NBER WORKING PAPER SERIES

THE RELATIONSHIP BETWEEN IN-PERSON VOTING, CONSOLIDATED POLLING LOCATIONS, AND ABSENTEE VOTING ON COVID-19: EVIDENCE FROM THE WISCONSIN PRIMARY

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Working Paper 27187
http://www.nber.org/papers/w27187

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
May 2020

We thank Safegraph for providing access to their data. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

The Relationship between In-Person Voting, Consolidated Polling Locations, and Absentee Voting on Covid-19: Evidence from the Wisconsin Primary
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NBER Working Paper No. 27187
May 2020
JEL No. D72,H75,I1,I18

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 contract-tracing analysis by the Wisconsin Department of Health identified 52 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. Furthermore, we find the consolidation of polling locations, and relatively fewer absentee votes, increased positive testing rates two to three weeks after the election. Our results offer estimates of the potential increased costs of in-person voting as well as potential benefits of absentee voting during a pandemic.

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1 Introduction

A headline on the New York Times website on April 7^{th} 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 April 28^{th}, the Wisconsin Department of Health Services had directly traced and linked 52 confirmed cases of COVID-19 to in-person voting that occurred on April 7^{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 attempt to estimate the relationship between in-person voting and the number of cases of COVID-19 using data aggregated at the county level. Our aim is to offer a general estimate on 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 combine information on the number of tests for COVID-19 and number of positive test results from the Wisconsin Department of Health Services with information on in-person and absentee voting from the Wisconsin Elections Commission to examine the trajectory of COVID-19 in counties with higher in-person vs. absentee voting.

Our results indicate that Wisconsin counties with higher levels of in-person voting per polling location led to increases in the weekly positive rate of COVID-19 tests. Furthermore, counties with higher absentee voting participation had lower rates of detecting COVID-19 two to three weeks after the election. We show that this finding is unlikely to be a function of differing trajectories by population density, and controls for demographics and measures of social distancing do not explain our findings either.

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 and deaths, 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 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).

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 relationship at hand. Our work looks at geographical differences in voting/quantity of polling locations and COVID-19 cases and positive test rates 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), our work 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. Our sample was taken from the state of Wisconsin, USA, which had a statewide election on April 7, 2020.

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]

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

[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.

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

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) chose to consolidate 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 infection data provided by the Wisconsin Department of Health Services (WDHS). From March 30, 2020 to May 3, 2020 (the observation window of this study), the WDHS updated their database daily and exclusively reported laboratory-confirmed COVID-19 cases as well as the total number of tests performed. The primary items of interest from this database are (1) total positive cases and (2) total negative cases, each at the county level, from which we construct weekly measures of the percent of total COVID-19 tests that are positive.

[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 will exceed 100%.

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) 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.

In addition, we use Safegraph Weekly Patterns over the period of March 1st to May 2nd. This dataset also uses GPS pings from smartphones but provides 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 70,000 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

We first show the geographic variation in voter density and the striking correlation between voter density and the evolution of the COVID-19 Pandemic. Figure 1a provides a visual representation of voter density by county (created using Kahle and Wickham (2013)), as represented by the average number of in-person votes per county voting location open during the election. Figures 1b and 1c demonstrate the variation in the positive COVID-19 test rates across counties and overtime across Wisconsin counties. Collectively, these figures show increases in positive test results are much higher in locations with higher in-person voting.

Table 1 offers summary statistics on our primary measures relevant to the empirical analysis presented below. We 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. Consistent with Figures 1b and 1c, Table 1 shows that COVID-19 positive test rates are approximately twice as high (5.1% versus 2.7%) in above-median counties. Individuals in above-median counties are 2.6 percentage points (61.6% versus 64.2%) less likely to leave home and are approximately 7 percentage points (26.6% versus 19.5%) 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). Therefore, it is important that we be diligent in designing our specifications to account for the dynamic effect of population density on the evolution of COVID-19 growth. Furthermore, we illustrate the robustness of our results to the omission of population dense areas like Milwaukee County.

While voter data provide an imperfect measure of the number of individuals traveling to a voting location, 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. Figure 2 displays mean visits to approximately 70,000 POIs in Wisconsin for the fourteen days before and after April 7th. We use the coordinates of the POI data to focus on visits to businesses and buildings directly next to, or including, voting locations. It is clear that POIs within 50 meters and over 50 meters exhibit parallel trends in visitation before and after April 7th. While visits to POIs greater than 50 meters from voting polls are unaffected by voting, visits to POIs less than 50 meters from a polling location exhibit a remarkable increase.

