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Designing pandemic-resilient voting systems

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A R T I C L E   I N F O

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A B S T R A C T

The 2020 general election occurred while many parts of the nation were under emergency orders related to the COVID-19 pandemic. This led to new requirements and considerations for voting systems. We introduce a model of the voting process to capture pandemic-related changes. Using a discrete event simulation case study of the Milwaukee, WI, we study how to design in-person voting systems whose performance are robust to pandemic conditions, such as protective measures implemented during the COVID-19 pandemic. We assess various voting system designs on the voter wait times, voter sojourn times, line lengths at polling locations, voter time spent inside, and the number of voters inside. The analysis indicates that poll worker shortages, social distancing, and personalized protective equipment usage and sanitation measures can lead to extremely long voter wait times. We consider several design choices for mitigating the impact of pandemic-related changes on voting metrics. The case study suggests that long wait times can be avoided by staffing additional check-in locations, expanding early voting, and avoiding consolidated polling locations. Additionally, the analysis suggests that implementing a priority queue discipline has the potential to reduce waiting times for vulnerable populations at increased susceptibility to health risks associated with in-person voting.

1. Introduction

Election officials spend months preparing for an election and implementing strategies to ensure that voting is effective, equitable, accessible, and quick [41]. Often, challenging resource allocation and design decisions must be made prior to election day so that voters can cast their ballots without facing long voting queues or disenfranchise-ment [12]. However, these decisions must be made before the actual conditions on an election day are known, which motivates the need to study these systems using statistical models.

The 2020 general election occurred while many states operated under emergency orders related to the COVID-19 pandemic. The COVID-19 pandemic placed unusual strains on the voting system that made design decisions even more challenging. For instance, voting systems are reliant on volunteer poll workers. However, most election volunteers are over the age of 60 and at high-risk to COVID-19 [16,37]. Election commissions had to consider how to maintain the necessary number of poll workers, while also designing the voting process such that poll workers (and voters) had minimal exposure to COVID-19 on Election Day [12]. The performance criteria for the 2020 general election expanded to also address the health and safety of voters. This has led to new questions for the design and operation of in-person voting systems including sanitation of shared spaces [48], enforcement of social distancing [48], and mandatory use of personal protective equipment.

The 2020 general election suggests that mitigating the risks associated with COVID-19 without impacting voting systems is extremely challenging. The Wisconsin 2020 spring election and presidential preference primary on April 7, 2020 was the first election in the US with in-person voting to be held during a statewide “stay-at-home” order associated with the pandemic [32]. Many areas in Wisconsin faced a shortage of poll workers [8,18,37] causing some cities to consolidate polling locations. The City of Milwaukee held its 2020 spring election at five consolidated polling locations, instead of the standard 182 polling sites, to allow for social distancing and to mitigate the impact of poll worker shortages. The decision to consolidate polling locations drew national attention to the issues surrounding the design of in-person voting processes to mitigate COVID-19 risks. A number of lawsuits followed the Wisconsin 2020 spring election, highlighting the need for more robust planning for the 2020 general election and beyond.

In this paper, we study how to design and operate in-person voting systems that are robust to pandemic-related disruptions. To support this study, we introduce a discrete event simulation of the in-person voting process and include variations to capture pandemic-related changes. We use a case study of the Milwaukee election system to explore these
design decisions. Using this case study, we first quantify to what extend personal protective equipment, sanitation of voting areas, social distancing, and poll worker shortages disrupt voting metrics. Subsequently, we quantify the benefit of various mitigating policies and actions on voting metrics. Specifically, our analysis considers the actions election officials can take to expand access to early voting, increase poll worker recruitment, add additional ballot scanners, expand the physical footprint of polling locations, implement priority queues for at-risk voters, and consolidate polling locations. The results included within this paper are intended to support election planning during a pandemic.

Novel aspects of the simulation model and analysis within this paper include the consideration of health-related metrics, social distancing, personalized protective equipment, and various pandemic-related mitigations (e.g., the consolidation of polling locations). The analysis indicates that the pandemic-related disruptions of poll worker shortages, social distancing, and personalized protective equipment usage and associated protective measures can lead to extremely long voter waiting times, increase the time voters spend inside a polling location, and increase the number of individuals inside a polling location. We find that expanding access to early and absentee voting and increasing poll worker recruitment efforts are critical to mitigating the impact of pandemic-related disruptions. We also find that expanding the physical footprint of polling locations to allow for the distant placement of voting booths can improve voting metrics and that priority queues for at-risk voters can reduce the health risks associated with voting for the most at-risk populations. We demonstrate that increasing the number of ballot scanners has a minimal impact on voting metrics. Finally, we show that in most cases, consolidating polling locations is not an effective mitigating policy in general, although in some cases it may be necessary.

The remainder of this paper is organized as follows. Section 2 reviews the existing operations management-based elections literature. Section 3 introduces a discrete simulation model of the voting process. Section 4 describes the case study of Milwaukee, Wisconsin. Section 5 discusses the model validation. Sections 6 and 7 presents the results of the case study. Section 8 provides a discussion of case study results and limitations of our analysis.

2. Literature review

The operation of in-person voting systems has drawn the attention of many researchers. Often, multiple criteria are used to evaluate the performance of voting systems [30], and voter wait times in queues has emerged as one of the most important considerations for designing in-person voting systems. It has been argued that the queueing of voters must be taken into account when considering voting access [40]. For example, experts estimate that more than 200,000 voters in Florida may have been deterred to vote in the 2012 Presidential Election due to long voting queues [34].

Some literature aims to describe the voting process. Stein et al. [39] present a multi-county observational study of voting during the 2016 Presidential election. They investigate the time it takes voters to complete steps within the voting process and how the design of the voting system impacts expected process times. Spencer and Markovits [36] present an observational study of thirty polling location in three California counties and study the attrition rate of voters in a queue, the check-in service rate, the time to vote, and poll worker characteristics.

A stream of papers has focused on the allocation of voting machines to polling locations, since voting machines have been recognized as a bottleneck in the voting process [52]. Methods to allocate voting booths or machines to reduce wait times include simulation [52], queueing theory [2], simulation optimization [53], integer programming [45], a combination of queueing and simulation [54], and robust optimization [55]. Li et al. [25] use simulation optimization to demonstrate that average voting times can be reduced by better allocating voting booths to voting polling locations. Wang et al. [45] examine how to allocate resources such as voting machines that balance trade-offs across equity and efficiency using integer programming models. Yang et al. [55] develop a robust optimization model to study how to mitigate worst-case voting queues. Rather than allocation, some research focuses on selecting resource types to improve in-person voting systems. Edelstein [19] compares voter waiting times using lever machines, direct recording electronic (DRE) voting machines, and paper ballot scan systems. Edelstein and Edelstein [20] investigate the use of DRE voting machines and paper ballot optical scanners to determine which best mitigates long lines and voter disenfranchisement.

Other research attempts to determine, after the election occurred, if voting system design resulted in voter disenfranchisement. Highton [23] attempts to determine if available voting machine resources caused lower-than-expected turnout in the 2004 general election in Ohio and whether the change in turnout would have changed the election results. Buell et al. [6] audit election results for the 2010 Democratic primary in South Carolina by analyzing audit trail files from DRE machines to determine if some votes were not counted. Buell [7] uses simulation to verify that media reports of a large number of voters waiting in line for several hours and detect the causes of the long waits during the 2012 general election in South Carolina. Allen and Bernshetyn [2] use queueing theory to determine that voters were deterred from voting in Franklin County, Ohio in 2004 due to the allocation of voting machines.

Few papers study how to design voting systems in addition to resource allocation decisions. Three broad mechanisms to reduce wait times have been noted in the literature. The first is to reduce the number of voters who come to a polling place [40]. The second is to increase the number of service points, such as check-in booths, voting booths, and ballot scanners [40]. The third is to reduce the average “transaction” time of voters [40]. Stein et al. [39] study how changes in the voting system, such as the use of voting identification requirements, impact voting times. Bernardo et al. [4] use a discrete event simulation to investigate the impact of separating provisional voters at check-in and find that doing so improves the average time voters spend in the system.

The 2020 COVID-19 pandemic motivates the need to consider the impact of methods to mitigate disease transmission and protect voter safety during elections [32]. To our knowledge, there are no studies that have investigated the operation of voting systems in terms of the health and safety of voters.

