 | Oct. 1 | April-Oct | May-Oct |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Share Workers Meat | 354.33 | 324.29 | 294.81 | 273.05 | 273.49 | 163.15 |
| Processing Plants | (64.51) | (62.35) | (66.45) | (72.13) | (73.44) | (67.74) |

Panel B: **2SLS**

| | **Change in Trump Vote** from 2016 to 2020 | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | |
| Cumulative COVID | -0.0100 | -0.0109 | -0.0120 | -0.0130 | -0.0130 | -0.0217 |
| Cases per 10,000 | (0.0035) | (0.0037) | (0.0041) | (0.0044) | (0.0044) | (0.0084) |
| State FE | Yes | Yes | Yes | Yes | Yes | Yes |
| IV Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Demographic Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Socioeconomic Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Social Distancing | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 2,689 | 2,689 | 2,689 | 2,689 | 2,689 | 2,689 |
| F-Statistics | 208.59 | 134.76 | 74.13 | 48.38 | 49.08 | 21.15 |

Notes: Election data from Dave Leip's Atlas of US Presidential Elections. An observation is a county. Robust standard errors are in parentheses, adjusted for clustering by state. We present the first stage (Panel A) and the 2-stage estimates (Panel B) of specification (2) in which we instrument COVID-19 incidence in a first stage by the share of employment in processing meat factories. In Panel A, the dependent variable is the cumulative number of COVID-19 cases per 10,000. We rely on different dates to calculate the cumulative number of cases. For instance, column 1 reports the estimates for the cumulative number of cases as of July 1st. In Panel B, the dependent variable is the differential in vote for Trump in 2020 and 2016. Demographic controls include population, female population share, foreign-born population, Non-Hispanic Black population, Non-Hispanic White population and the share of the population by age groups. Socioeconomic controls include: share of the population with a college degree and four occupational indexes. IV controls include variables for the share of employment in manufacturing and in food manufacturing.

Table A7: The Impacts of COVID-19 Cases (2SLS) for Swing States: PAP vs Paper

Panel A: **First Stage**

| | | | **Cumulative COVID Cases** | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Share Workers Meat | 229.51 | 272.93 | 351.35 | 204.58 |
| Processing Plants | (117.19) | (92.16) | (131.29) | (85.23) |

Panel B: **2SLS**

| | | | **Change in Trump Vote** from 2016 to 2020 | |
|---|---|---|---|---|
| | Swing States PAP | Non Swing States PAP | Swing States Not PAP | Not Swing States Not PAP |
| | (1) | (2) | (3) | (4) |
| Cumulative COVID | -0.0231 | -0.0074 | -0.0156 | -0.0098 |
| Cases per 10,000 | (0.0050) | (0.0038) | (0.0050) | (0.0047) |
| State FE | Yes | Yes | Yes | Yes |
| IV Controls | Yes | Yes | Yes | Yes |
| Demographic Controls | Yes | Yes | Yes | Yes |
| Socioeconomic Controls | Yes | Yes | Yes | Yes |
| Social Distancing | Yes | Yes | Yes | Yes |
| Observations | 908 | 1,781 | 1,079 | 1,610 |
| F-Statistics | 9.34 | 27.10 | 26.35 | 13.61 |

Notes: Election data from Dave Leip's Atlas of US Presidential Elections. An observation is a county. Robust standard errors are in parentheses, adjusted for clustering by state. In Panel A, the dependent variable is the cumulative number of COVID-19 cases per 10,000. In Panel B, the dependent variable is the differential in vote for Trump in 2020 and 2016. We report the second stage estimates of our 2SLS (equation 2). Columns 1 and 2 restrict the sample to swing and non-swing states using the list of swing states listed in the PAP. Columns 3 and 4 restrict the sample to swing and non-swing states using the list of swing states listed in the paper. The variables of interest are the cumulative number of COVID-19 cases per 10,000 (Panel A) and COVID-19 deaths per 100,000 (Panel B), respectively. Demographic controls include population, female population share, foreign-born population, Non-Hispanic Black population, Non-Hispanic White population and the share of the population by age groups. Socioeconomic controls include: share of the population with a college degree and four occupational indexes. IV controls include variables for the share of employment in manufacturing and in food manufacturing.

