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The Relationship between In-Person Voting and COVID-19: Evidence from the Wisconsin Primary
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ABSTRACT

On April 7, 2020, Wisconsin held a major election for state positions and presidential preferences for both major parties. News reports showed pictures of long lines of voters due to fewer polling locations and suggested that the election may further the spread of the SARS-CoV-2 virus. A contact-tracing analysis by the Wisconsin Department of Health Services identified 71 confirmed cases of COVID-19 to in-person voting, but no research has conducted a broader analysis of the extent to which in-person voting increased the number of COVID-19 cases. We use county level data on voting and COVID-19 tests to connect the election to the spread of the SARS-CoV-2 virus. We find a statistically and economically significant association between in-person voting and the spread of COVID-19 two to three weeks after the election. Results indicate that on average a 10% difference in in-person voters per polling location between counties is associated with approximately a 17.7% increase in the positive test rate. Further, extrapolation of estimates from the average county suggests that in-person voting was related to approximately 700 more COVID-19 cases in Wisconsin during the weeks following the election, or about 7.7% of the total number of confirmed cases during the five week post-treatment time period studied.

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1 Introduction

A headline on the New York Times website on April 7$^{\text{th}}$, 2020, read, "Wisconsin Primary Recap: Voters Forced to Choose Between Their Health and Their Civic Duty" (New York Times, 2020). The headline referred to the Wisconsin election for state positions and presidential preferences for both major parties held on that day. The New York Times article referenced long lines, especially in Milwaukee, where only five polling places were open, and concerns that in-person voting would lead to increased COVID-19 cases. It is well established that increased social interactions increase the probability of the transmission of the SARS-CoV-2 virus, and as of May 15$^{\text{th}}$, the Wisconsin Department of Health Services had directly traced 71 confirmed cases of COVID-19 to in-person voting that occurred on April 7$^{\text{th}}$. While the test and trace method used to determine the sources of infection cannot exclude other potential sources, the investigation also missed cases caused by in-person voting activity that were not successfully tested and traced by the state's Department of Health (Associated Press, 2020).

To circumvent these issues, we estimate the relationship between in-person voting and the spread of COVID-19 using county-level data on in-person voters per polling location and testing information regarding COVID-19. Our aim is to offer a general estimate of the increased spread of infection, if any, related to in-person voting during a pandemic, and by extension provide insights into the potential benefits of absentee voting (vote-by-mail). We first use cellphone location data provided by SafeGraph, combined with information on in-person voting and polling locations from the Wisconsin Elections Commission, to examine whether the April 7$^{\text{th}}$ election was related to increased visits to areas of polling locations relative to baseline behavior. Our results suggest that areas around polling locations saw a drastic increase in visits on April 7$^{\text{th}}$, with no evidence of changes to visits to other locations on that day or changes in visits to areas near election locations on the days preceding or following April 7$^{\text{th}}$. We also show that counties with higher in-person voters per polling location had higher levels of visits to the areas of polling locations, but only on the day of the election.

We then use information on the number of tests for COVID-19 and number of positive test results from the Wisconsin Department of Health Services to examine the relationship between in-person votes per polling location and the spread of COVID-19. Our event-study results indicate that trends in COVID-19 cases in counties with higher and lower levels of in-person voting per polling location are similar in the weeks leading up to the April 7$^{\text{th}}$ election. However, counties with higher levels of in-person voting per polling location are associated with increases in the weekly positive rate of COVID-19 tests and weekly new cases of COVID-19 in the weeks after the April 7^{th} election. This finding is unlikely to be a function of differing trajectories by population density, differing county-level demographics, or measures of social distancing behaviors.

Our work relates to the literature on modeling the trajectory of new cases of COVID-19 in a community. The trajectory, or number of cases, deaths, or the share of positive tests of the COVID-19 pandemic is often modeled by larger structural models such as the highly publicized report from an Imperial College team, Flaxman, Mishra, Gandy, Unwin, Coupland, Mellan, Zhu, Berah, Eaton, Perez Guzman et al. (2020), or alternatively, IHME and Murray (2020). These are based to differing degrees on the "standard epidemiological model," or SIR model (refer to Avery, Bossert, Clark, Ellison, and Ellison (2020) for a COVID-19 related survey). As we are investigating a potential link between behavior and the virus's spread, we take an alternative reduced-form approach that builds on the general understanding that increased socialization is a primary vector for transmission of the virus. Our strategy is very similar to other economics papers which examine associations between the virus and various social factors (e.g. Allcott, Boxell, Conway, Gentzkow, Thaler, and Yang, 2020; Bursztyn, Rao, Roth, and Yanagizawa-Drott, 2020; Courtemanche, Garuccio, Le, Pinkston, and Yelowitz, 2020a,b; Dave, Friedson, Matsuzawa, McNichols, and Sabia, 2020; Mangrum and Niekamp, 2020).

The aforementioned Wisconsin Department of Health Services investigation directly traced and linked COVID-19 cases to in-person voting, which confirms transmission in this circumstance, yet the investigation was not comprehensive and doesn't allow for a broad conversation about the overall community experience in Wisconsin or the relationship at hand. Our work looks at geographical differences in voting/quantity of polling locations, COVID-19 positive case test rates, and number of positive cases to estimate how voting impacted the disease's spread. As a result, our work relates to Harris (2020), Almagro and Orane-Hutchinson (2020) and Kuchler, Russel, and Stroebel (2020) among others looking at how geographical differences in behavior (e.g., public transit availability or occupation characteristics) affects the spread of COVID-19. As we measure the impact of polling locations, we also inform models such as Goscé, Barton, and Johansson (2014) who analyze the impact of the proximity of persons on the spread of a disease. Relatedly, an emerging literature examines the determinants and effects of social distancing orders on the spread of COVID-19 cases (Andersen, 2020; Courtemanche et al., 2020a,b; Friedson, McNichols, Sabia, and Dave, 2020).

Due to the political nature of the decision in switching to absentee voting (vote-by-mail), this work also relates to an emerging economics literature suggesting that political beliefs and actions may impact the spread of the SARS-CoV-2 virus. Allcott et al. (2020) uses cellphone location data from Safegraph to suggest that areas with higher Republican vote share in the 2016 presidential election engaged in less social distancing than areas with higher Democratic vote share in the 2016 presidential election. Relatedly, Adolph, Amano, Bang-Jensen, Fullman, and Wilkerson (2020) also analyze differing social distancing policy responses for COVID-19 based on the politics of the local government(s). Finally, Bursztyn et al. (2020) suggests that people responded to the COVID-19 pandemic differently based on likely viewership of the two most widely-viewed cable news shows, *Tucker Carlson Tonight* and *Hannity*. Also, as our work may inform future public debate on switching to absentee voting, our work offers insights on the costs and benefits of absentee voting. Therefore, we tie into the analysis of districts switching to absentee voting (vote-by-mail).

2 Data

In this section we outline the data used to study the effect of in-person voting on the measurable spread of COVID-19 in the state of Wisconsin.

The timing of Wisconsin's election, in conjunction with the spread of COVID-19 throughout the state, makes it uniquely suited to offer relevant insights into the effects of voting on the spread of COVID-19. First, voting took place during a "Safer at Home" order where Wisconsin residents were restricted to essential activities only, allowing for better identification of the effect of in-person voting. Second, the "Safer at Home" order was issued only two weeks prior to the date of the election, on March 23, 2020, making it difficult for all eligible voters to receive and return an absentee ballot before election day.[1] And third, the Wisconsin Elections Commission allowed County and Municipal Clerks to alter the voting setup and number of voting locations at their own discretion in the weeks leading up to the election. Among those clerks who modified the voting locations available to their registered voters, nearly all sought to consolidate – a decision that almost certainly increased the in-person voter density per voting location.[2]

[1] On April 6, 2020 – the day before the election – Wisconsin governor Tony Evers issued an executive order that moved the election to June 9, 2020. Later that same day, the State Supreme Court ruled that the Governor cannot unilaterally move the date of an election, thus maintaining the in-person voting.

[2] In some cases reductions in the number of voting locations were significant. For example, the city of Green Bay, WI (in Brown County), which typically has 31 voting locations, had only two open during the April 7th election, resulting a significant consolidation of in-person voters.