3. Simulation modeling approach

We introduce a discrete event simulation model of the in-person voting process. In most elections, voters are assigned to one polling location to which they travel and cast a vote on an election day. This is achieved by partitioning an area into geographic regions called voting precincts or wards. We describe and model the operation of the voting process. First, (A) the voter enters the voting system and enters a queue to check-in. Then, once poll worker(s) are available, (B) the voter registers (if necessary), checks-in, and obtains their ballot. Then, (C) the voter enters a queue for a voting booth, and once a voting booth is available, (D) the voter marks their ballot. ‘The voter then (E) enters a queue to submit their ballot to an optical ballot scanner. Lastly, once a ballot scanner becomes available, (F) the voter leaves the queue and submits the ballot in the optical ballot scanner. Once the ballot is approved, the voter leaves. In addition to the described steps, (G) a poll worker may need to clean or sanitize the voting booth after a voter marks their ballot, and a voter cannot use that booth until sanitation is complete. This step is typically not done during a normal election. The queues (in steps A, C, and E) are traditionally first-come, first-served
(FCFS) queues. Within a polling location, there are three main resources: check-in booths (step B), voting booths (step D), and optical ballot scanners (step F). The number of resources shown in Fig. 1 are for illustration purposes and may vary at each polling location. The logic to create a computer simulation of this process is provided in Fig. 2.

We assume each polling location has a maximum capacity defining the number of voters that can be inside, after poll workers are accounted for. We define the number of voters inside as the total number of voters in steps B, C, D, E, and F. If the number of voters within the polling location is equal to the maximum capacity, then no new voters can progress from queue A to process B until a voter already inside completes the voting process and leaves the polling location.

In a given jurisdiction, the in-person voting process of all polling locations are likely to follow the same logic, but the inputs (e.g., number of voting booths in D) may vary. Some polling locations may use electronic voter poll books within step B while other use paper books. Some polling locations may use electronic voting machines in step D rather than votes being cast on a paper ballot. In this case, steps D and F are merged, paper ballots and voting booths are no longer used, and the queue E no longer exists (except to get “I Voted” stickers). Different electronic voting machines may have different processing time and user-error rates that require help from a poll worker. The optical ballot scanner in step F may also vary by location, when a ballot scanner is used. Different ballot scanners have different functionalities, different processing times, and different reliability of functioning on an election day. Some locations may not use an optical ballot scanner and instead count votes by hand. The same model of the system can be used with appropriate inputs for different steps of the process to represent the setting at hand.

There are many metrics used to evaluate the in-person voting system during a non-pandemic election, and there are trade-offs between many of these metrics [30]. Some well-known metrics include voter wait time, voter sojourn time, voter turnout, polling location line length, and ballot rejection rate [30]. It is also expected that polling locations are close to

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**Fig. 1.** A model of the in-person voting process.

**Fig. 2.** Logic used in the computer simulation of a polling location.
the voters who are expected to use them so that the “cost” to vote is low. Voter wait times is a major area of focus. The Presidential Commission on Election Administration has set a goal that no citizen should have to wait more than 30 min to vote [33]. Some areas have more stringent goals, such as no voter waiting more than 15 min [3]. Note that wait time is generally measured as the time spent waiting for a check-in booth to become free (A), but there are also other queues within the system (C and E). Typically, the time spent in A is much longer than C or E. However, the wait in C or E could be longer depending on operating conditions. This could be a result, for example, of a long ballot causing voters to take more time to vote or an insufficient number of optical ballot scanners. The wait times of C and E contribute to the amount of time a voter spends inside.

In addition to these metrics, the COVID-19 pandemic has caused election officials to consider health-related metrics, including the amount of time spent inside (especially for high-risk voters) and the number of voters inside, since they are indicators for the risk of COVID-19 transmission [12]. These metrics are used to estimate disease transmission rates, but rates depend on the setting and disease. Table 1 describes the performance metrics of interest for all in-person (election day) voters and polling locations that are considered in this study.

3.1. Pandemic-related disruptions

While the introduced model of the in-person voting system captures the normal operations of the in-person voting process at each polling location, a pandemic changes how the in-person voting system can operate. We briefly describe how the pandemic-related disruptions of personal protective equipment and sanitation requirements, social distancing, and poll worker shortages impact the in-person voting process at a polling location. We investigate the impact of these changes in the subsequent sections.

3.1.1. Personal protective equipment and sanitation requirements (PPE)

In previous elections, apart from those held during the COVID-19 pandemic, a minimal amount of personal protective equipment has been used and minimal sanitation of voting space has been conducted. For the 2020 general election, the Centers for Disease Control and Prevention (CDC) suggested rigorous personal protective equipment usage and sanitation policies at all polling locations to mitigate health risks [12]. This may also be implemented in response to future public health emergencies. We assume that personal protective equipment usage and sanitation affect the voting process in two ways. First, the average time to check-in a voter in step B increases due to protective methods, such as to ensure the voter has appropriate personal protective equipment (e.g., a mask), verify the voter’s photo-identification while the voter wears a face covering, or ensure adequate spacing during the check-in process. Second, step G of the voting process introduced in Fig. 1 is activated and a poll worker must sanitize a voting booth once a voter finishes using it.

3.1.2. Social distancing (SD)

As was seen during the COVID-19 pandemic, social distancing can be implemented to reduce the likelihood of airborne disease spread and protect the health of voters and poll workers. We consider the impact of social distancing in two ways. First, we assume that the maximum capacity of the polling location is reduced. Second, to ensure proper space between voters, the number of voting booths is reduced. We capture the extent to which the maximum capacity and number of voting booths is reduced through the use of a capacity factor. The capacity factor defines the proportion of the normal level of the maximum capacity and number of voting booths (rounded up) that are retained within the polling location. For example, if there are typically 9 voting booths and a maximum capacity of 31 voters in a polling location, a capacity factor of 50% allows for 5 voting booths and a maximum capacity of 16 voters.

3.1.3. Poll-worker shortages (PWS)

We capture the impact of poll worker shortages by reducing the number of check-in booths that can be staffed. The number of check-in booths at a polling location is relatively flexible, while the required number of poll workers for other tasks are not. In many locations, a poll worker shortage would first impact the number of check-in booths, so we take this approach to model its impact. A reduction in the number of check-in booths increases the maximum capacity of voters by the number of poll workers typically staffing a check-in booth.

4. Case study: Milwaukee, Wisconsin data

We create a case study for the City of Milwaukee, Wisconsin to investigate the operation of a voting system during a pandemic. We first describe the details of the voting process in Milwaukee during a non-pandemic election and then describe pandemic-specific details.

Milwaukee is the largest city in the state of Wisconsin with an estimated 590,157 residents [43]. Due to the COVID-19 outbreak, election officials placed an increased emphasis on ensuring the health and safety of voters, particularly in-person voters who are vulnerable to risks associated with in-person voting. Age is the single largest risk factor for severe illness from COVID-19 [13] and for many other diseases. An estimated 13.8% of the voting age population in Milwaukee is 65 or older [43]. Later, we use this as an estimate for the fraction of in-person voters who are “high-risk” to pandemic-related health issues. According to the CDC, individuals younger than 65 years of age with preexisting conditions may be at high-risk to COVID-19 [13], which would increase the percentage of voters who are high-risk. However, we assume that a disproportionate number of high-risk individuals use early/absentee voting methods or do not self-identify as high-risk for in-person voting, leading to 13.8% of in-person voters on the 2020 Election Day self-identifying as high-risk.

The City of Milwaukee has 327 voting wards, which have an official assignment to one of the 182 standard polling locations throughout the city [15,28]. This assignment is made by the Milwaukee Election Commission (MEC). To estimate the voting aged population in each of the voting wards, we use the 2011 voting age population in each ward, which is the most recent report provided by the city [15]. Between 2010 and 2019, there was an estimated population change of −0.72% in Milwaukee [21], so we assume the 2011 population in each ward is a reasonable estimate for the voting age population in 2020.

The details surrounding the specifics of the in-voting process at each polling location within our case study design are as follows. The distributions of the process times for each step of the in-person voting process at each polling location is summarized in Fig. 3. These distributions are

### Table 1

| In-person Voter Metrics | Unit | Description |
|-------------------------|------|-------------|
| Average Wait Time       | Minutes | Average time spent in A |
| Average Time Inside     | Minutes | Average time spent in steps B, C, D, E, and F |
| Average Sojourn Time    | Minutes | Average time spent in steps A, B, C, D, E, and F |
| 15 Minute Wait          | N/A   | Proportion of voters spending 15 min or more in A |
| 30 Minute Wait          | N/A   | Proportion of voters spending 30 min or more in A |
| Distance to Poll        | Miles | The distance between the voter and polling location |

### Polling Location Metrics

| Metric | Unit | Description |
|--------|------|-------------|
| Average Line Length     | Voters | Average number of voters in A |
| Average Voters Inside   | Voters | Average number of voters in steps B, C, D, E, or F |
Step A. Voters arrive according to a non-stationary Poisson process and they enter a queue to check-in to vote, which follows a first-come, first-served (FCFS) policy. The interarrival times are therefore exponentially distributed with a rate of \( r = \frac{f \times p \times v \times (1 - e)}{30} \) where \( f \) = fraction of voters arriving during the 30 min period, \( p \) = the voting age population assigned to the polling location, \( v \) = voter turnout, and \( e \) = the proportion of voters who vote early or absentee. The percentage of voters, on average, that arrive during each 30 min interval is shown in Fig. 4. This distribution comes from a previous study of a mock election in a region with comparable demographics to Milwaukee [54]. This is also the only known research where the authors report the numerical arrival rate at such granularity. In reality, arrival rates at polling locations may be different due to socioeconomic status. We assume that the early voting rate, expected voter turnout, and expected arrival pattern is the same in all voting ward; however, the actual turnout and arrival pattern of voters at each polling location vary within the simulation due to stochasticity within the arrival process. We also assume that the number of individuals who vote in every ward is independent of the polling location to which the ward is assigned.