3 Methods

3.1 Counts of New COVID-19 Cases

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. While another strategy may be to examine new confirmed COVID-19 cases, it is likely that the implementation of testing can inhibit this analysis.[7] 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 percentage of positive tests. Specifically, Almagro and Orane-Hutchinson (2020) analyze the percent of positive tests, rather than the number of new cases, because,

> "First, random testing has not been possible in NYC,[8] 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)

As a result, we follow Almagro and Orane-Hutchinson (2020) and focus on estimating the impact on the proportion of positive tests, or

$$\begin{aligned}\text{Positive Rate}_{c,t} \quad = \quad & \delta\left(\frac{\text{IPV}}{\text{Location}}\right)_c + \delta_t\left(\frac{\text{IPV}}{\text{Location}}\right)_c \times \text{Week}_t \\ & + \beta\text{Absentee}_c + \beta_t\text{Absentee}_c \times \text{Week}_t + \gamma X_c + \eta_t\text{Week}_t + \epsilon_{c,t}\end{aligned} \tag{1}$$

where Positive Rate$_{c,t}$ is the proportion of positive cases per week in each county, $\frac{\text{IPV}}{\text{Location}}$ is in-person votes (in 1000s) per polling location, Absentee$_c$ is absentee ballots returned (in 10,000s) per county, Week$_t$ are weekly dummies, with the week of the election (April 7th) serving as the reference category, and X_c are county level controls. Based on the conclusions of Papke and Wooldridge (1996) and Papke and Wooldridge (2008), we estimate a fractional logistic regression model with robust standard errors (clustered at the county-level).

[7] While suffering from this concern, analyses on the number of new COVID-19 cases, rather than the positive case test rate was robust.

[8] Refer to Wahlberg (2020) among many others discussing limited testing capacity.

To account for the incubation period of the disease, lags associated with seeking testing, and lags in labs acquiring results, we interact voting metrics and weekly dummies as we should not see a relationship between voting behavior and COVID-19 cases prior to a week after the election. As a result, the key estimates of interest (treatment variables) are the estimates of the interaction between the weekly dummies, which run from one week before the election to three weeks after the election, with voting per location (δ_t) and absentee voting (β_t). In addition to the treatment variables, we control for the demographic and social distancing measures outlined in Section 2. We additionally interact population density with the week dummies in some specifications to account for differential trends in COVID-19 cases by population density. In one specification, we also include the number tests per capita to control for the prevalence of testing by county and across time.

4 Results

Table 2 shows results from our models described in Equation (1). The table shows the logit coefficients, standard errors in parentheses, and marginal effects in brackets. Moving from left to right, we systematically add in controls, culminating in our preferred specification in Column (4). Column (5) adds in controls for the cumulative number of tests per capita.[9] In Column (6), we remove Brown County, which contains the City of Green Bay, and which saw a large outbreak of COVID-19 traced to a meat-packing facility. Finally, in Column (7), we remove Milwaukee County to confirm that the long lines in Milwaukee are not the sole driver of any relationship we find.

Across all models we see a large increase in COVID-19 cases in the weeks following the election in counties that had more in-person votes per voting location, all else equal. Our results support and extend the Wisconsin Department of Health Services findings on the link between the spread of COVID-19 and in-person voting. The coefficient magnitudes and statistical significance levels are remarkably consistent across the different models. Furthermore, in one to three weeks following the election, we observe a decreased number of new positive COVID-19 cases in counties with relatively more absentee votes. These differences are measured after accounting for differences in in-person voting, county level COVID-19 testing, and population measures.[10]

We also find very little evidence of pre-trends in the week preceding the election, where the

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

[10] We also conduced analyses on the number of new COVID-19 cases using a Poisson specification and find similar results. These results are available upon request.

coefficients are much smaller in magnitude and not statistically significant.

Beyond finding a statistically significant impact, we provide more clarity on the economic significance of the relationship with the marginal effects from the models reported in brackets below each corresponding standard error in Table 2. When the average number of votes per voting location increases by 100 (a 0.10 unit change), the rate of positive tests in a county rises by roughly 0.034 to 0.035 (3.4 to 3.5 percentage points) two to three weeks after the election. With an average weekly positive test share of 0.039, these estimates suggest that counties with higher numbers of voters per polling location see notably higher increases in their positive test rate in the weeks following the election, relative to those with lower in-person votes per location realities. The estimates from absentee ballot voting suggest that every unit increase in absentee ballots (an additional 10,000 absentee ballots), lead to decreases in the positive rate of between 0.07 and 0.08 percentage points two to three weeks after the election.