2.1 Voting Data

We use voting data provided by the Wisconsin Elections Commission (WEC). The WEC maintains a publicly available database of official election results and voter participation metrics, all of which are available at the county level.[3] Of particular interest to this paper are the data on (1) total in-person votes, (2) total absentee ballots requested, (3) total absentee ballots returned, (4) number of registered voters, and (5) number of voting locations. Total in-person votes is the only item that is not directly reported by the WEC. To measure this, we use official county-level vote data provided by the County Clerks for the State Supreme Court seat election, adjusting for the number of over/under-votes, and then from that number subtract the total absentee ballots returned.[4]

According to a memorandum released by the WEC on March 30, 2020, County and Municipal Clerks expressed concern with hosting voters in buildings serving relatively vulnerable portions of the population (e.g. nursing homes, senior centers).[5] As a result on March 12, 2020, the WEC gave County and Municipal Clerks the ability to consolidate polling places. Of course, the decision to consolidate polling locations poses a unique problem for these Clerks: closing locations can create some insulation to the relatively vulnerable, but it also increases the likelihood of infection at the remaining locations due to the increase in voter density.

Between March 12, 2020 and April 4, 2020, County and Municipal Clerks in 22 counties (of 72) consolidated the number of polling locations offered to voters, the average reduction among these counties being approximately 15%. In total, Wisconsin used 2,132 voting locations for this election, each of which can be categorized by the venue's normal purpose. Statewide, approximately 90% of the voting locations were hosted in governmental buildings (e.g. city halls, fire stations), approximately 10% were hosted in social or commercial locations (e.g. churches, VFWs, grocery stores), and 5% were hosted in local primary, secondary, and post-secondary education buildings.[6]

2.2 COVID-19 Data

We use COVID-19 test data provided by the Wisconsin Department of Health Services (WDHS). The WDHS maintained a database reporting the number of laboratory-confirmed COVID-19 cases

[3] See `https://elections.wi.gov/` for more information on these data.

[4] If a number of absentee ballots are returned but not counted (an outcome we are unable to observe), then our measure of in-person voting exposure would be biased downward.

[5] See `https://elections.wi.gov/sites/elections.wi.gov/files/2020-03/Consolidated%20Polling%20Places.pdf`.

[6] Some locations shared functions across our categories (e.g. a town hall that houses a senior center), thus their collective representation exceeds 100%.

and the total number of tests performed, which was updated daily. The primary items of interest from this database are (1) total and new positive cases, (2) total and new negative cases, and (3) total and new COVID-19 tests performed, each at the county level. While WDHS reports data for positive cases beginning on March 15, 2020, the data for negative and total tests begin on March 30, 2020. Thus, from March 30, 2020 to May 17, 2020 (the primary observation window of this study) we construct weekly measures of new COVID-19 cases and the percent of total COVID-19 tests that are positive.

We aggregate the COVID-19 testing data to the weekly level to account for within week patterns of testing that vary by day of week and to eliminate noise associated with daily reporting at the county-level. We then construct weeks from these dates as follows for our results incorporating the number of tests.

Week -1	**Week 0**	**Week 1**	**Week 2**
March 30 - April 5	April 6 - April 12	April 13 - April 19	April 20 - April 26
Week 3	**Week 4**	**Week 5**	
April 27 - May 3	May 4 - May 10	May 11 - May 17	

Week 0 contains the week of the April 7$^{\text{th}}$ election. To utilize the additional data available for (1), we also estimate specifications only examining the number of positive cases. For these specifications, we are able to introduce two more pre-election weeks, which we define as **Week -3** (March 16 - March 22) and **Week -2** (March 23 - March 29).

2.3 Demographics and Social Distancing Measures

Additionally, we supplement the voting and COVID-19 data with measures of social distancing and county-level demographics.

We use SafeGraph Social Distancing Metrics data, which are collected from anonymized GPS pings derived from smartphone app usage. The dataset provides daily metrics of human movement at a highly granular level (Geohash-7, i.e. precision within a 153x153 meter grid) and is continuously updated with a three day lag. We use median home dwelling time, percent of devices completely home, and median distance traveled from home to provide a localized measure of social distancing. While SafeGraph data are reported at the Census Block Group level by day, we aggregate the data to the county by week level to match the level COVID-19 and voting data.[7]

[7] All social distancing measures have been lagged one week to better account for the delay in detecting a the COVID-19 infection after transmission.

In addition, we use SafeGraph Weekly Patterns data linked with SafeGraph Core Places data. These datasets also use GPS pings from smartphones but provide device counts to specific Points-of-Interest (POIs) for every day of the week. SafeGraph provides a 6-digit NAICS code and a text string of the business or building name for every POI. After merging this dataset with SafeGraph POI data, we have the coordinates of approximately 79,000 POIs in Wisconsin. We then calculate the distance between each POI and the closest of the 2,132 voting locations in Wisconsin. Matching these three datasets allows us to measure increases in traffic to highly localized voting locations that would not be visible in Social Distancing Metrics. While measuring general human traffic during pandemics is important, it is especially pertinent to measure the impact that policies have on forcing individuals into population dense situations.

We also include estimates of county population and population density, both of which are provided by the US Census Bureau (2010 Census data), and a number of additional demographics from the 2018 5-Year American Community Survey Estimates, including the percent of the population without a high school degree, the percent of the population with at least a bachelor's degree, the 2018 unemployment rate, the median household income, and the percent of the population age 65 or older.

2.4 Summary Statistics

Table 1 offers summary statistics on our primary measures relevant to the empirical analysis presented below. Alongside state-wide reporting, we also split the summary statistics by counties which have above-median numbers of in-person votes per polling location compared to counties which are below the median. This split shows that COVID-19 positive test rates are approximately twice as high (5.6% versus 2.6%) in above-median counties. Individuals in above-median counties are 2.4 percentage points (62.2% versus 64.6%) less likely to leave home and are approximately 7 percentage points (26.6% versus 19.6%) more likely to have at least a Bachelor's degree. In addition, above-median counties are higher income and have younger populations. There is a significant difference in population density between above-median and below-median in-person vote counties (298.1 versus 34.3). We therefore suggest it is important to design specifications that can account for the dynamic effect of population density on the evolution of COVID-19 growth. For example, we investigate the robustness of the results to the omission of population dense areas like Milwaukee County.

While there was substantial variation in the voter density at the county level (as visualized by

Figure A1), it alone provides an imperfect measure of the number of individuals traveling to a voting location, as they do not indicate how many individuals visit these buildings or surrounding areas on other days of the year. Any detrimental impact of in-person voting on COVID-19 cases would be derived from excess human activity above and beyond baseline levels of typical activity observed at that time. To identify deviations from baseline levels of activity, we use the coordinates of SafeGraph POI data on visits to businesses and buildings directly next to, or including, voting locations in the weeks surrounding the election. Specifically, for approximately 79,000 POIs, we calculate the ratio of visits on date d to visits seven days prior d-7 to estimate excess human activity. Figure 1a displays the mean ratio of visits to seven days prior by distance to the nearest poll.[8] The data points for April 7th (election day) imply that POIs less than 50 meters from a voting poll received over 3.5 times more foot traffic than the previous Tuesday. While POIs 50-100 meters and 100-200 meters from a voting location also exhibit excess visitation, the ratio of visits to seven days prior converges to one as the distance from a POI to the nearest polling location increases. Estimates of excess visitation on April 7th exhibit a strong distance gradient, firmly supporting the claim that in-person voting caused a highly-localized increase in human activity above and beyond typical foot traffic in the relevant time period. We also plot the estimates of excess visitation for April 6th and 8th, the days surrounding voting day. Averages of the ratio of visits to seven days prior hover tightly around one for all distances, mitigating concerns that other events surrounding April 7th might drive results.[9]

3 Methods

To understand the impact of in-person voting on the spread of COVID-19 we focus on the percent of COVID-19 tests that are positive in each county and week. We also extend our analysis to an investigation of the effect of voting metrics on the number of new COVID-19 cases as well (see Section 4.2).

There are concerns that cases alone might not accurately gauge actual outbreak, as they may be inhibited by the implementation of COVID-19 testing and related capacity. Schmitt-Grohé, Teoh, and Uribe (2020) document concerns that testing is not random and widespread. Almagro and Orane-Hutchinson (2020) also recognizes this issue and as a result analyzes changes in the

[8] To provide additional clarity, we provide Figure A2a, which displays mean visits to POIs in Wisconsin for the fourteen days before and after April 7th.

[9] To bolster the figures referenced above, we also provide Figure A3, which reports estimates from event study specifications that compare visits to POIs near versus far from polling locations.

percentage of positive tests.[10]

In assessing what the appropriate model specification and design is for this investigation, we recognize that there is a notable lag in the time between infection with the SAR-CoV-2 virus and its record (if any) in the WDHS database. According to Lauer (2020), the median incubation period from infection with SARS-CoV-2 to onset of symptoms is approximately 5.1 days, with 97.5% of infected people who are symptomatic exhibiting symptoms within 11.5 days. Once symptoms occur, there are likely to be lags associated with seeking testing and acquiring lab results. The WDHS provides data on cases by date of symptom onset, which, in aggregate, allow us to estimate the average lag associated between onset of symptoms and a positive test showing up in the WDHS data.[12] Figure A4 plots the cumulative number of cases from the date of symptom onset and the date of COVID-19 test reporting at the state level. Panel (a) of Figure A4 shows a notable relationship between these measures exists, while panel (b) identifies the distribution of time lag (in days) between symptom onset and positive case diagnosis.[13] According to this measure the median lag from onset date to recorded positive date is 7.5 days across the time series. Taken collectively with a median incubation period of 5.1 days, we would expect any effects of the election on the COVID-19 outbreak on new cases to become most pronounced around 12.6 days, or roughly two weeks, after the election.