Step B. Each polling location has a receiver and registration table for each ward assigned to the polling location, plus additional tables where voter registration is higher (Personal Communication with MEC 4/29/2021). To account for this, we add 36 tables (approximately 20% of 182) to the polling locations with the highest ratio of voting aged population to the number of tables. For the remainder of this paper, we refer to the receiver and registration tables as “check-in booths.” Each check-in booth is staffed by two poll workers who use paper registration lists. The time to check in a voter follows the lognormal distribution in Fig. 3a with an average of 1.85 min. This distribution is based on research conducted by Stein et al. [39] of polling locations across the country, including a polling location in Dane County, WI. They stratify results by key structural designs (e.g., same day registration) that we use to identify an appropriate distribution that also leads to simulation outputs that match known values for election metrics. In reality, there are two classes of voters: those fitted to the best available data to represent voting within Milwaukee.

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**Fig. 3.** Probability distributions describing the time to complete each step of the voting process.

**Fig. 4.** Percent of voters arriving during each 30 min increments on average.
that are already registered and those who have not yet registered. Voters in the two classes are likely to have different expected lengths of time at a check-in booth. However, to the knowledge of the authors, there is no publicly available data or study that provides estimates for the check-in time stratified by voter type.

Step C. The queue for a voting booth is a FCFS queue.

Step D. We estimate the number of voting booths at each polling location using the voting age population assigned to vote at a polling location. We assume each polling location has \( \lceil 2 \times 4.038 \times \text{voting age population}/(13 \times 60) \rceil \) voting booths, where 4.038 represents the average number of minutes to vote \([54]\) and 13 \times 60 represents the number of minutes during the voting period. The use of two ensures the system can manage fluctuations in the rate of voter arrivals. The actual number of voting booths at each polling location in Milwaukee were not available from the MEC (Personal Communication with MEC 4/29/2021). The distribution of voting time follows the lognormal distribution described in Fig. 3c. This distribution is adopted from a previous study of the time to mark a ballot stratified by the use of paper ballots and electronic voting machines \([39]\).

Step E. The queue to submit a ballot to an optical ballot scanner is FCFS.

Step F. Most polling locations have one DS200 optical ballot scanner and a small number of sites have two (Personal Communication with MEC 4/29/2021). In our study, we assume each location has a single scanner. Our results indicate that voting metrics are unlikely to substantially change with an additional ballot scanner, since the utilization of the ballot scanners is relatively low. The time to submit a ballot is captured by the distribution in Fig. 3e. This distribution is determined using publicly available training videos of DS200 machines \([1,44]\).

We assume that the size of each polling location is selected as to appropriately fit the needed number of resources, voting booths, and queues. As a result, we set the “typical” maximum capacity at each polling location to be equal to the sum of the number of check-in booths, two times the number of voting booths (to account for queues), and the number of optical ballot scanners. This equation was calibrated to information provided by the MEC (Personal Communication with MEC 4/29/2021).

4.1. Pandemic-related disruption inputs

We briefly introduce the inputs to the simulation model that are specific to pandemic-disrupted elections.

4.1.1. Personal protective equipment and sanitation requirements (PPE)

Personal protective equipment and sanitation requirements impact the in-person voting process in two ways. First, the time to check-in a voter increases. We assume the average time to check-in increases by 20 s. The distribution of time to check-in a voter when personal protective equipment and sanitation are required is illustrated in Fig. 3b. These requirements also lead to a sanitation step, step G, in the voting process. We assume the time to sanitize a voting booth from the moment a voter leaves the voting area to when a new voter can use the voting booth follows a distribution as illustrated in Fig. 3d. A poll worker must recognize the voting area needs to be cleaned, walk to the location, sanitize the location, and then indicate that the booth has been sanitized.

4.1.2. Social distancing (SD)

Social distancing reduces both the number of voting booths at a polling location and the maximum capacity of the polling location. During an election where social distancing is enforced, we set the capacity factor to 25% (from 100%). This is based on the CDC recommended social distancing distance of a 6 foot radius around each voter, which requires 4 times the space as a 3 foot radius.

4.1.3. Poll-worker shortages (PWS)

A poll worker shortage can be caused by either a lower than normal poll worker turnout or the same poll worker turnout with additional tasks to complete, as might be expected during a pandemic. In both cases, we assume that polling locations remove one check-in booth in response to poll worker shortages, since the booths cannot be staffed. It is possible that fewer check-in booths may be staffed, but this represents the minimal impact that poll worker shortages may have on a voting process.

5. Model validation

We took a three step approach to model validation for elections held in the City of Milwaukee. First, we presented the simulation model to a professor of Political Science at the University of Wisconsin-Madison with expertise in Wisconsin elections to establish face validity. Second, we discussed the structural and data assumptions used for the case study simulation with this same expert. Third, we ran the simulation using inputs from three previous elections to compare the simulation model outputs to the known outputs from the actual in-person voting system, given the conditions in which the elections were held. These elections include the 2016 general election, the 2020 spring election, and the 2020 general election. It is not common practice to record voting metrics during an election day at each polling location, unless reported by the media. As a result, we use publicly available media reports and research studies where possible to validate our model. We acknowledge this is an area for future work when such a process can be done safely. Considering the very nature of health risks of observing elections during a pandemic and the importance of releasing such information to the public in time to be useful, we validated the model to the extent existing data allow. The results presented in this and the remaining sections were obtained from a simulation implemented in Python. Throughout the paper we use 50 replications of the simulation*.

5.1. 2016 general election

In November 2016, the City of Milwaukee \([27]\) had a 57.2% voter turnout given the number of voting aged individuals we consider. In Milwaukee County, 29.6% of ballots cast were using early/absentee methods \([46,47]\). This was the most granular data reported, so we use this rate for the City of Milwaukee. We run the discrete event simulation for each of the 182 polling locations and aggregate the results. The mean values and standard deviations of seven voting metrics across fifty replications of the simulation are presented in Table 2.

To validate our model, we compare the outputs from our simulation to an analysis that uses smart phone data to estimate the length of time voters spent at their polling locations during the 2016 election day \([14]\). Most metrics were reported at a national level, but some were reported for Wisconsin’s 4th district, which includes the City of Milwaukee \([14]\). The 95% confidence interval for the mean average sojourn time output by the simulation is 15.0 ± 0.9 min, which includes the estimated sojourn time of 15.50 min (Bayesian adjusted estimate of 15.58) by Chen et al. \([14]\) for Wisconsin’s 4th district. Chen et al. \([14]\) also estimate the maximum sojourn time experienced by voters in the United States at 119.50 min. This was the most granular data reported. The 95% confidence interval for the mean maximum sojourn time output by our simulation is 6.5 ± 1.2 min.

Table 2

Simulated mean value (standard deviation) of in-person voting metrics for the 2016 general election across 50 replications.

| Avg. Wait | Avg. Time Inside | Avg. Sojourn Time | 15 Minute Wait | 30 Minute Wait | Avg. Line Length | Avg. Voters Inside |
|-----------|-----------------|-------------------|---------------|---------------|-----------------|-------------------|
| 9.2       | 6.5             | 15.6 (3.1)        | 0.21          | 0.12          | 11.3            | 7.9 (0.4)         |
| (3.1)     | (0.1)           | (0.06)            | (0.04)        | (4.2)         |                 |                   |
The number of people who were able to enter some polling locations to vote was limited due to space availability and poll worker shortages [11,17]. To capture this, we set the number of check-in booths to five for each polling location. The City of Milwaukee used five polling locations to which residents in the 327 wards were assigned [11]. According to available accounts, the number of optical ballot scanners and check-in booths were limited due to space availability and poll worker shortages [11,17]. To capture this, we set the number of check-in booths at each polling location to ten and the number of ballot scanners to five. The mean values and standard deviations of seven voting metrics across fifty replications are presented in Table 3.