Our hypothesis suggests that in-person voting is most associated with the incidence of new COVID-19 cases through higher numbers of voters in each polling location. However, it is also likely that the simple number of in person votes in a county matters as well. Thus, in addition to analyzing in-person voting per location and absentee voting, we also provide an analysis of the impact of overall in-person voting (not accounting for variation in the number of voting locations per county) and absentee voting on new cases in Table 3. Here, the major difference is that we have replaced in-person votes per polling location with in-person votes in ten thousands. We still see a similar pattern between in-person voting and the percent of positive cases as well as the negative relationship between absentee voting and the percent of positive cases.

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 much larger potential relationship. 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 find a consistent negative relationship between absentee voting and the rate of positive COVID-19 tests. Similar to patterns with in-person voting, this association appears two to three weeks after the election and persists across a number of specification tests, but is not observed in the pre-trend week prior to the election.

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, 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 large increases in the rate of positive COVID-19 tests two and three weeks following the election, and the estimates are to some extent driven by variation in voter density. These increases arrive when one would anticipate the effect of in-person voting on infection spread to manifest, and they 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, as neither parameter is significant in Table 2.

Given these results, it may be prudent, to the extent possible, that policy makers and election clerks take steps to either expand the number of polling locations or encourage absentee voting for future elections held during the COVID-19 pandemic.

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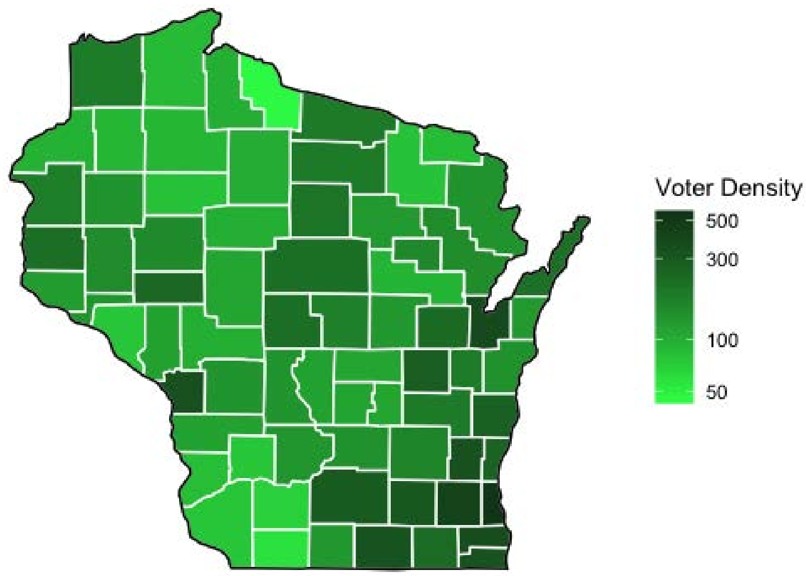
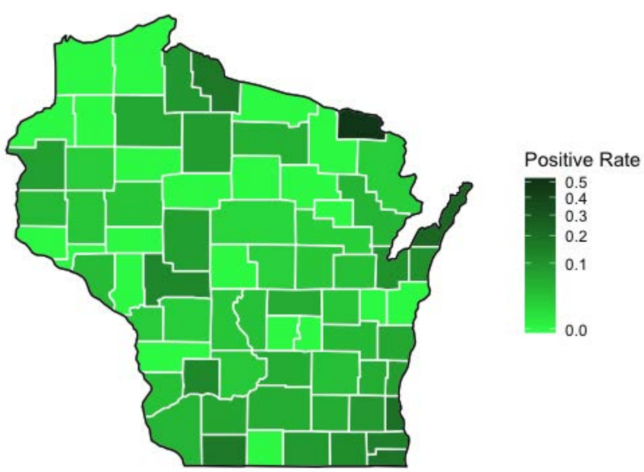
Figure 1: Average Voter Density and Positive Test Rates Over Time, by County