Given these considerations, our primary analysis is an event study approach where we capture the impact of in-person voting per location on the proportion of positive tests, or

$$\begin{aligned} \text{Positive Rate}_{c,t} \quad &= \quad \alpha + \delta \text{IVL}_c + \text{Week}_t + \sum_{t=-1,1,\ldots,5} \delta_t \text{IVL}_c \times \text{Week}_t \\ &\quad + \beta X_c + \gamma SD_{c,t} + \psi PD_{c,t} + \epsilon_{c,t} \end{aligned} \tag{1}$$

[10]Specifically, Almagro and Orane-Hutchinson (2020) analyze the percent of positive tests, rather than the number of new cases, stating *"First, random testing has not been possible in NYC,*[11] *as only those with certain conditions are tested because of limited capacity. Second, Borjas (2020) points out that the incidence of different variables on positive results per capita is composed of two things: A differential incidence on those who are tested, but also a differential incidence on those with a positive result conditional on being tested. Therefore, we believe that the fraction of positive tests is the variable that correlates the most with the actual spread of the disease within a neighborhood throughout our sample." (p. 2)*

[12]WDHS symptom onset data provides new cases information by self-reported date of when an individual's symptoms began, rather then the date that positive test was recorded in the WDHS database following a positive PCR test. In general, symptom onset date is meaningful because this date will be closer to the date in which infection occurred. Unfortunately, if symptoms onset date is missing, or if the patient was asymptomatic, rather than omitting the cases from the onset data base (or imputing it), WDHS assigns the date in which the positive diagnosis (PCR test) was recorded (e.g., these cases keep the recorded case date). This mis-coding introduces bias to the measure, the extent of which is unknown.

[13]Specifically, for the number of positive cases on a given date, we count the number of days one must go back until the number of onset cases is at least as large. Panel (b) then plots the distribution of these values.

where Positive $\text{Rate}_{c,t}$ is the proportion of positive cases in week t for each county c, IVL_c is in-person votes (in 1000s) per polling location and Week_t are weekly dummies, with the week of the election (April 7th) serving as the reference (omitted) category $t = 0$. Our independent variables of interest are the interactions between IVL_c and Week_t. The coefficients on these variables, δ_t, provide estimates of the evolution of the in-person votes per location in the week preceding the election and in the weeks after the election. Given the incubation period of COVID-19, lags associated with seeking testing, and lags in labs acquiring results, we should not see a relationship between voting behavior and the COVID-19 test rate prior to a week after the election.

We also include other time-invariant county demographic controls in X_c, which we describe above. Further, we include county-level social distancing measures, including the SafeGraph measures of social distancing aggregated to the county by week level and lagged by one week (e.g., average time in dwelling, percentage of time leaving home, and average distance traveled), and absentee votes per capita interacted with week, which captures differences in social distancing habits specifically related to voting (and voters) across counties and the corresponding effects over time. These measures are all represented in $SD_{c,t}$. We also interact county population density and week, to allow the evolution of COVID-19 testing in each county to vary by population density, represented in $PD_{c,t}$. Based on Papke and Wooldridge (1996, 2008), we estimate models associated with equation (1) using a fractional logistic regression model with robust standard errors clustered at the county-level.[14] We also estimate equation (1) where we replace all time-invariant county controls with county fixed effects. In these cases, we utilize OLS estimation, owing to the incidental parameters problem.

4 Results

The mechanism by which in-person voting could increase COVID-19 spread is via a localized increase in human interaction beyond baseline levels. Therefore, before estimating equation 1 it is important to show that the key explanatory variable, in-person votes (in 1000s) per polling location, has a strong relationship with increases in localized human activity. Figure 1b plots the mean of the ratio of visits to POIs on April 7th to visits 7 days prior, by county. POIs more than 200 meters from a voting poll exhibit no excess visitation, no matter the value of voters per location. However, the

[14] Papke and Wooldridge (1996, 2008) note that the usual least-squares approach to estimating fractional response models suffers from a retransformation problem in using the estimated parameters to infer the magnitude of responses. The implication is that the usual marginal effects should be considered biased when calculated from estimates of the transformed model. They instead suggest estimation directly by quasi-likelihood (e.g., fractional logistic regression).

estimates of excess visitation to POIs less than 50 meters from a polling location have a remarkably positive relationship with voters per location. Focusing on POIs less than 50 meters from a poll, counties with less than 200 voters per location averaged 1.8 times more foot traffic than the previous Tuesday while counties with over 300 voters per location averaged 5.8 times more than the previous Tuesday. This strong relationship lends credence to the claim that in-person voting (in 1000s) captures excess human activity due to voting.

4.1 Results using COVID-19 Positive Test Rates

Table 2 and Figure 2 show results from our models described in Equation (1). Columns (1) - (4) of the table show logit coefficients, standard errors in parentheses, and marginal effects in brackets from estimating fractional logit specifications. Moving from left to right, we systematically add in controls, culminating in our preferred specification in Column (3). In particular, in Column (1) we begin with a parsimonious model that only accounts for time fixed effects and county demographic characteristics.[15] Column (2) adds social distancing measures, which include explicit measures of mobility tracked by cell-phone data, and absentee voting habits. Column (3) adds interactions of population density with the week dummies to account for differential trends in outbreak related to density, and Column (4) adds in controls for the number of tests performed that week.[16] In Column (5) we change the regression to estimate an OLS model, including county fixed-effects into the model to fully account for all time-invariant differences between counties, including all time-invariant county demographics variables. As this estimation is conducted using OLS, the coefficients represent marginal effects, and we show standard errors clustered at the county level in parentheses. In Figure 2, we graphically display the marginal effects and related 95% confidence intervals of our preferred fractional logit specification in Column (3) and the OLS fixed effects estimate in Column (5).

Across all models, we find an increase in the positive share of COVID-19 cases in the weeks following the election in counties that had more in-person votes per voting location, all else equal, and the coefficient magnitudes and statistical significance levels are consistent across the different models. The marginal effects are similar in size three weeks after the election, but begin to fade in subsequent weeks. The marginal effects two weeks after the election suggest that on average every

[15] Week 0, the week of the election, serves as a reference category.

[16] While measures of testing may be endogenous, Almagro and Orane-Hutchinson (2020) argue that including measures of testing are important as controls.

additional 100 voters per location (a tenth of a unit increase in voters per location) is associated with an increase in the positive test rate in the preferred specification (Column 3) of about 0.42 percentage points. Transforming this into an elasticity, a 10% difference in in-person voters per polling location between counties is associated with approximately a 17.7% increase in the positive test rate.

Lastly, in Columns (1) - (4) of Appendix Table A1, we investigate the sensitivity of these estimates to removing Brown and Milwaukee Counties from our main empirical specifications. Brown County contains the City of Green Bay, and saw a large outbreak of COVID-19 traced to a meat-packing facility. Milwaukee County has the highest population density in Wisconsin and reported long lines at the polls on the election day. Overall the results are relatively consistent to those presented in Tables 2 and 3, although effects seem to fade faster and are somewhat smaller when Milwaukee County is excluded from the sample. This is not unexpected given that Milwaukee had one of the greatest number of in-person voters per polling location in the state, and indicates that the effect in Milwaukee County was likely more pronounced than in the state overall.

4.2 Extension: COVID-19 Cases

Despite the aforementioned limitations of studying the spread of the SARS-CoV-2 virus using the number of positive COVID-19 test cases reported (see Section 3), we nonetheless explore the effect of in-person voting according to this measure. Doing so serves several purposes, including (1) offering a robustness check of our preferred measure of positive test rates, (2) providing a point of comparison to several studies using this measure in other contexts (e.g. Courtemanche et al., 2020a,b; Dave et al., 2020; Friedson et al., 2020; Mangrum and Niekamp, 2020), and (3) introducing two additional weeks of data to the beginning of our time frame of study, a result that is due to the WDHS's reporting of only positive test results prior to March 30th. Specifically because of (3), we are able to extend our observation period prior to the election by two additional weeks, thus introducing Week -2 (March 23 - March 29) and Week -3 (March 16 - March 22).