There was no effort to collect voter metrics during the election in Milwaukee (Personal Communication with MEC 4/29/2021) or to estimate these using other techniques. In addition, there were no media reports of long wait times in the City of Milwaukee, suggesting that wait times were relatively short. Our simulation estimates the average wait time experienced during the 2020 general election to be 0.2 ± 0.04 min. According to the MEC, no polling location reached the capacity limit in November of 2020 (Personal Communication with MEC 4/29/2021). Our simulation estimates that polling locations were at capacity 0.56% ± 0.16% of the time, or just under 4.4 min. In 8 of the 50 replications, the polling locations were at capacity an average of 0.1% (47 s) of the time or less. This suggests that a capacity factor of 25% may be more restrictive than what was implemented during the 2020 general election. Less restrictive capacity factors do not lead to substantial changes in any of the voting metrics.

### 6. Case study results: impact of pandemic-related disruptions

At the time of writing, the 2016 general election is the most recent presidential election not held during a pandemic. Thus, the simulation outputs for this election serve as a baseline to which we can analyze the impact of social distancing (SD), personal protective equipment and sanitation (PPE), and poll worker shortages (PWS) for future elections. The simulation is run using the voter turnout (57.2%) and early voting participation (5.3%) for the 2020 general election across 50 replications.

We conduct a full factorial analysis for PPE, SD, and PWS. When the disruption impacts the election, we let the code equal one (e.g., PPE = 1). When the disruption does not occur, the code equals zero (e.g., PPE = 0). Figs. 5, 6, and 7 provided in the appendix present the histograms of the metrics across the 50 replications when each disruption is experienced independently. Table 6 presents the simulated mean and standard deviation of metric values for six voter metrics.

We highlight the main findings from these results. First, each of the pandemic-related disruptions are associated with increases in the average wait time, the average line length, 15 min wait, and 30 min wait to varying degrees as indicated by statistically significant, positive coefficient values. A PWS has the largest impact on average wait time and line length.

| Disruption Code | Election Process Inputs |
|-----------------|-------------------------|
| PPE and Sanitation Policies | Code = 0 | Code = 1 |
| Social Distancing | SD | Capacity Factor – 100% | Capacity Factor – 25% |
| Poll worker shortage | PWS | Not experienced | Experienced |

### Table 4

Simulated mean value (standard deviation) of in-person voting metrics for the 2020 general election across 50 replications.

| Metric | Value (Standard Deviation) |
|--------|---------------------------|
| Avg. Wait Time | 0.2 (0.1) |
| Avg. Time Inside | 6.7 (0.1) |
| Avg. Sojourn Time | 6.9 (0.2) |
| 15 Minute Wait | 0.00 (0.00) |
| 30 Minute Wait | 0.00 (0.00) |
| Avg. Line Length | 0.1 (0.1) |
| Avg. Voters Inside | 4.0 (0.2) |

### Table 5

Variables and values used within the full factorial analysis.

| Disruption Code | Election Process Inputs |
|-----------------|-------------------------|
| PPE and Sanitation Policies | Code = 0 | Code = 1 |
| Social Distancing | SD | Capacity Factor – 100% | Capacity Factor – 25% |
| Poll worker shortage | PWS | Not experienced | Experienced |

### Table 3

Simulated mean value (standard deviation) of in-person voting metrics for the 2020 spring primary across 50 replications.

| Metric | Value (Standard Deviation) |
|--------|---------------------------|
| Avg. Wait Time | 110.4 (53.4) |
| Avg. Time Inside | 6.6 (0.0) |
| Avg. Sojourn Time | 117.9 (53.4) |
| 15 Minute Wait | 0.89 (0.16) |
| 30 Minute Wait | 0.84 (0.18) |
| Avg. Line Length | 471.5 (233.4) |
| Avg. Voters Inside | 30.0 (1.3) |
average line length, PPE has the second largest, and SD the third. Second, a PWS reduces the average time inside and average number of voters inside, since the utilization of check-in booths increases and voters are blocked from beginning step B within the voting process. Once inside, the utilization of the voting booths and optical ballot scanners are low, and voters can move through relatively quickly. Third, SD causes the largest increase to the amount of time spent inside and number of voters spent inside, since the number of voting booths is reduced. Fourth, we find significant interactions between the disruptions for many of the metrics. Some of these interactions indicate a compounding effect of disruptions, while others suggest the opposite. For example, when a poll worker shortage and PPE requirements are experienced (PWS = 1 and PPW = 1), the average wait time increases by an additional 32.7 min over the combined increase of each disruption alone. As a result, the expected average wait time increases to 111.5 min. On the other hand, when a poll worker shortage and social distancing is experienced (PWS = 1 and SD = 1), the average wait time is 4.1 min less than the combined increase of each disruption alone. As a result, the expected average wait time increases to 66.0 min. Fifth, Figs. 5–7 in the appendix highlight that the range of observed values increases for many voting metrics. Thus, given the same inputs, the probability of observing a value far from the mean is higher when compared to an election when no disruption is experienced. Election officials and voters must prepare for more unpredictability during a pandemic-disrupted election.

7. Case study results: mitigating pandemic-related disruptions

We consider six mitigations to disruptions and quantify the benefits of each. These mitigations are to expand access to early voting, increase efforts to recruit poll workers, increase the number of optical ballot scanners, expand the physical footprint of polling locations, implement a priority queue for at-risk voters, and consolidate polling locations. We describe each mitigation in more detail in the subsections below. For each, we compare the outputs of the simulation when mitigating practices are put in place to an election without any mitigating practices but pandemic-related disruptions are experienced. Namely, PPE, SD, and PWS are all set to 1. Throughout this section, p-values are calculated using a paired t-test for the difference between the no-mitigation, pandemic-disruption election and an election with the various mitigating policies implemented unless otherwise noted. The baseline, no-mitigation inputs are indicated by “*” in each table, and baseline simulation outputs are presented in the first row of each table.

7.1. Expand access to early voting (EV)

As seen during the 2020 elections, there is a natural response by voters to avoid voting in-person on an election day during a public health emergency and instead use the absentee voting process. A Marquette poll conducted in May 2020 found that 54% of Wisconsin voters planned on voting early during the 2020 general election [22]. In the Wisconsin 2020 spring election, 74.4% of those who voted in Wisconsin voted early [49]. However, the access to absentee voting systems varies by jurisdiction and by state. As of May 2021, at least 12 states have moved to restrict access to mail based voting following the 2020 elections [5], which could reduce the number of people who can vote early. As a response to pandemic-related disruptions, state governments or election commissions may expand access to absentee voting to improve in-person election day voting metrics and protect voter health. We quantify the impact of doing so.

Table 7 presents the mean values and standard deviations of the in-person voting metrics across 50 replications for varying values of the early voting rate between 29.6% (baseline) – 75%. We find that increased early voting rates can substantially improve all in-person voting metrics, since the volume of voters served in-person on an election day is reduced. In the case of Milwaukee, WI, an early voting rate of 64.5% results in a mean average sojourn time (sum of wait time and time inside) of 11.95 ± 0.63 min. Even with an early voting rate of 54%, the voting metrics are substantially reduced from the pandemic-disrupted values shown in the first row of the table. When an early voting rate of 41.8% is experienced, many voting metrics are still high.

7.2. Increase poll worker recruitment (PWR)

Due to the COVID-19 pandemic, we evaluate the possibility of a shortage of poll workers that results in a reduced number of check-in booths. As a response to this, jurisdictions may increase efforts to recruit poll workers or request the National Guard to serve as poll workers. To support this decision, we quantify the impact of various policies to increase the number of check-in booths. The pandemic-disrupted baseline is referred to as 100%–1, since poll worker shortages reduce the...
number of check-in booths at each polling location by one. We consider three mitigation policies. The first is to add a check-in booth at 91 (half of 182) polling locations. We select the polling locations with the highest ratio of voting aged population to check-in booths. We refer to this mitigating policy as “50% – 1,” since only half of the polling locations have one fewer check-in booth compared to the normal number. The second is to ensure all 182 polling locations retain their pre-pandemic number of check-in booths, referred to as “100%.” The third is to retain the normal number of check-in booths and add an additional check-in booth at the 91 (half of 182) polling locations with the highest ratio of voting aged population, referred to as “50% + 1.” The “50 – 1%” may be considered when there is a surplus of potential poll workers as was experienced during the 2020 general election in many areas [35] and they are not needed in any other capacity. Instead of turning away potential poll workers, polling locations could increase the number of check-in booths.