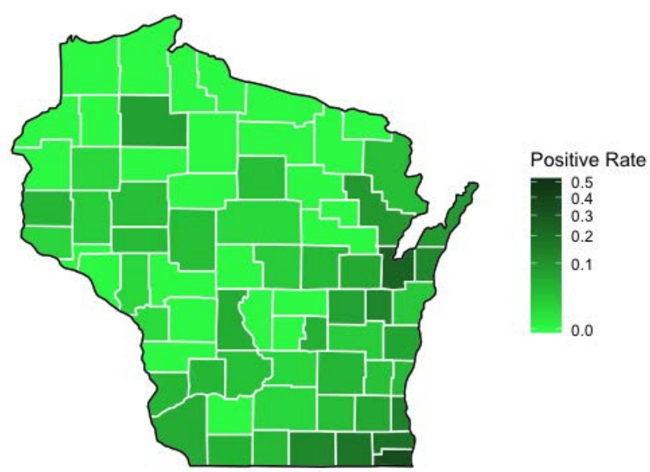
(a) Average Voter Density



(b) COVID-19 Positive Rate: Week of Election

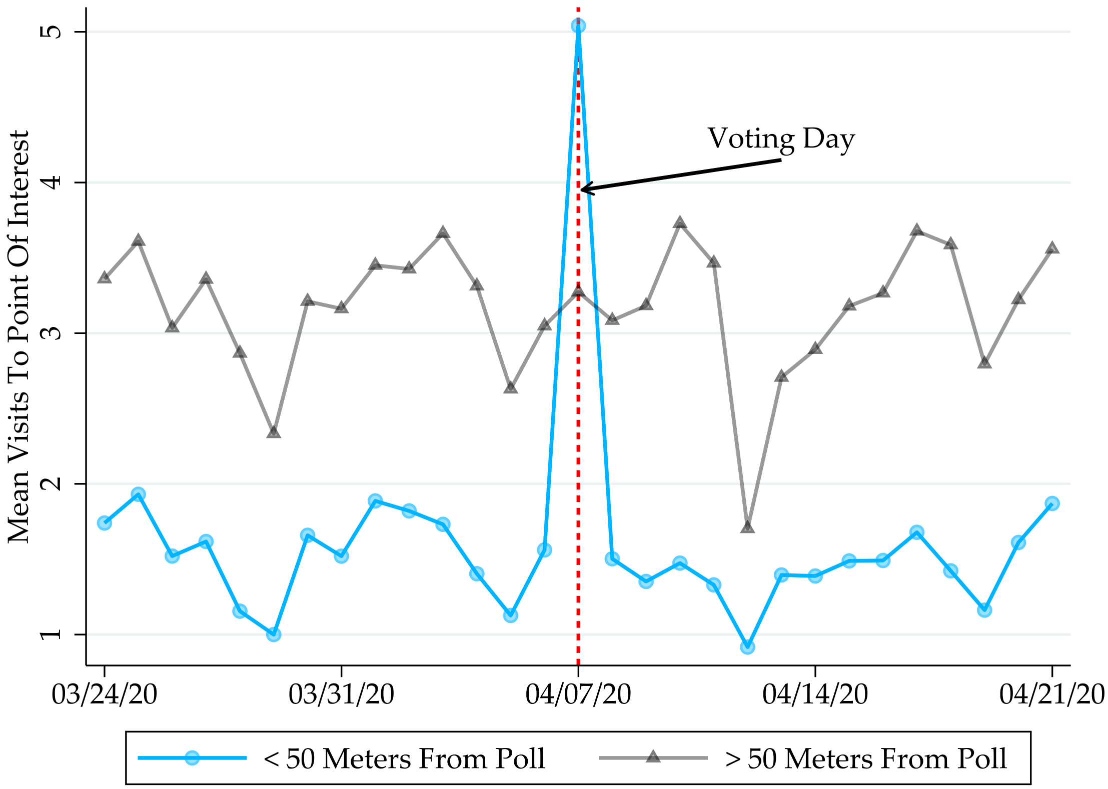


(c) COVID-19 Positive Rate: 3 Weeks After Election



Notes: Voting data in 1a from the Wisconsin Elections Commission; Positive COVID-19 test rates in 1b and 1c from the Wisconsin Department of Health Services.

Figure 2: Average Visits To POIs By Distance From Voting Location



Notes: Figure displays mean visits to approximately 70,000 points of interest (POIs) in Wisconsin for the fourteen days before and after April 7th. Data demonstrate that visits to POIs greater than 50 meters from voting polls are unaffected on election day, while visits to POIs less than 50 meters from a polling location exhibit a large increase. 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.