Given our interest in the number of positive COVID-19 test cases, we focus on estimating several models according to

$$\begin{aligned}\text{Cases}_{c,t} &= \alpha + \text{Week}_t + \chi_c + \sum_{t=-3}^{-1} \beta_t \text{IVL}_c \times \text{Week}_t + \sum_{t=1}^{5} \beta_t \text{IVL}_c \times \text{Week}_t \\ &\quad + \sigma SD_{c,t} + \omega PD_{c,t} + \epsilon_{c,t}\end{aligned} \tag{2}$$

where $\text{Cases}_{c,t}$ represents one of three outcomes related to the number of positive cases in each county. The first dependent variable we examine is the log growth rate in cases, defined as $\ln(\text{Total Cases}_{c,t}) - \ln(\text{Total Cases}_{c,t-1})$.[17] Second, we examine the cumulative number of cases per capita for each county and week, and third, we examine the new weekly cases per capita. For these three outcomes, we estimate OLS models weighted by population, although estimates are robust to unweighted specifications. For each dependent variable, we examine weekly cases first as defined by the date of test, and second by the date of symptom onset. The coefficients of interest in Equation (2) are again the β_t's, the coefficients on the interactions between IVL_c and Week_t. As noted above, we are able to examine two additional weeks in Equation (2) than in Equation (1) The social distancing controls are the same as those in Equation (1), except that we do not include any time invariant county characteristics since they are absorbed by the county fixed effects χ_c.

Panel A of Table 3 and the first column of Figure 3 (Figures 3a, 3c, and 3e) report the results from our models described in Equation (2) using the WDHS's recorded date of the positive COVID-19 test. Across all the various specifications we find a similar pattern of results to those reported in Table 2: counties with greater voter density experienced a greater number of COVID-19 cases, either measured by case growth rate, or cases per-capita. In particular, estimates indicate that every 100 voters per location (a tenth of a unit increase in voters per location) is associated with an increase in new cases per capita of about 0.035 new cases per 100,000 people three weeks after the election. In looking at total cases per capita we we observe that 100 voters per location is associated with a total of 0.1353 more total cases per 100,000 residents in the average county five weeks after the week of the election. [18,19]

Lastly, Panel B of Table 3 and Figures 3b, 3d, and 3f present results utilizing date of symptom onset instead of the recorded date of the positive COVID-19 test.[20] Given that symptoms can appear during the end of week 0 (election week), for this analysis we use Week -1 as our reference week to

[17] As some counties had zero confirmed cases during our sample period and the natural log of zero is undefined, we add 0.001 to total cases before calculating log growth rates.

[18] These results are robust to controlling for the number of COVID-19 tests run in each county. See Appendix Figure A5 for a graphical representation of these results. Notably, after accounting for variation in testing, precision of estimation is improved.

[19] Results are again robust to excluding counties with relatively large numbers of COVID-19 cases, Brown County (containing Green Bay) and Milwaukee County (containing Milwaukee) we find similar results (see Table A1 in the appendix). Some models, however, lack the same level of statistical support for the timing of the relationship. For example, estimating the in-person voting effect on the number of new cases or the total number of cases yields a statistically significant relationship at the 10% level.

[20] These data still suffer from issues of testing associated with the recorded case data but also have some concerns owing to systematic coding of symptom onset date as the date that the positive PCR test was recorded in situations where symptoms information is missing or the case was asymptomatic and, hence, may be less reliable than the test record data (see footnote 12).

allow for appropriate comparison.[21] Results of this analysis present a very similar pattern to what was shown in Panel A of Table 3, however we find the differences in total cases begin to appear nearly immediately. Further, new cases per capita are a near perfect mimic to those presented using the record date data (in Panel A), but shifted back one week. Overall, patterns are consistent with both the patterns seen using the recorded positive case data and with how symptom-based timing should manifest with COVID-19 onset based on a clinical understanding of the disease (Lauer, 2020).

5 Conclusion

Using county level data from the entire state of Wisconsin, we analyze whether the election held in Wisconsin on April 7, 2020 is associated with the spread of COVID-19.

Our results confirm the Wisconsin Department of Health Services findings on the link between the spread of COVID-19 and voting using testing and tracing methods. However, the tracing investigation undertaken was not comprehensive, and our results indicate a notable association between the concentration of in-person voters and positive test rates of COVID-19. Specifically, results show that counties which had more in-person voting per voting location (all else equal) had a higher rate of positive COVID-19 tests than counties with relatively fewer in-person voters. Furthermore, we also find a similar relationship between in-person voter density voting and differences in COVID-19 cases directly.

To put our results in context, we can use the coefficient in Table 3 for the total cases-per capita to estimate how many additional COVID-19 cases are associated with in-person voting. Taking the coefficient of 1.353 five weeks after the election suggests that every 1000 additional voters per polling location is associated with 1.353 COVID-19 cases per 100,000 individuals. This effect translates to approximately 700 additional COVID-19 cases in the state of Wisconsin related to in-person voting during the post-election treatment period studied in this analysis.[22] Given there were 9,115 new

[21] The election occurred on the second day of week 0, so there is enough time for cases associated with the election to have onset dates during Week 0.

[22] Our calculation here is as follows: 1000 additional voters per polling location is associated with an estimated 1.353 COVID-19 cases per 100,000 people (see Table 3, column 2, week 5 estimate for total cases per 100,000). These estimates come from population weighted estimates, where the weighted average county population is 293.7 votes per polling location. Hence, we can extrapolate that without in-person voting, the average county would have seen a reduction of 0.397 cases per polling location per 100,000 people ($1.353 * 293.7/1000 = 0.397$). There were 30.7 polling locations in the average county in Wisconsin during the April 7th election, so $0.397 * 30.7 = 12.2$ cases per 100,000 people. According to the U.S. Census Bureau data used in this analysis, the average WI county has approximately 80,225 residents, so $12.2 * (80,255/100,000) = 9.79$ more COVID-19 cases per county, on average. Finally, there are 72 counties in Wisconsin, so $9.79 * 72 \approx 705$ more estimated cases associated with in-person voting on April 7th statewide.

COVID-19 cases confirmed by PCR testing during this five week post-election time period (April 13th - May 17th), this increase would account account for approximately 7.7% of all marginal cases observed.

An important policy consideration among County and Municipal Clerks is that of location consolidation for forthcoming elections, and the results reported here may aid in their decision on the matter. As discussed in Section 2.1, when given the ability to modify the location of polling places at their own discretion, the overwhelming majority of clerks that made changes chose to consolidate locations, which effectively led to increases in voter density per location. Our results show such an increase in density is associated with increase in the rate of positive COVID-19 tests beginning two weeks following the election. The delayed increase is expected and the findings are statistically significant at the 5% or 1% level across different specifications. Likewise, the data support the hypothesis that voter density per polling location will not vary with the positive rate in the week immediately preceding or during the the election, again as expected, as neither parameter is significant as seen in Tables 2 and 3.

The relationship we find between COVID-19 and voting provides an additional piece of evidence towards a causal link. Although our results are not definitive, they do suggest it may be prudent, to the extent possible during the COVID-19 epidemic and weighed against other factors, for policy makers and election clerks to take steps to either expand the number of polling locations, voting times, early voting opportunities, or encourage absentee voting in order to keep the population density of voters as low as possible.