Table 8 presents the mean values and standard deviations of the in-person voting system metrics across 50 replications for each of the policies. Increasing the number of check-in booths can be an effective mitigation to pandemic-related disruptions. The 50% – 1 mitigation significantly reduces the average wait time and the proportion of voters waiting 15 or 30 min or more to vote as compared to the baseline 100% – 1 case. However, this comes at a cost. The average time inside and average number of voters inside increases. As the number of check-in booths increases, the number of voting booths begins to constrain how quickly voters can move through the voting process. Adding more check-in booths also reduces the maximum capacity of the polling location, since space must be dedicated to the check-in booth and poll workers. The results suggest that increasing the number of check-in booths from the pandemic-disrupted level (100% – 1) has a marginally decreasing benefit to the voting metrics and that adding check-in booths cannot completely mitigate the impact of pandemic-related disruptions.

### 7.3. Number of optical ballot scanners (OBS)

Election officials may also consider increasing the number of optical ballot scanners to minimize the number of voters waiting in a queue inside to submit a ballot. The baseline number of optical ballot scanners is referred to as 100%, which represents a single scanner at each polling location. We consider the mitigation of adding an additional optical ballot scanner to each polling location (so that each has two), referred to as “100% + 1.” Adding this additional scanner reduces the maximum capacity of the polling location by one, since there is less space for voters.

Table 9 presents the mean values and standard deviations of the in-person voting system metrics across 50 replications for both levels of the number of optical ballot scanners. There is a statistically significant benefit of adding optical ballot scanners to the average time inside and the average number of voters inside, although the benefits are small and may not be practically significant. However, adding an optical ballot scanner increases the average wait time, 15 min wait, 30 min wait, and average line length, which may be counterintuitive. The worsening of voting metrics is a result of a reduced maximum capacity to allow for the space needed for the scanner.

### 7.4. Expand physical footprint (EPF)

To combat the impact of social distancing, polling locations may attempt to increase the footprint of the polling location, including the use of outdoor spaces. This would allow more individuals “within” the polling location and to retain a higher number of voting booths. To describe the impact of social distancing, we use the concept of a capacity factor, which is introduced in Sections 3.1.2 and 4.1.2. The pandemic-disrupted baseline is a capacity factor of 25% (relative to the pre-pandemic-capacity factor of 100%), which represents the implementation of a six-foot social distancing policy without increasing the footprint of the polling location. Increases to the capacity factor represents increases to the footprint of the polling locations while maintaining the six-foot radius. We study the impact of various levels of the capacity factor on six voter metrics.

Table 10 presents the mean values and standard deviations of the in-person voting system metrics across 50 replications for the considered levels of the capacity factor from 25%–50%. Increasing the capacity factor from 25% to 33.3% impacts all metrics. The average wait time is reduced by 3.4 min, the time inside is reduced by 0.7 min, the proportion of voters waiting 15 min is reduced by 0.06, the proportion of voters waiting 30 min is reduced by 0.06, the average line length is reduced by 4.3 voters, and the average number of voters inside is reduced by 0.9 voter. The impact of increasing the capacity factor past 33.3% is minimal on any metric in the absence of other mitigations.
7.5. Queuing style (QS)

A FCFS queuing discipline is widely used in polling locations and is viewed as equitable [24]. However, a FCFS queuing discipline can lead to disparate health outcomes when voters have different health risks due to factors such as age. To address health concerns for subpopulations that are at heightened risk to the COVID-19 disease, election officials may consider implementing a self-identifying nonpreemptive priority queue (PQ) for high-risk voters in steps A, C, and E of the voting process. A priority queue would allow self-identifying high-risk voters to move to the front of the queue, but behind other high-risk voters already waiting. This reduces the time high-risk voters must wait, but also increases the wait time of low-risk voters. We examine a priority queue’s impact on both high-risk and low-risk voters. In practice, a priority queue would likely be implemented by having a separate line for self-identifying high-risk voters. When voters self-identify, we assume no additional poll workers are needed to manage this system. Many polling locations already have a poll worker outside to manage lines and to inform voters of the necessary documents, and these poll workers can help support the management of a priority queue if necessary.

Table 11 presents the mean values and standard deviations of the in-person voting metrics across 50 replications for voting systems that use the traditional FCFS queuing policy and those that implement a priority queuing policy. Table 12 presents the mean and standard deviation of the average wait time and average sojourn time experienced by low-risk and high-risk sub-populations.

Implementing a priority queue policy reduces the mean proportion of voters waiting at least 15 min (from 0.82 to 0.72) and at least 30 min (from 0.75 to 0.67). This is because high-risk voters who experience a long wait time when a FCFS queuing policy is used are served more quickly when a priority queueing policy is used. High-risk voters wait 0.8 min on average while low-risk voters wait 133.3 min when a priority queue is implemented. High-risk voters also spend less time inside when priority queues are implemented (6.8 min) versus FCFS queues (7.5 min). However, implementing a priority queue requires consideration of the impact of queuing policy on all components of the election system by election officials, not just the process based metrics analyzed within this paper. If a priority queue is implemented, election officials should take care to address the psychological injustice associated with priority queues [24].

7.6. Consolidate polling locations (CPL)

In response to poll worker shortages and to manage the complexity of in-person voting during a pandemic, election commissions may consider consolidating polling locations as was done in Milwaukee for the 2020 spring election [11]. To study the impact of such a decision, we employ the polling location consolidation scheme that was used for the 2020 spring election. Other consolidation schemes may be employed depending on the circumstance. However, selecting which polling locations should remain and how to assign wards to polling locations are decisions that requires extensive study and falls outside the scope of this paper. The approach used in this paper provides an estimate on the impact of any consolidation scheme and provides insights for election planning.

We compare the traditional election system with 182 polling locations to four different mitigating policies. The first is to reduce the number of polling location to five and retain the same total number of check-in booths and ballot scanners within the system. We redistribute the resources to the five polling locations according to how wards were assigned to polling locations in the 2020 spring election. We refer to this policy as ‘5 [100%]’ as we have 5 polling locations and 100% of the resources retained. However, this results in an average of 101.6 check-in booths and 36.4 ballot scanners located at each of the five polling locations. This is unrealistic due to space limitations and managerial complexities. Additionally, having enough poll workers to staff all of the check-in booths would eliminate much of the need to consolidate polling locations. Therefore, the other three mitigating policies represent voting systems with a reduced number of check-in booths and ballot scanners. The first of these is ‘5 [80%]’, which represents a voting system with 5 polling locations and 80% of the number of check-in booths and ballot scanners. This is, on average, 81.8 check-in booths and 29.4 ballot scanners. The second is ‘5 [60%]’, which represents a voting system with 5 polling locations and 60% of the number of check-in booths and ballot scanners (an average of 61.4 check-in booths and 22.2 ballot scanners). The last is ‘5 [40%]’, which represents a voting system with 5 polling locations and 40% of the number of check-in booths and ballot scanners (an average of 41.2 check-in booths and 15.0 ballot scanners). In each case, we recalculate the number of voting booths and the capacity of the consolidated polling locations according to the formulas described in Section 4. Table 13 presents the mean values and standard deviations of the in-person voting system metrics across 50 replications under each mitigating policy.

We find that consolidating polling location can improve the average

Table 11
Simulated mean value (standard deviation) of in-person voting metrics across 50 replications with first-come, first-served (FCFS) or priority queue (PQ) queuing styles.

| Queuing Style | Avg. Wait Time | Avg. Time Inside | 15 Min. Wait | 30 Min. Wait | Avg. Line Length | Avg. Voters Inside |
|---------------|----------------|-----------------|--------------|--------------|------------------|-------------------|
| FCFS *        | 115.0          | 7.5             | 0.82         | 0.75         | 108.2            | 8.7 (0.3)         |
|               | (16.0)         | (0.1)           | (0.05)       | (0.05)       | (17.6)           |                   |
| PQ            | 115.0          | 7.5             | 0.72         | 0.67         | 108.1            | 8.7 (0.3)         |
|               | (16.0)         | (0.1)           | (0.04)       | (0.05)       | (17.6)           |                   |

*Baseline no-mitigation, pandemic-disrupted election.
††(†) Statistically different than the baseline no-mitigation, pandemic-disrupted election at a level of 0.05 (0.01).

Table 12
Mean value (standard deviation) of average wait time and average sojourn time for low- and high-risk voters across 50 replications for first-come, first-served (FCFS) and priority queue (PQ) queuing policies.

| Queuing Style | Low-risk Voters | High-risk Voters | 
|---------------|-----------------|------------------|
|               | Avg. Wait Time  | Avg. Sojourn Time|
|               | Time            | Time             |
| FCFS *        | 115.0 (16.0)    | 122.6 (16.2)     |
|               | 115.1 (16.1)    | 122.5 (16.1)     |
| PQ            | 133.3 (18.6)††  | 140.9 (18.7)††   |
|               | 0.8 (0.0)††     | 7.6 (0.1)††      |

*Baseline no-mitigation, pandemic-disrupted election.
††(†) Statistically different than the baseline no-mitigation, pandemic-disrupted election at level 0.05 (0.01).