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
In-Person Votes (10k)	0.591	0.633	0.918	0.756	0.263	0.119	0.000
Absentee Votes (10k)	1.581	2.987	2.803	3.850	0.359	0.256	0.000
Polling Locations Open	30.708	16.927	36.083	20.844	25.333	9.059	0.000
COVID-19 Testing Variables							
Weekly New Positive Covid-19 Cases	19.033	77.968	36.489	107.564	1.578	3.018	0.000
Weekly New Positive Covid-19 Tests	235.692	584.584	407.950	788.666	63.433	60.944	0.000
Weekly Positive Covid-19 Test Rate	0.039	0.062	0.051	0.069	0.027	0.052	0.000
Demographic Variables							
Population Density	166.249	475.398	298.134	646.326	34.363	23.455	0.000
% Population with less than a H.S. Degree	8.400	2.533	7.497	1.814	9.303	2.817	0.000
% Population with at least a B.A. Degree	23.065	7.529	26.578	8.177	19.553	4.692	0.000
Unemployment Rate (2018)	3.307	0.738	3.131	0.645	3.483	0.784	0.000
Median Household Income ($k)	58.009	9.133	61.087	8.984	54.930	8.217	0.000
Percent of Population Age 65 or Older	20.161	4.341	18.489	3.994	21.832	4.029	0.000
SafeGraph Social Distancing Variables							
Average Time in Dwelling (SafeGraph)	742.481	120.613	777.306	121.979	707.657	108.897	0.000
% Leaving Home (SafeGraph)	0.629	0.037	0.616	0.036	0.642	0.033	0.000
Average Distance Traveled (SafeGraph)	10074.431	3355.867	9126.853	3343.025	11022.010	3099.185	0.000
County-Week Observations	360		180		180		
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 and In-Person Voting per Polling Location and Absentee Voting

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
IPV/Loc × Week -1	2.801	3.061	2.744	2.801	2.817	3.143	5.724
	(1.987)	(2.259)	(2.292)	(2.344)	(2.357)	(2.618)	(4.498)
	[0.0422]	[0.0972]	[0.1317]	[0.1343]	[0.1367]	[0.1249]	[0.2585]
IPV/Loc × Week 1	5.522*	5.826*	5.694*	5.727*	5.767*	4.550	5.167
	(2.889)	(3.088)	(3.053)	(3.053)	(3.076)	(3.118)	(4.823)
	[0.2056]	[0.2361]	[0.2478]	[0.2495]	[0.2519]	[0.1894]	[0.2449]
IPV/Loc × Week 2	11.100***	11.620***	11.708***	11.638***	11.797***	8.880***	11.593**
	(3.602)	(3.614)	(3.637)	(3.500)	(3.603)	(2.967)	(4.544)
	[0.3377]	[0.3856]	[0.4173]	[0.4161]	[0.4226]	[0.2850]	[0.4411]
IPV/Loc × Week 3	10.064***	10.650***	10.951***	11.065***	11.336***	10.612***	9.099**
	(2.776)	(2.934)	(2.885)	(2.864)	(3.010)	(2.940)	(3.871)
	[0.3494]	[0.3937]	[0.4259]	[0.4302]	[0.4412]	[0.3848]	[0.3777]
AV × Week -1	-0.054	-0.066	-0.068	-0.067	-0.066	-0.071	-0.030
	(0.040)	(0.050)	(0.055)	(0.061)	(0.061)	(0.064)	(0.031)
	[-0.0025]	[0.0060]	[0.0064]	[0.0069]	[0.0064]	[0.0012]	[0.0088]
AV × Week 1	-0.082	-0.099*	-0.104*	-0.071	-0.073	-0.061	-0.072
	(0.051)	(0.060)	(0.063)	(0.054)	(0.055)	(0.055)	(0.049)
	[-0.0037]	[-0.0007]	[-0.0007]	[0.0008]	[0.0005]	[-0.0008]	[0.0015]
AV × Week 2	-0.197**	-0.226***	-0.234***	-0.150**	-0.155*	-0.136**	-0.149**
	(0.079)	(0.077)	(0.075)	(0.076)	(0.079)	(0.057)	(0.075)
	[-0.0071]	[-0.0018]	[-0.0018]	[0.0012]	[0.0007]	[-0.0011]	[0.0022]
AV × Week 3	-0.194***	-0.224***	-0.243***	-0.252***	-0.260***	-0.256***	-0.246***
	(0.057)	(0.061)	(0.057)	(0.063)	(0.065)	(0.066)	(0.050)
	[-0.0076]	[-0.0039]	[-0.0043]	[-0.0044]	[-0.0049]	[-0.0067]	[-0.0029]
N	360	360	360	360	360	355	355
Demographic Controls		Y	Y	Y	Y	Y	Y
Social Distancing Controls			Y	Y	Y	Y	Y
Pop. Dens × Week Controls				Y	Y	Y	Y
Tests per Capita					Y		
No Green Bay						Y	
No Milwaukee							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. 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. Stars denote statistical significance levels: * 10% ** 5% and *** 1%.