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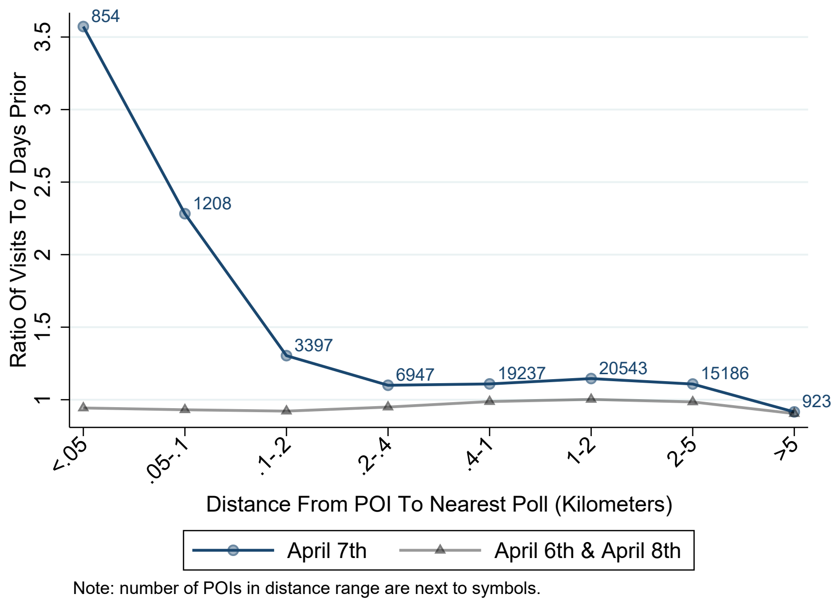
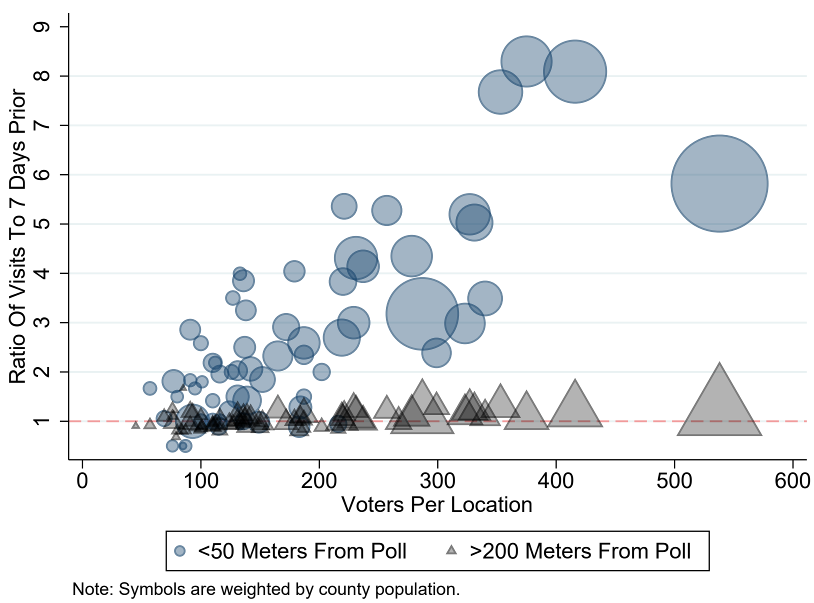
Figure 1: The Impact Of In-Person Elections On Visits To Points Of Interest

(a) Ratio Of Visits To 7 Days Prior



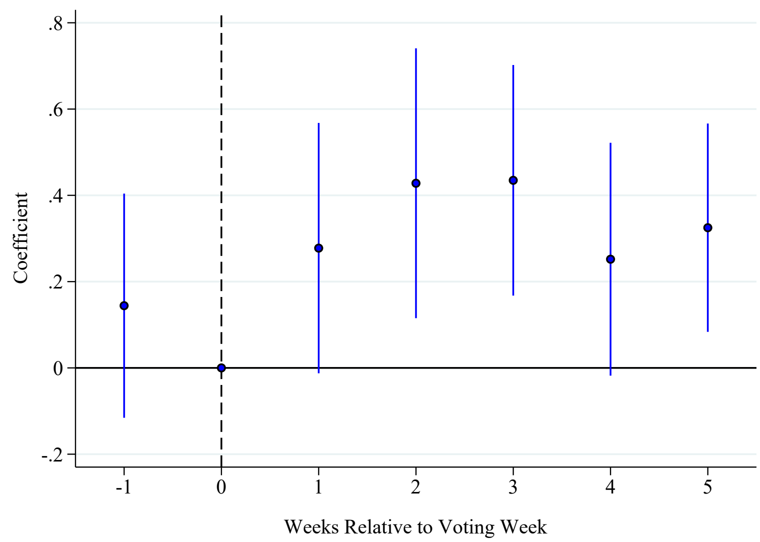
(b) Voters Per Location And Excess Visitation



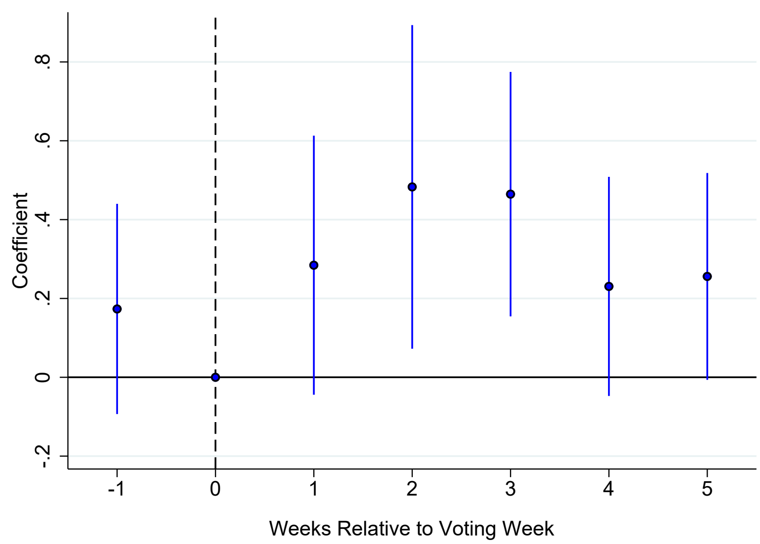
Notes: Subfigure (a) displays the mean of the ratio of visits to 7 days prior for approximately 79,000 points of interest (POIs) in Wisconsin, split by April 7th (Voting Day) and two days sandwiching April 7th. Subfigure (b) illustrates that our key explanatory variable, voters per polling location, has a strong and positive relationship with excess visitation to POIs near polls. Data are from Safegraph Core Places and Weekly Patterns, which use GPS pings from smartphones to track devices that enter a point of interest each day. POIs consist of restaurants, religious institutions, schools, and other commonly visited locations.

Figure 2: Event Studies of Relationship between in-Person Voting and COVID-19 Positive Test Rates

(a) COVID-19 Positive Test Rate - Fractional Logit



(b) COVID-19 Positive Test Rate - OLS County Fixed Effects

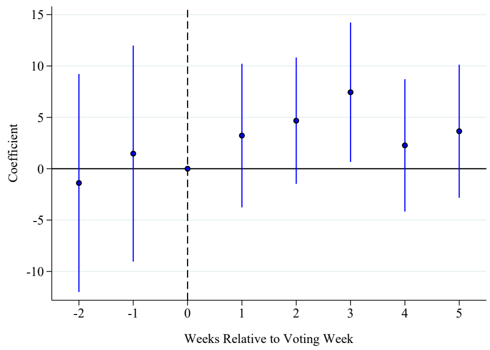


Notes: Figure 2a and 2b plot the marginal effects and corresponding 95% confidence intervals from Table 2, column (3) and column (5), respectively.

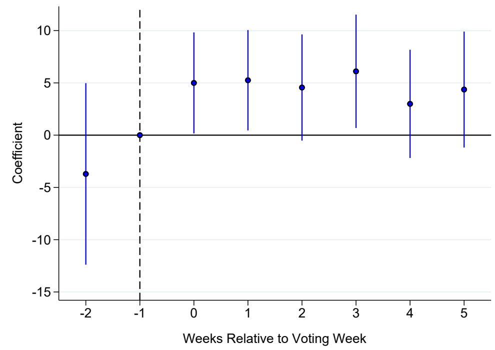
Figure 3: Event Studies of Relationship between in-Person Voting and COVID-19 Cases

Log Growth Rate of COVID-19 Cases

(a) Record Data

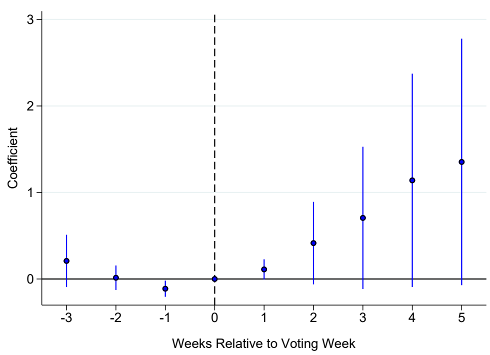


(b) Symptom Onset Data

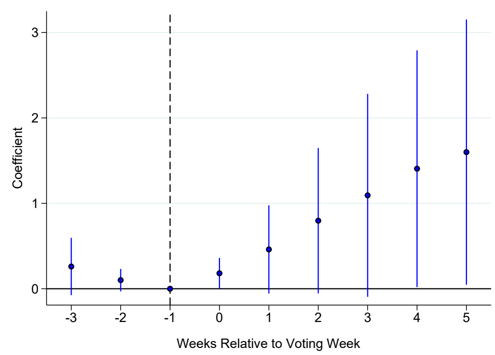


Total COVID-19 Cases Per Capita

(c) Record Data

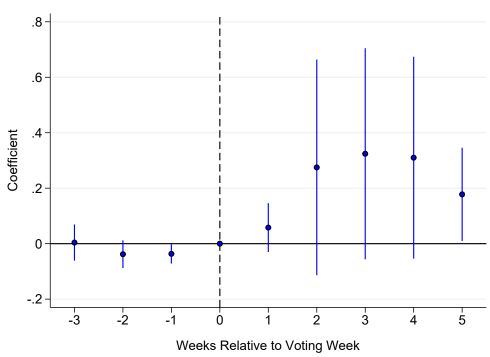


(d) Symptom Onset Data

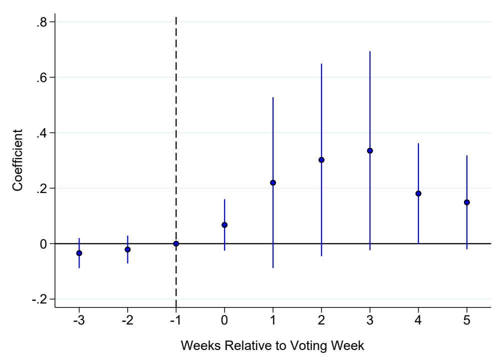


New Weekly COVID-19 Cases Per Capita

(e) Record Data



(f) Symptom Onset Data



Notes: Figures 3a, 3c and 3e plot the coefficient estimates and corresponding 95% confidence intervals from Table 3, Panel A. Figures 3b, 3d and 3f plot the coefficient estimates and corresponding 95% confidence intervals from Table 3, Panel B.