Table 13
Simulated mean value (standard deviation) of in-person voting metrics across 50 replications with various polling location consolidation schemes.

| Polling Locations | Avg. Wait Time | Avg. Time Inside | 15 Min. Wait | 30 Min. Wait | Avg. Line Length | Avg. Voters Inside |
|-------------------|----------------|-----------------|--------------|--------------|------------------|-------------------|
| 182*              | 115.0          | 7.5             | 0.82         | 0.75         | 108.2            | 8.7               |
| 5 [100%]          | 66.8           | 6.7             | 0.86         | 0.78         | 2813.1           | 305.1             |
| 5 [80%]††         | 159.7††         | 6.6             | 0.97         | 0.94         | 5558.8           | 248.6             |
| 5 [60%]††         | 321.6††         | 6.6             | 1.0          | 1.0          | 8490.9           | 187.8             |
| 5 [40%]††         | 640.2††         | 6.6             | 1.0          | 1.0          | 11430.7††        | 126.8             |

*Baseline no-mitigation, pandemic-disrupted election.
††(†) Statistically different than the baseline no-mitigation, pandemic-disrupted election at level 0.05 (0.01).
wait time and the average time inside if the same number of check-in booths and ballot scanners can be retained within the voting system (the 5 [100%] case). However this comes at a cost in an increase in the average line length and the average number of voters inside, which average 2813.1 and 305.1 in the 5 [100%] case. The former can discourage voters from entering the line to vote at a polling location. The latter can increase the likelihood of disease spread, depending on the infectious disease under consideration and the layout at the polling location.

When the number of check-in booths and ballot scanners must be reduced (the 5 [80%], 5 [60%], and 5 [40%] cases), the average wait time, 15 min wait, 30 min wait, and average line length substantially increase to levels that would not be sustainable during an election. With 80% of the resources, the average wait time increases to over two and a half hours, and with 60% of the resources, the average wait time increases to over 5 h.

These results indicate that there are major drawbacks to consolidating polling locations when the number of check-in booths and ballot scanners must be reduced. In addition, consolidating polling locations increases the distance a voter must travel to a polling location in nearly all cases, which can suppress voter turnout. We estimate the average geodesic distance of voters from their assigned polling location when there are 182 or 5 polling locations used by using random voter locations within each ward. We estimate a voting aged individual in Milwaukee to be 0.38 miles from their polling location when there are 182 polling locations and 2.16 miles from their consolidated polling location when there are 5 polling locations. The maximum distance a voter is from their polling location is 3.04 miles and 7.61 miles for the 182 and 5 polling locations, respectively. Research indicates that the likelihood a voter casts a ballot decreases with the distance they must travel to a polling location [10]. Initial research from the 2020 spring election in Milwaukee suggests the voter turnout decreased by 8.5% overall and by 10.2% among the Black voting population due to the consolidation of polling locations [31]. Moreover, consolidating polling locations requires voters from many locations to congregate in a single, centralized location. This increases the likelihood of inter-community disease spread while also reducing the ability for public health officials to perform contact tracing.

Avoiding the consolidation of polling locations may be particularly difficult when election officials are unable to recruit poll workers, since there are often legal requirements for the number of election inspectors at each polling location.

### 7.7. Identifying a mitigation portfolio

Thus far, we have focused on the impact of the each mitigation independently. However, two mitigations may address the same concern in an election process and, others may be symbiotic and further improve the performance of the in-person voting process. We create a full factorial design for the four mitigations we found to be reasonable minimally viable mitigations to pandemic-related disruptions based on the analysis in Section 7.1–7.6. This analysis quantifies the benefit of various mitigation portfolios that election officials can implement. The first, EV, is to expand access to early voting so that the voter turnout rate increases to 54% (from 29.6%). The second, PWR, is to devote effort to poll worker recruitment so that fewer locations lose a check-in booth (50%–1) (instead of all polling locations losing a check-in booth). This means that the 91 polling locations with the highest ratio of voting aged individuals to check-in booths retains its normal (pre-pandemic) level. The third, EPF, is to expand the physical footprint so the capacity factor at all polling locations is increased to 33.3%. Lastly, QS, is to change the queueing policy from FCFS to PQ throughout the voting process. Table 14 summarizes the mitigations, the parameter it changes, and levels considered within the design.

Table 15 presents the simulated mean and standard deviation values for the voter metrics. The first row indicates the output from the

### 8. Discussion

The COVID-19 pandemic has highlighted the need to mitigate disruptions to in-person voting systems. Elections held during the COVID-19 pandemic motivate consideration of new alternatives for the design and operation of in-person voting systems to ensure that voting systems are resilient to poll worker shortages, social distancing, and the use of PPE and sanitation and to mitigate the risk of infectious disease transmission. Rigorous planning and analysis using analytical methods such as discrete event simulation can help election officials mitigate disruptions by prioritizing planning efforts. We provide recommendations for election officials preparing for an election using a case study of Milwaukee, WI.

As with any model of a system, there are dynamics of the voting process that are not captured in great detail, and there are several limitations of the analysis presented in this paper. First and foremost, this simulation and case study focuses on the queueing dynamics of the voting process. Other technical and social aspects should be considered when designing a voting system. We assume that changes to the in-person voting process have no impact of the voter turnout or early voting rates. It is likely that changes and improvements to the voting process may influence voter choices, which we do not consider. For example, mitigating efforts to reduce voter wait times and the distances voters must travel to polling locations may result in higher voter turnout, since the “cost” of casting a vote is lower [8]. Our analysis does not explicitly account for the impact of long lines on voter turnout. Due

| Mitigation | Code | Impacted Parameter | Parameter Value |
|------------|------|--------------------|-----------------|
| Expand early voting | EV | Early voting rate | 29.6% |
| Poll worker recruitment | PWR | Check-in Booths | 100% |
| Expand physical footprint | EPF | Capacity factor | 25% |
| Queue Style | QS | Queuing style | FCFS |

### Table 14 Mitigation variable values.

| Mitigation | Code | Impacted Parameter | Parameter Value |
|------------|------|--------------------|-----------------|
| Expand early voting | EV | Early voting rate | 29.6% |
| Poll worker recruitment | PWR | Check-in Booths | 100% |
| Expand physical footprint | EPF | Capacity factor | 25% |
| Queue Style | QS | Queuing style | FCFS |

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to a pandemic, voters may be required to wait outside before checking-in to reduce the viral load inside, even if there is room within the polling location. Social distancing in the check-in queue may give the appearance of longer lines compared to elections that occurred before the pandemic. The appearance of long lines may discourage participation in the voting process, since voters may (incorrectly) assume the cost to vote is high [8,24]. We do not consider curbside voting, which may increase the utilization of existing volunteer resources or require dedicated volunteers. We also assume that voters’ use of PPE does not impact the time to mark a ballot. It is possible that voting times may increase slightly due to mask wearing (e.g., fogging of eyeglasses). Moreover, depending on the election, the number of items to vote on can change the length of time it takes to mark a ballot. Additional analysis reported in Appendix A.4 of this paper suggests the impact of this is relatively small, although the impact increases when disruptions occur. However, when the maximum capacity and number of voting booths is reduced, the impact of increased voting times is larger. Lastly, in our analysis, we assume a constant expected voter turnout. The expected voter turnout may vary depending on the election. In the appendix, we provide the regression coefficient tables for both pandemic-related disruptions and mitigating policies for voter turnout rates of 47.2% and 67.2%. The results suggest a change in voter arrival pattern compared to previous elections. With more voters working from home during a pandemic, this pattern may change. If the pattern becomes more evenly distributed throughout the day, various metrics associated with wait times and line lengths would improve. An increase in early voting rates may also shift the demographics of in-person voters on an election day. This may change the time to complete each step of the voting process. An analysis of poll conditions is needed to evaluate whether there were changes to voter arrival patterns and demographics. The number of individuals who would self-identify as high-risk is also unknown before an election and likely varies between polling locations due to socioeconomic status and health of the community. With more individuals self-identifying as high-risk, low-risk voters must wait longer while high-risk voters go through the voting process. Additionally, when the lines are very long, some dedicated poll workers may be needed to ensure high-risk voters are aware of the priority queue. Finally, the simulation model does not explicitly consider check-in booth or ballot scanner downtime. When resource downtime is experienced, this introduces additional delays that lead to longer wait times and line lengths. A system with more polling locations experiences a larger impact from resource downtime [7].

Planning for an election is a topic of national concern, with elections considered to be part of our nation’s critical infrastructure. This paper presents a detailed analysis of a discrete event simulation model that supports planning for elections. The results can be used to inform election planning decisions and help election officials operate elections that are efficient, equitable, accessible, and safe.