Table A8: The Impact of COVID-19 Cases: Commuting Zones

Panel A: **First Stage**

| | | | | **Cumulative COVID Cases** | | |
|---|---|---|---|---|---|---|
| | | | | (4) | (5) | (6) |
| Share Workers | | | | 605.55 | 438.54 | 356.74 |
| Meat Plants | | | | (163.03) | (179.02) | (178.54) |

Panel B: **OLS and 2SLS**

| | | | **Change in Trump Vote** from 2016 to 2020 | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Cumulative COVID | -0.0023 | -0.0021 | -0.0015 | -0.0143 | -0.0185 | -0.0183 |
| Cases per 10,000 | (0.0009) | (0.0010) | (0.0011) | (0.0056) | (0.0113) | (0.0106) |
| State FE | Yes | Yes | Yes | Yes | Yes | Yes |
| IV Controls | | | | Yes | Yes | Yes |
| Demo. Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Socioecon. Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Social Distancing | | Yes | Yes | | Yes | Yes |
| Unemp. Change | | | Yes | | | Yes |
| Observations | 668 | 668 | 668 | 668 | 668 | 668 |
| F-Statistics | | | | 15.59 | 8.04 | 5.39 |

Notes: Election data from Dave Leip's Atlas of US Presidential Elections. An observation is a commuting zone. Robust standard errors are in parentheses. We present OLS estimates in columns 1–3 of specification 1. We present the first stage (Panel A) and the 2-stage estimates (Panel B) of specification (2) in columns 4–6 in which we instrument COVID-19 incidence in a first stage by the share of employment in processing meat factories. In Panel A, the dependent variable is the cumulative number of COVID-19 cases per 10,000 (columns 4–6). In Panel B, the dependent variable is the differential in vote for Trump in 2020 and 2016. Demographic controls include population, female population share, foreign-born population, non-Hispanic Black population, non-Hispanic White population and the share of the population by age group. Socioeconomic controls include: share of the population with a college degree and four occupational indexes. IV controls include variables for the share of employment in manufacturing and in food manufacturing.

Table A9: The Impact of COVID-19 Cases: Weighted Estimates

Panel A: **First Stage**

| | **Cumulative COVID Cases** | | |
|---|---|---|---|
| | (4) | (5) | (6) |
| Share Workers | 307.34 | 268.28 | 262.34 |
| Meat Plants | (78.90) | (79.96) | (76.05) |

Panel B: **OLS and 2SLS**

| | **Change in Trump Vote** from 2016 to 2020 | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Cumulative COVID | -0.0011 | -0.0010 | -0.0010 | -0.0125 | -0.0138 | -0.0140 |
| Cases per 10,000 | (0.0007) | (0.0007) | (0.0007) | (0.0040) | (0.0045) | (0.0042) |
| State FE | Yes | Yes | Yes | Yes | Yes | Yes |
| IV Controls | | | | Yes | Yes | Yes |
| Demo. Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Socioecon. Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Social Distancing | | Yes | Yes | | Yes | Yes |
| Observations | 2,689 | 2,689 | 2,689 | 2,689 | 2,689 | 2,689 |
| F-Statistics | | | | 50.32 | 37.86 | 35.82 |

Notes: Election data from Dave Leip's Atlas of US Presidential Elections. An observation is a county. Robust standard errors are in parentheses, adjusted for clustering by state. The estimates are weighted using the natural log of population. We present weighted OLS estimates in columns 1–3 of specification 1. We present the first stage (Panel A) and the 2-stage weighted estimates (Panel B) of specification (2) in columns 4–6 in which we instrument COVID-19 incidence in a first stage by the share of employment in processing meat factories. In Panel A, the dependent variable is the cumulative number of COVID-19 cases per 10,000 (columns 4–6). In Panel B, the dependent variable is the differential in vote for Trump in 2020 and 2016. Demographic controls include population, female population share, foreign-born population, non-Hispanic Black population, non-Hispanic White population and the share of the population by age group. Socioeconomic controls include: share of the population with a college degree and four occupational indexes.