Table 1: Summary Statistics

	All Counties		Above Median Votes/Polling Location		Below Median Votes/Polling Location		
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	T-Test
Election Variables							
In-Person Votes (k) per Polling Location	0.171	0.095	0.240	0.089	0.102	0.024	0.000
Absentee Votes (10k)	1.581	2.986	2.803	3.847	0.359	0.255	0.000
Polling Locations Open	30.708	16.920	36.083	20.828	25.333	9.052	0.000
COVID-19 Testing Variables							
Weekly New Covid-19 Cases	22.683	90.647	43.397	124.871	1.968	3.519	0.000
Weekly New Covid-19 Tests	268.135	629.793	455.242	846.017	81.028	93.894	0.000
Weekly Positive Covid-19 Test Rate	0.041	0.061	0.056	0.069	0.026	0.047	0.000
Demographic Variables							
Population Density	166.249	475.209	298.134	645.810	34.363	23.437	0.000
% Population with less than a H.S. Degree	8.400	2.532	7.497	1.812	9.303	2.814	0.000
% Population with at least a B.A. Degree	23.065	7.526	26.578	8.170	19.553	4.688	0.000
Unemployment Rate (2018)	3.307	0.738	3.131	0.645	3.483	0.783	0.000
Median Household Income ($k)	58.009	9.129	61.087	8.977	54.930	8.210	0.000
Percent of Population Age 65 or Older	20.161	4.339	18.489	3.991	21.832	4.025	0.000
SafeGraph Social Distancing Variables							
Average Time in Dwelling	724.826	119.178	762.356	117.592	687.296	108.662	0.000
% Leaving Home	0.635	0.036	0.622	0.035	0.647	0.032	0.000
Average Distance Traveled	9552.961	3604.933	8533.556	3402.363	10572.366	3518.540	0.000
County-Week Observations	504		252		252		
Counties	72		36		36		

Notes: Data from the Wisconsin Department of Health Services, the Wisconsin Department of Health Services, the U.S. Census, The American Community Survey, and Safegraph.

Table 2: Relationship between COVID-19 Positive Test Rates and In-Person Voting per Polling Location

	Fractional Logit				OLS
	(1)	(2)	(3)	(4)	(5)
IVL × Week -1	2.175	2.778	2.945	2.969	0.173
	(1.448)	(2.452)	(2.477)	(2.471)	(0.134)
	[0.1199]	[0.1372]	[0.1442]	[0.1467]	
IVL × Week 1	3.292	6.371**	6.379**	6.243**	0.284*
	(2.038)	(3.103)	(3.035)	(3.024)	(0.165)
	[0.1007]	[0.2716]	[0.2777]	[0.2671]	
IVL × Week 2	5.276*	12.006***	11.886***	11.646***	0.483**
	(2.733)	(3.719)	(3.422)	(3.199)	(0.206)
	[0.1220]	[0.4218]	[0.4280]	[0.4113]	
IVL × Week 3	4.491*	10.992***	11.084***	10.072***	0.465***
	(2.327)	(2.802)	(2.786)	(2.716)	(0.156)
	[0.1261]	[0.4247]	[0.4349]	[0.3907]	
IVL × Week 4	2.829	6.276**	6.301**	5.059*	0.231
	(2.095)	(2.941)	(2.951)	(2.777)	(0.139)
	[0.0446]	[0.2417]	[0.2519]	[0.2030]	
IVL × Week 5	4.604**	9.483***	9.567***	8.506***	0.256*
	(2.100)	(2.645)	(2.695)	(2.956)	(0.132)
	[0.0667]	[0.3108]	[0.3250]	[0.2839]	
N	504	504	504	504	504
Time Fixed Effects	Y	Y	Y	Y	Y
Demographic Controls	Y	Y	Y	Y	
Social Distancing Controls		Y	Y	Y	Y
Pop. Dens × Week Controls			Y	Y	Y
Control for Tests				Y	
County Fixed Effects					Y

Notes: Data sources are identical to Table 1. The table shows logit coefficients, standard errors clustered at the county level in parentheses, and marginal effects in brackets for the first four columns and OLS coefficients and standard errors clustered at the county level in the last column. In-person voters per polling location are measured in 1000s of voters. Controls include county population, population density, the percent of the population without a high school degree, the percent of the population with at least a bachelor's degree, the 2018 unemployment rate, the median household income, and the percent of the population age 65 or older. The Safegraph Social Distancing Controls include median home dwelling time, percent of devices completely home, and median distance traveled from home and are lagged by one week. Stars denote statistical significance levels: * 10% ** 5% and *** 1%.

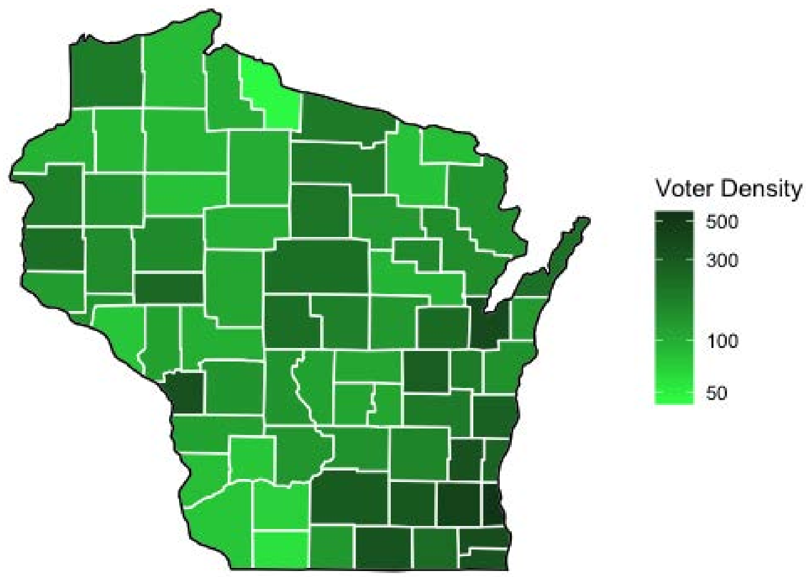
Table 3: Relationship between COVID-19 Cases and In-Person Voting per Polling Location

	Panel A Recorded Positive Case Date			Panel B Symptom Onset Date		
	LN Case Growth Rate	Total Cases Per-Capita	New Cases Per-Capita	LN Case Growth Rate	Total Cases Per-Capita	New Cases Per-Capita
IVL × Week -3		0.209	0.004		0.260	-0.034
		(0.152)	(0.033)		(0.168)	(0.027)
IVL × Week -2	-1.391	0.014	-0.038	-3.709	0.101	-0.021
	(5.321)	(0.071)	(0.025)	(4.354)	(0.066)	(0.025)
IVL × Week -1	1.470	-0.112**	-0.037**			
	(5.274)	(0.047)	(0.018)			
IVL × Week 0				4.997**	0.181**	0.068
				(2.422)	(0.090)	(0.047)
IVL × Week 1	3.226	0.111*	0.058	5.251**	0.460*	0.220
	(3.505)	(0.058)	(0.044)	(2.406)	(0.259)	(0.154)
IVL × Week 2	4.676	0.415*	0.275	4.557*	0.797*	0.302*
	(3.086)	(0.239)	(0.195)	(2.548)	(0.427)	(0.174)
IVL × Week 3	7.445**	0.706*	0.324*	6.105**	1.093*	0.335*
	(3.404)	(0.412)	(0.191)	(2.720)	(0.596)	(0.180)
IVL × Week 4	2.270	1.140*	0.310*	2.994	1.406**	0.181*
	(3.233)	(0.619)	(0.183)	(2.597)	(0.695)	(0.091)
IVL × Week 5	3.648	1.353*	0.178**	4.364	1.600**	0.149*
	(3.249)	(0.715)	(0.084)	(2.781)	(0.779)	(0.085)
N	576	648	648	576	648	648
Time Fixed Effects	Y	Y	Y	Y	Y	Y
Social Distancing Controls	Y	Y	Y	Y	Y	Y
Pop. Dens × Week Controls	Y	Y	Y	Y	Y	Y
County Fixed Effects	Y	Y	Y	Y	Y	Y

Notes: The data sources are identical to Table 2. Each regression is estimated using OLS using the same controls as the last column in Table 2. In-person voters per polling location are measured in 1000s of voters. Total cases and new cases are measured per 100,000 county residents. This table shows coefficients and standard errors clustered at the county level in parentheses. Stars denote statistical significance levels: * 10% ** 5% and *** 1%.