CRediT authorship contribution statement

Adam Schmidt: Methodology, Software, Validation, Data curation, Writing – original draft, Writing – review & editing, Visualization. Laura A. Albert: Conceptualization, Methodology, Writing – original draft, Writing – review & editing.

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A Appendix.

A.1 Histograms of voting metrics when disruptions are experienced

Fig. 5 presents the histograms of the value of six voting metrics in the 50 replications of the simulation during an election with no pandemic-related disruptions. The expected voter turnout used is 57.2% and the early voting rate 29.6%.

| Code Value | PWR | EPP | QS | EV | Avg. Wait | Avg. Time | 15 Minute Wait | 30 Minute Wait | Avg. Line | Avg. Voters | Avg. Line | Avg. Voters |
|------------|-----|-----|----|----|-----------|-----------|----------------|---------------|-----------|-------------|-----------|-------------|
| 0 0 0 0 0 |     |     |    | 0 | 115.0 (16.0) | 7.5 (0.1) | 0.82 (0.05) | 0.75 (0.06) | 108.2 (17.6) | 8.7 (0.3) |          |          |
| 1 0 0 0 0 |     | 20.2 (5.8) | 6.9 (0.1) | 0.30 (0.07) | 0.21 (0.06) | 15.1 (4.9) | 5.8 (0.3) |          |          |          |          |
| 0 1 0 0 0 | 44.4 (12.0) | 7.8 (0.1) | 0.69 (0.09) | 0.58 (0.10) | 53.3 (15.7) | 10.0 (0.5) |          |          |          |          |          |
| 0 0 1 0 0 | 111.6 (14.9) | 6.8 (0.0) | 0.76 (0.04) | 0.69 (0.05) | 103.9 (16.1) | 7.8 (0.2) |          |          |          |          |          |
| 0 0 0 1 1 | 115.0 (16.0) | 7.5 (0.1) | 0.72 (0.04) | 0.67 (0.05) | 108.1 (17.6) | 8.7 (0.3) |          |          |          |          |          |
| 1 1 0 0 0 | 3.0 (1.8) | 7.0 (0.1) | 0.07 (0.06) | 0.01 (0.02) | 2.4 (1.5) | 6.0 (0.4) |          |          |          |          |          |
| 1 0 1 0 0 | 38.6 (10.1) | 6.8 (0.0) | 0.60 (0.08) | 0.49 (0.09) | 46.1 (13.2) | 8.8 (0.3) |          |          |          |          |          |
| 1 0 0 1 0 | 44.5 (12.0) | 7.8 (0.1) | 0.61 (0.07) | 0.53 (0.08) | 53.3 (15.7) | 10.0 (0.5) |          |          |          |          |          |
| 0 1 1 0 0 | 20.0 (5.7) | 6.6 (0.0) | 0.30 (0.07) | 0.21 (0.06) | 14.9 (4.8) | 5.6 (0.3) |          |          |          |          |          |
| 1 1 0 1 1 | 20.2 (5.8) | 6.9 (0.1) | 0.27 (0.07) | 0.20 (0.06) | 15.0 (4.9) | 5.8 (0.3) |          |          |          |          |          |
| 0 0 1 1 1 | 111.5 (14.9) | 6.8 (0.0) | 0.67 (0.04) | 0.62 (0.04) | 103.9 (16.0) | 7.8 (0.2) |          |          |          |          |          |
| 1 1 1 0 1 | 2.8 (1.5) | 6.7 (0.0) | 0.06 (0.05) | 0.01 (0.02) | 2.2 (1.3) | 5.7 (0.3) |          |          |          |          |          |
| 1 1 0 1 0 | 3.0 (1.8) | 7.0 (0.1) | 0.07 (0.06) | 0.02 (0.02) | 2.4 (1.5) | 6.0 (0.4) |          |          |          |          |          |
| 1 0 1 1 1 | 38.6 (10.1) | 6.8 (0.0) | 0.53 (0.07) | 0.45 (0.08) | 46.1 (13.2) | 8.8 (0.3) |          |          |          |          |          |
| 0 1 1 1 1 | 20.0 (5.7) | 6.6 (0.0) | 0.27 (0.06) | 0.20 (0.05) | 14.9 (4.8) | 5.6 (0.3) |          |          |          |          |          |
| 1 1 1 1 1 | 2.8 (1.5) | 6.7 (0.0) | 0.06 (0.05) | 0.01 (0.02) | 2.2 (1.3) | 5.7 (0.3) |          |          |          |          |          |

*Baseline no-mitigation, pandemic-disrupted election.
†† Statistically different than no-mitigation, pandemic-disrupted election at level 0.05 (0.01).
disruptions (−) and when PPE = 1 (−). The histogram of each metric shifts to the left indicating an increase in the metric. The histograms for the average wait time and average line length also widen indicating that the value of the voting metrics during a single replication is less predictable given the same inputs.

Fig. 5. Histogram of voting metric values across 50 replications for a baseline election and when PPE and sanitation policies implemented.

Fig. 6 presents the histograms of the value of six voting metrics across the 50 replications of the simulation during an election with no pandemic-related disruptions (−) and when PWS = 1 (−). The histogram of each metric shifts to the left indicating an increase in the metric. The histograms for the average wait time, average line length, average time inside, and average voters inside also widen indicating that the value of the voting metrics during a single replication is less predictable given the same inputs.

Fig. 6. Histogram of voting metric values across 50 replications for a baseline election and when poll worker shortage (PWS) is experienced.

Fig. 7 presents the histograms of the value of six voting metrics across the 50 replications of the simulation during an election with no pandemic-related disruptions (−) and when SD = 1 (−). The histogram of each metric shifts to the left indicating an increase in the metric. The histograms for all metrics also widen indicating that the value of the voting metrics during a single replication is less predictable given the same inputs.

Fig. 7. Histogram of voting metric values across 50 replications for a baseline election and when poll worker shortage (PWS) is experienced.
Fig. 7. Histogram of voting metric values across 50 replications for a baseline election and when social distancing (SD) is enforced.

A.2 Regression coefficients for voting metrics when disruptions are experienced for different voter turnout rates

Tables 16 and 17 present the simulated mean and standard deviation of metric values for six voter metrics when various pandemic-related disruptions with voter turnout rates of 47.2% and 67.2%, respectively. These are interpreted the same as Table 6 within the main text. When voter turnout is 47.2%, the impact is of pandemic-related disruptions is less than when the voter turnout rate is 57.2%. However, the relative magnitude of primary and interaction effects are the similar to when the voter turnout rate is 57.2%. Conversely, when the voter turnout rate is 67.2%, the impact of pandemic-related disruptions is larger than when the voter turnout rate is 57.2%.

Table 16
Simulated mean value (standard deviation) of in-person voter metric across 50 replications when experiencing poll worker shortages (PWS), PPE and sanitation requirements (PPE), and social distancing requirements (SD). The expected voter turnout used is 47.2% and the early voting rate 29.6%.

| Code Value | Avg. Wait | Avg. Time | 15 Minute | 30 Minute | Avg. Line | Avg. Voters |
|------------|-----------|-----------|-----------|-----------|-----------|-------------|
| PWS PPE SD | Time      | Inside    | Wait      | Wait      | Wait      | Inside      |
| 0 0 0     | 2.6 (1.2) | 6.3 (0.0) | 0.06 (0.04)| 0.01 (0.02) | 2.6 (1.3) | 6.4 (0.3)   |
| 1 0 0     | 7.6 (2.8) | 6.7 (0.0) | 0.18 (0.06)| 0.10 (0.04)| 7.7 (3.2) | 7.2 (0.3)   |
| 0 1 0     | 4.1 (2.2) | 6.9 (0.1) | 0.11 (0.08)| 0.02 (0.03)| 4.2 (2.4) | 7.0 (0.4)   |
| 1 1 0     | 56.0 (10.9) | 6.6 (0.0) | 0.57 (0.06)| 0.48 (0.06)| 48.2 (10.8) | 6.9 (0.2)   |
| 0 0 1     | 28.7 (7.1) | 6.7 (0.1) | 0.39 (0.08)| 0.29 (0.07)| 26.3 (7.5) | 6.7 (0.3)   |
| 0 1 1     | 10.7 (4.6) | 7.5 (0.1) | 0.28 (0.11)| 0.14 (0.09)| 11.0 (5.1) | 8.1 (0.5)   |
| 1 1 1     | 57.0 (11.5) | 7.2 (0.1) | 0.60 (0.08)| 0.49 (0.08)| 49.2 (11.4) | 7.4 (0.3)   |

*Baseline no-disruption election.
† Statistically different than the baseline no-disruption election at a level of 0.05.