Table 3: Relationship between New COVID-19 Cases and In-Person Voting and Absentee Voting

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
IPV × Week -1	0.644	0.923	0.736	0.739	0.739	0.771	0.895
	(0.859)	(1.244)	(1.173)	(1.160)	(1.163)	(1.160)	(1.249)
	[0.0468]	[0.0813]	[0.0820]	[0.0824]	[0.0826]	[0.0597]	[0.0792]
IPV × Week 1	1.492	2.228	2.359*	2.363*	2.361*	2.054	2.087
	(0.991)	(1.436)	(1.356)	(1.330)	(1.328)	(1.294)	(1.402)
	[0.0714]	[0.1105]	[0.1176]	[0.1179]	[0.1179]	[0.0948]	[0.1024]
IPV × Week 2	2.189**	3.067**	3.286**	3.228**	3.230**	2.715**	2.811*
	(1.001)	(1.513)	(1.453)	(1.375)	(1.377)	(1.247)	(1.439)
	[0.0927]	[0.1391]	[0.1494]	[0.1477]	[0.1480]	[0.1100]	[0.1268]
IPV × Week 3	1.973**	2.718*	2.612*	2.709**	2.712**	2.507**	2.013
	(0.974)	(1.457)	(1.349)	(1.294)	(1.297)	(1.263)	(1.338)
	[0.0886]	[0.1289]	[0.1275]	[0.1312]	[0.1314]	[0.1093]	[0.1011]
AV × Week -1	-0.114	-0.155	-0.129	-0.131	-0.131	-0.134	-0.128
	(0.144)	(0.199)	(0.186)	(0.177)	(0.178)	(0.175)	(0.172)
	[-0.0104]	[0.0017]	[0.0016]	[0.0014]	[0.0011]	[-0.0033]	[0.0002]
AV × Week 1	-0.249	-0.351	-0.368*	-0.373*	-0.372*	-0.338*	-0.377*
	(0.161)	(0.227)	(0.212)	(0.202)	(0.202)	(0.203)	(0.203)
	[-0.0128]	[-0.0115]	[-0.0123]	[-0.0125]	[-0.0126]	[-0.0122]	[-0.0125]
AV × Week 2	-0.379**	-0.493**	-0.520**	-0.500**	-0.499**	-0.449**	-0.525**
	(0.160)	(0.238)	(0.224)	(0.195)	(0.195)	(0.188)	(0.206)
	[-0.0175]	[-0.0124]	[-0.0136]	[-0.0131]	[-0.0132]	[-0.0124]	[-0.0137]
AV × Week 3	-0.350**	-0.446*	-0.426**	-0.480**	-0.480**	-0.467**	-0.503***
	(0.156)	(0.228)	(0.209)	(0.200)	(0.199)	(0.205)	(0.185)
	[-0.0168]	[-0.0136]	[-0.0130]	[-0.0150]	[-0.0152]	[-0.0158]	[-0.0151]
N	360	360	360	360	360	355	355
Demographic Controls		Y	Y	Y	Y	Y	Y
Social Distancing Controls			Y	Y	Y	Y	Y
Pop. Dens × Week Controls				Y	Y	Y	Y
Tests per Capita					Y		
No Green Bay						Y	
No Milwaukee							Y

Notes: The data sources and models are identical to Table 2, with the exception that we replace in-person voting per location with in-person votes (in ten thousands). The table shows logit coefficients, standard errors clustered at the county level in parentheses, and marginal effects in brackets. Stars denote statistical significance levels: * 10% ** 5% and *** 1%.