6 Appendix Figures and Tables

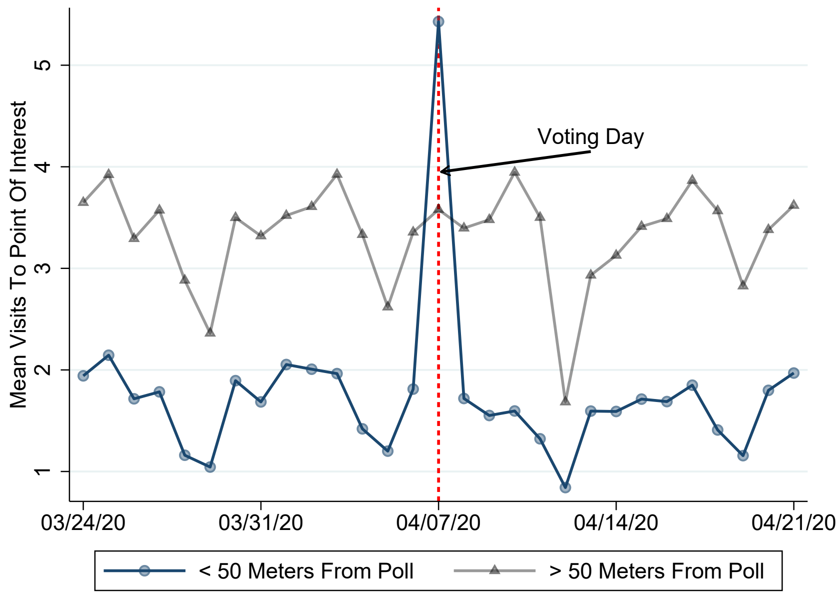
Figure A1: Average Voter Density by County



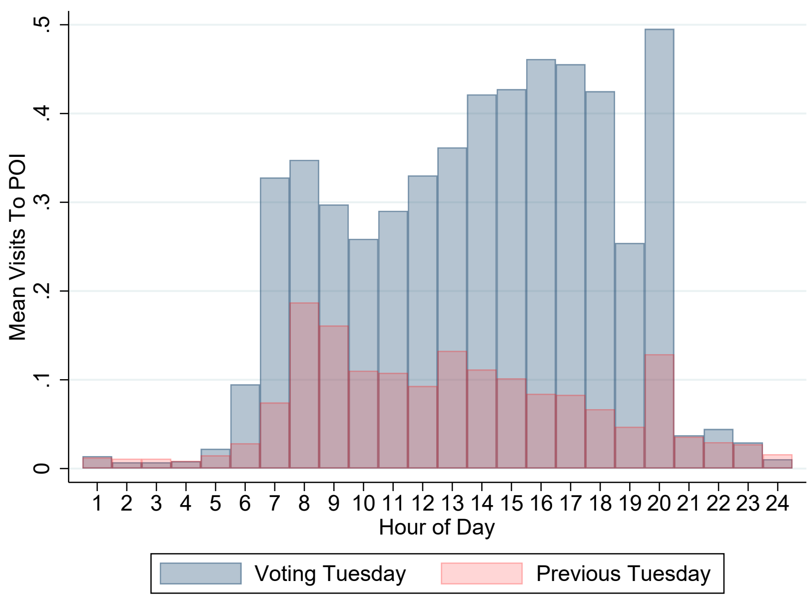
Notes: Voting data provided by the Wisconsin Elections Commission. Created using Kahle and Wickham (2013).

Figure A2: The Impact Of In-Person Voting On Visits To Points Of Interest

(a) Average Visits To POIs By Distance From Voting Location

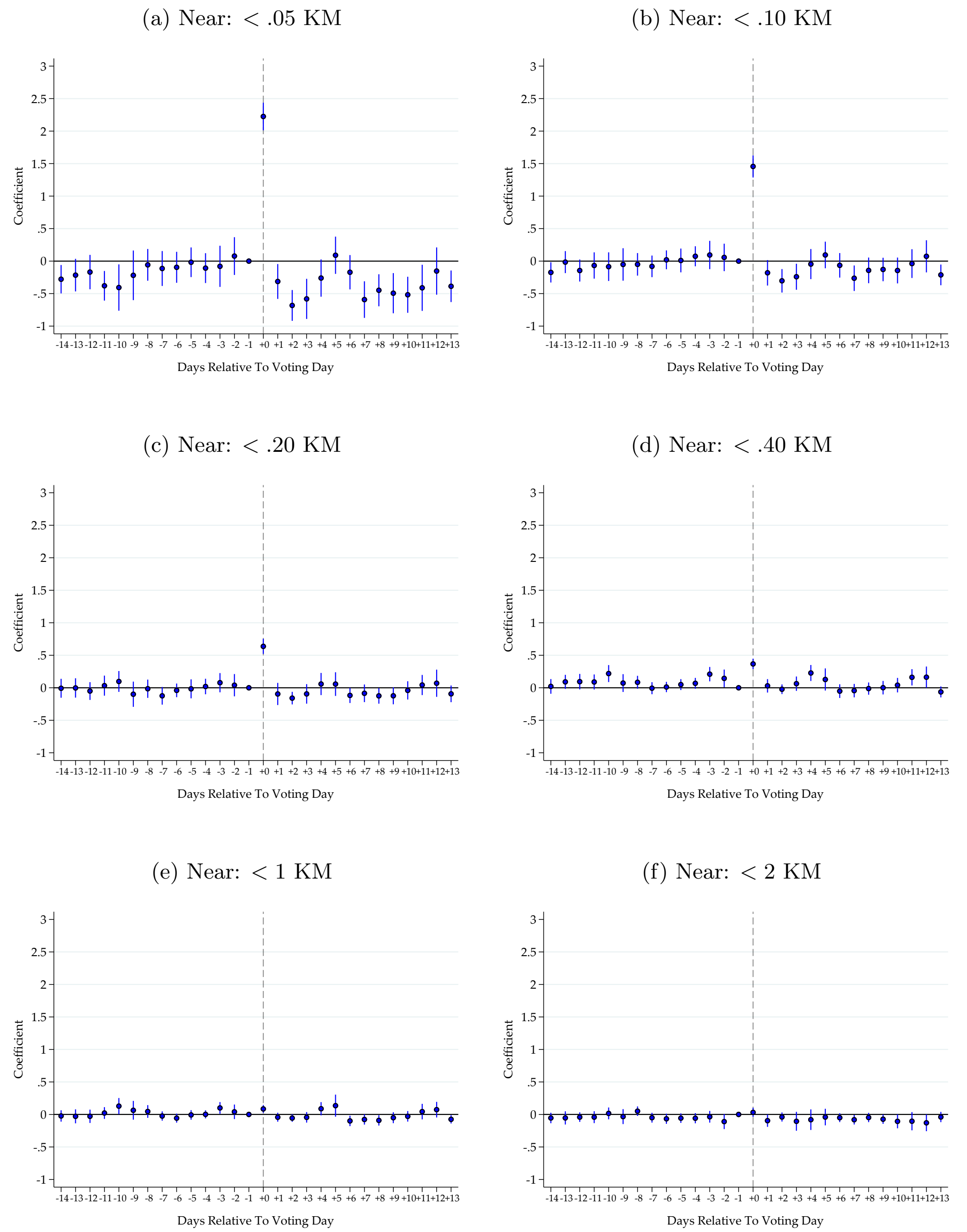


(b) Voters Per Location And Excess Visitation



Notes: Subfigure (a) displays mean visits to approximately 79,000 points of interest (POIs) in Wisconsin for the fourteen days before and after April 7th. Subfigure (b) displays mean visits by hour for April 7th (Voting Tuesday) and the previous Tuesday. Data are from Safegraph Core Places and Weekly Patterns, which use GPS pings from smartphones to track devices that enter a point of interest. POIs consist of restaurants, religious institutions, schools, and other commonly visited locations.