Table 17
Simulated mean value (standard deviation) of in-person voter metric across 50 replications when experiencing poll worker shortages (PWS), PPE and sanitation requirements (PPE), and social distancing requirements (SD). The expected voter turnout used is 67.2% and the early voting rate 29.6%.

| Code Value | Avg. Wait | Avg. Time | 15 Minute | 30 Minute | Avg. Line | Avg. Voters |
|------------|-----------|-----------|-----------|-----------|-----------|-------------|
| PWS PPE SD | Time      | Inside    | Wait      | Wait      | Wait      | Inside      |
| 0 0 0     | 34.5 (5.9) | 6.6 (0.1) | 0.42 (0.07)| 0.31 (0.07) | 34.5 (9.3) | 9.4 (0.4)   |
| 1 0 0     | 112.1 (13.7) | 6.5 (0.0) | 0.76 (0.04)| 0.69 (0.04)| 122.4 (17.4) | 8.2 (0.2)   |
| 0 1 0     | 54.5 (9.5) | 6.8 (0.0)| 0.62 (0.06)| 0.53 (0.06)| 70.7 (14.0) | 10.0 (0.3)  |
| 0 0 1     | 41.6 (10.9) | 7.7 (0.1) | 0.68 (0.09)| 0.57 (0.10)| 58.9 (17.1) | 11.0 (0.5)  |
| 1 1 0     | 176.6 (17.4)| 6.7 (0.0) | 0.87 (0.03)| 0.82 (0.03)| 172.5 (19.9) | 8.2 (0.1)   |
| 1 0 1     | 118.2 (15.5) | 7.3 (0.1) | 0.84 (0.05)| 0.78 (0.06)| 131.0 (20.2) | 9.3 (0.3)   |
| 0 1 1     | 81.9 (15.9) | 8.4 (0.1)| 0.88 (0.05)| 0.81 (0.07)| 107.3 (22.4) | 12.0 (0.3)  |
| 1 1 1     | 185.3 (19.5) | 7.7 (0.1)| 0.94 (0.02)| 0.90 (0.03)| 183.9 (22.5) | 9.5 (0.1)   |
A.3 Regression coefficients for voting metrics when mitigations are implemented for different voter turnout rates

Table 18 presents the simulated mean and standard deviation of metric values for six voter metrics when various mitigations are in place with voter turnout rates of 47.2% and 67.2%, respectively. These are interpreted the same as Table 15 within the main text. When voter turnout is 47.2%, the impact of mitigating policies is less than when the voter turnout rate is 57.2%. However, the relative magnitude of primary and interaction effects are the similar to when the voter turnout rate is 57.2%. Conversely, when the voter turnout rate is 67.2%, the impact of mitigating policies is larger than when the voter turnout rate is 57.2%.

Table 18
Simulated mean value (standard deviation) of in-person voter metric across 50 replications when various mitigations are implemented to address pandemic-related disruptions. The expected voter turnout used is 47.2% and the early voting rate 29.6%.

| Code Value | EV | PWR | EPF | QS | Avg. Wait | Avg. Time | 15 Minute | 30 Minute | Avg. Line | Avg. Voters |
|------------|----|-----|-----|----|----------|----------|----------|----------|----------|------------|
|            |    |     |     |    | Time     | Inside    | Wait     | Length    | Inside    | Inside     |
| 0 0 0 0    | 0  | 0   | 0   | 0  | 57.0 (11.5) | 7.2 (0.1) | 0.60 (0.08) | 0.49 (0.08) | 49.2 (11.4) | 7.4 (0.3) |
| 1 0 0 0    | 1  | 0   | 0   | 0  | 7.5 (2.9)     | 6.7 (0.1) | 0.13 (0.05) | 0.08 (0.03) | 4.9 (2.0)   | 4.8 (0.3) |
| 0 1 0 0    | 0  | 1   | 0   | 0  | 14.2 (5.6)    | 7.4 (0.1) | 0.35 (0.11) | 0.20 (0.10) | 14.5 (6.3)  | 7.9 (0.5) |
| 0 0 1 0    | 0  | 0   | 1   | 0  | 56.0 (10.9)   | 6.7 (0.0) | 0.57 (0.06) | 0.48 (0.06) | 48.2 (10.8) | 6.9 (0.2) |
| 0 0 0 1    | 0  | 0   | 0   | 1  | 57.0 (11.5)   | 7.2 (0.1) | 0.53 (0.07) | 0.45 (0.07) | 49.2 (11.4) | 7.4 (0.3) |
| 1 0 0 0    | 1  | 0   | 0   | 0  | 0.9 (0.6)     | 6.8 (0.1) | 0.01 (0.01) | 0.00 (0.01) | 0.6 (0.4)   | 4.8 (0.3) |
| 1 1 0 0    | 1  | 1   | 0   | 0  | 7.5 (2.8)     | 6.6 (0.0) | 0.13 (0.05) | 0.08 (0.03) | 4.9 (2.0)   | 4.7 (0.2) |
| 0 0 0 1    | 0  | 0   | 0   | 1  | 12.4 (4.7)    | 6.7 (0.0) | 0.29 (0.09) | 0.17 (0.08) | 12.7 (5.3)  | 7.3 (0.3) |
| 1 0 0 0    | 1  | 0   | 0   | 1  | 14.2 (5.6)    | 7.4 (0.1) | 0.32 (0.09) | 0.20 (0.09) | 14.5 (6.3)  | 7.9 (0.5) |
| 0 0 1 1    | 0  | 0   | 1   | 1  | 56.0 (10.9)   | 6.7 (0.0) | 0.50 (0.06) | 0.43 (0.06) | 48.2 (10.8) | 6.9 (0.2) |
| 1 1 1 0    | 1  | 1   | 0   | 0  | 0.9 (0.5)     | 6.6 (0.0) | 0.01 (0.01) | 0.00 (0.00) | 0.6 (0.4)   | 4.7 (0.2) |
| 1 1 0 1    | 1  | 0   | 1   | 0  | 0.9 (0.6)     | 6.8 (0.1) | 0.01 (0.01) | 0.00 (0.00) | 0.6 (0.4)   | 4.8 (0.3) |
| 0 1 0 1    | 0  | 1   | 0   | 1  | 7.5 (2.8)     | 6.6 (0.0) | 0.12 (0.05) | 0.08 (0.03) | 4.9 (2.0)   | 4.7 (0.2) |
| 1 0 1 1    | 1  | 0   | 1   | 1  | 12.4 (4.7)    | 6.7 (0.0) | 0.27 (0.08) | 0.18 (0.07) | 12.7 (5.3)  | 7.3 (0.3) |
| 1 0 0 1    | 1  | 0   | 0   | 1  | 0.9 (0.5)     | 6.6 (0.0) | 0.01 (0.01) | 0.00 (0.00) | 0.6 (0.4)   | 4.7 (0.2) |

A.4 Increased ballot marking time

Table 20 presents the mean and standard deviation of simulation outputs across 50 replications for different expected ballot marking times when either no disruptions occur or all disruptions occur.
Table 2

| Disruptions Experienced | Expected Voting Time | Avg. Wait Time | Avg. Time Inside | 15 Minute Wait | 30 Minute Wait | Avg. Line Length | Avg. Voters Inside |
|-------------------------|----------------------|----------------|-----------------|---------------|---------------|-----------------|------------------|
| None                    | 4.04 min             | 9.2 (3.1)      | 6.5 (0.1)       | 0.21 (0.06)   | 0.12 (0.04)   | 11.3 (4.2)      | 7.9 (0.4)        |
| 4.54 min                | 9.2 (3.1)            | 7.0 (0.1)      | 0.21 (0.06)     | 0.12 (0.04)   | 11.3 (4.2)    | 8.5 (0.4)       |
| 5.04 min                | 9.2 (3.1)            | 7.5 (0.1)      | 0.21 (0.06)     | 0.12 (0.05)   | 11.3 (4.2)    | 9.1 (0.4)       |
| PWS, PPE, SD            | 4.04 min             | 115.0 (16.0)   | 7.5 (0.1)       | 0.82 (0.05)   | 0.75 (0.06)   | 108.2 (17.6)    | 8.7 (0.3)        |
| 4.54 min                | 121.3 (17.9)         | 8.7 (0.2)      | 0.87 (0.05)     | 0.81 (0.06)   | 115.3 (19.7)  | 10.0 (0.4)      |
| 5.04 min                | 135.0 (19.0)         | 10.2 (0.1)     | 0.93 (0.03)     | 0.89 (0.04)   | 129.1 (20.3)  | 11.4 (0.2)      |

*Value used throughout paper.

The number of replications was determined by finding the maximum number of replications needed, n, across all comparisons within this paper to find an appropriate half width, h, using the formula $n \geq \frac{2 \times \hat{h}^2 \times \hat{\sigma}}{h^2}$. The value of $h$ depended on the comparison being made.

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