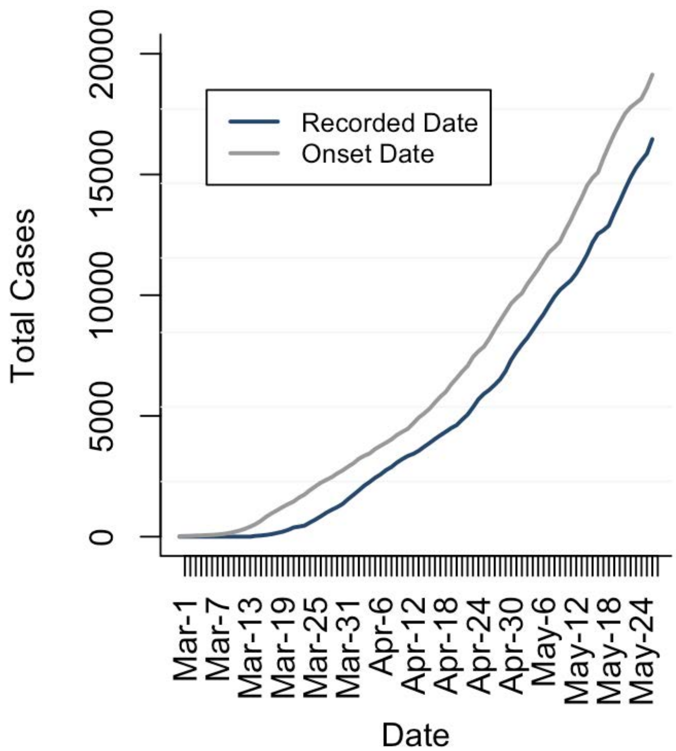
Figure A3: Event Studies Of Relationship Between In-Person Voting And Visits To POIs Near Polls



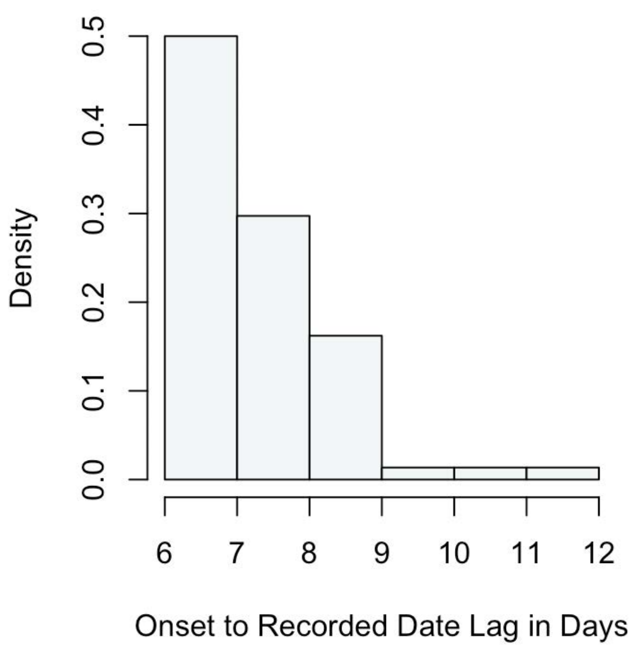
Notes: Figures plot estimates and 95% confidence intervals from event study specifications, with POI fixed effects and day-of-panel fixed effects, that compare visits to POIs near versus far from voting polls. The dependent variable is $Ln(visits_{pt} + 0.001)$, the natural log (+ 0.001, to account for zeroes) of visits to POI p on date t. Each figure presents estimates from a separate regression where treatment (whether a POI is within x kilometers of a voting poll) is defined by the distance in the caption. Standard errors are clustered at the county level. Data are from SafeGraph Core Places and Weekly Patterns. Results are robust to using a FE Poisson model. Event study estimates clearly show a marked increase in foot traffic to POIs near voting polls, with dissipating effects as "near" is defined more loosely.

Figure A4: Recorded & Onset Cases

(a) Total Cases by Recorded and Onset Date



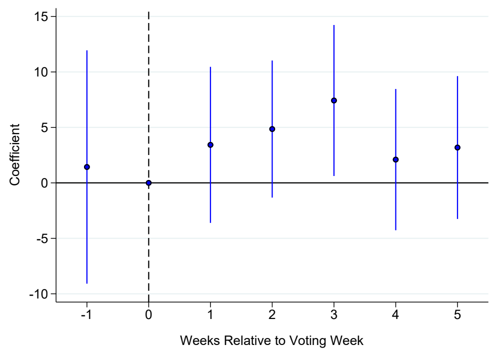
(b) Lag Distribution



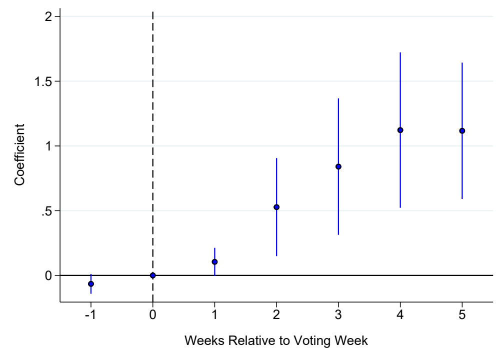
Notes: Data provided by the Wisconsin Department of Health Services.

Figure A5: Event Studies of Relationship between in-Person Voting and Covid-19 Cases: Accounting for Testing

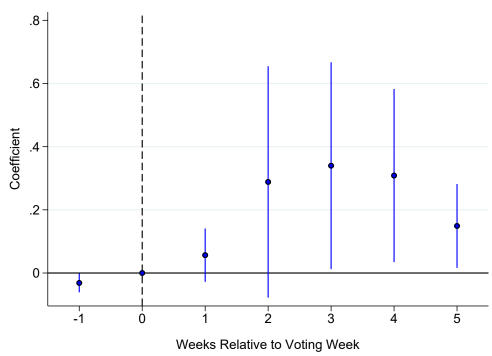
(a) Log Growth Rate of Covid-19 Cases



(b) Total Covid-19 Cases



(c) New Covid-19 Cases



Notes: Figures plot the coefficient estimates and corresponding 95% confidence intervals from equation 2, but include controls for county testing.

Table A1: Relationship between COVID-19 Cases and Voting
Excluding Green Bay and Milwaukee

	Covid-19 Positive Test Rate				Covid-19 New Cases	
	Frac Logit		OLS		LN Growth Rate (OLS)	
	(1)	(2)	(3)	(4)	(5)	(6)
IVL × Week -2					-0.647	2.793
					(5.636)	(8.828)
IVL × Week -1	3.549	6.332	0.205	0.291	1.704	5.632
	(2.640)	(4.263)	(0.142)	(0.204)	(5.643)	(8.972)
	[0.1742]	[0.3020]				
IVL × Week 1	5.173*	5.765	0.212	0.204	3.127	4.332
	(3.084)	(4.792)	(0.158)	(0.215)	(3.726)	(5.943)
	[0.2188]	[0.2683]				
IVL × Week 2	9.211***	12.377***	0.319**	0.378*	4.546	6.937
	(2.878)	(4.596)	(0.140)	(0.207)	(3.271)	(5.313)
	[0.3054]	[0.4673]				
IVL × Week 3	10.495***	9.509**	0.411**	0.261	7.890**	11.013*
	(2.895)	(3.893)	(0.156)	(0.181)	(3.638)	(6.453)
	[0.3890]	[0.3936]				
IVL × Week 4	5.394*	5.808	0.183	0.196	2.418	3.895
	(3.030)	(4.369)	(0.139)	(0.188)	(3.440)	(5.530)
	[0.2095]	[0.2669]				
IVL × Week 5	10.143***	8.298**	0.285**	0.213	4.035	6.748
	(2.841)	(4.164)	(0.137)	(0.173)	(3.426)	(5.632)
	[0.3278]	[0.3281]				
N	497	497	497	497	568	568
Time Fixed Effects	Y	Y	Y	Y	Y	Y
Demographic Controls	Y	Y				
Social Distancing Controls	Y	Y	Y	Y	Y	Y
Pop. Dens × Week Controls	Y	Y	Y	Y	Y	Y
County Fixed Effects			Y	Y	Y	Y
No Green Bay	Y		Y		Y	
No Milwaukee		Y		Y		Y

Notes: The data sources and models are identical to the respective models in Table 2 and 3, with the exception that we either remove Brown County (which contains Green Bay) or Milwaukee County (which contains Milwaukee).