Modeling Voting Service Times with Machine Logs

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Abstract

We propose a new method for estimating voting service times using machine log files from electronic voting machines, particularly the iVotronic DREs used in South Carolina. Estimating voting service times requires both parsing the relevant information from the files and estimating when machines are being used to capacity in the precincts to which they are deployed. After estimating average voting service times for each precinct in South Carolina in the 2016 presidential election, we conduct statistical analysis to explore correlates of service times with ballot features (number of candidates and offices), ballot behavior (straight-ticket voting and ballot rolloff), and demographics (age and race). This analysis is potentially helpful for both reaching a more nuanced understanding of why voting times vary, and for providing election administrators with a method for estimating ballot-marking times more comprehensively than previously possible.

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How long does it take a voter to mark a ballot, and what affect does the ballot-marking time have on the wait to vote at a polling place? These questions gained greater currency following the 2012 election, when polling place line lengths were singled out by President Barack Obama as a target for reform.

Estimating the average ballot-marking time and then tying those estimates to features of the ballot — how many offices are on the ballot, how long are the referendum questions, etc. — is more complicated than it might seem at first. Some election officials attempt to estimate the average ballot-marking time ahead of an election by collecting a sample of individuals and asking them to fill out ballots under the watchful eyes of election staff with stop watches. This method rarely has enough observations to produce statistically reliable results, and relies on samples of convenience that may not mimic the voting public. Researchers have sent observers to polling places, again with stop watches, to time voters as they mark their ballots (Spencer and Markovits, 2010; Herron and Smith, 2016; Stein et. al., 2017). While this method can result in more statically reliable results, it is very labor intensive, and thus is unlikely to be used very often, or at scale.

In this paper we explore an alternative method of measuring ballot-marking times that relies on the log files of computerized voting machines. The log files are of two types. The first are logs that record "events" executed by the machine's computer, including the time of day when a vote was cast. The second are logs that record the choices that voters make on their ballots, which have alternatively been called "cast vote records" (CVRs) and "ballot image files." The log files allow us to measure the time between votes cast on a voting machine, thus providing the most basic piece of information we need. The CVRs allow us to characterize what is on the ballot of every voter in every precinct we examine here, and also characterize important behavioral patterns on the ballots, such as the extent of ballot roll-off and straight-party voting.

This paper focuses on one particular state, South Carolina, which uses one particular voting machine, the iVotronic, manufactured by Election Systems & Software (ES&S). There are advantages and disadvantages of developing this method in a single state and on a particular voting machine. Among the advantages is the ability to hold voting technology constant within a state, allowing us to leverage observations from a wide variety of voting situations in exploring the method. The disadvantage is that the specific method may not be applicable to other machines with different log file formats. Also, the iVotronic system, despite being widespread, is old and likely to be replaced in the coming years, both in South Carolina and the other states where it is currently used. Furthermore, as we discuss below, the information available on the iVotronic machine logs is less-than-optimal from the perspective of estimating average ballot-marking times.

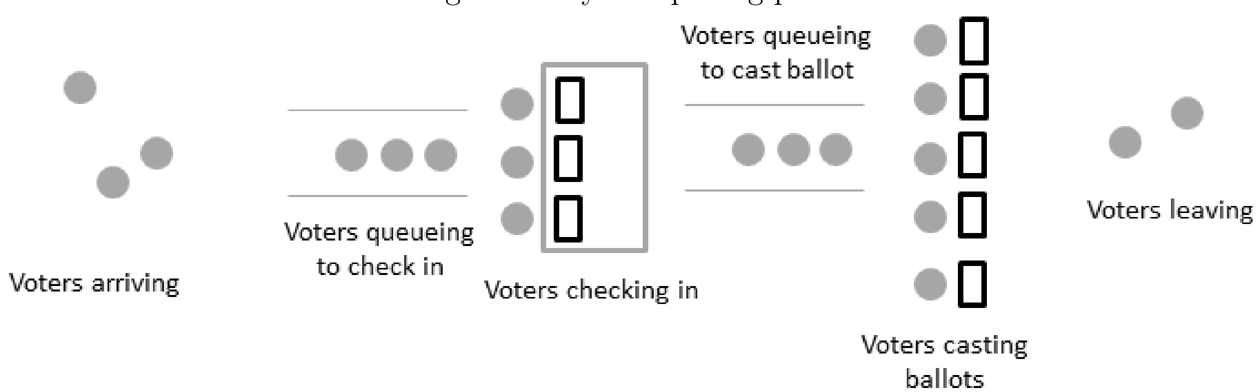
However, we believe the techniques developed here will become even more useful to administrators and scholars as newer voting technologies come onto the market with more complete machine records. For one thing, newer voting technologies are being designed with even more thorough logging records. The case we explore here is a "hard case," from the perspective of inferring ballot-marking times from the machine records. Future extensions of our method will undoubtedly be more accurate, as log files contain more service information.

The rest of this paper proceeds as follows. First, we describe the type of polling-place set-up that is the subject of investigation in this paper, and how information on the event logs relates to the behavior of voters in polling places. Second, we describe the data files in more detail. Third, we describe how we subset the complete dataset of voting service times down to a smaller dataset that was purged, as much as possible, of data from idle machines. Fourth, we discuss our findings, which explore the relationship between voting service times, on the one hand, and election administration and demographic factors, on the other. Finally, we discuss the implications of this analysis for the practice of election administration and for further academic and applied research.

Measuring Ballot-Marking Times Using Machine Records

The polling place set-up we examine here is common throughout the election administration landscape in the United States, and is illustrated in Figure 1. Voters come to a polling place, check in, cast their ballots at a machine located in a voting booth, and then leave the booth. Because the case we consider involves direct-recording electronic (DRE) devices, there is no ballot to be scanned, allowing the voter to leave the polling place after casting a ballot.

Figure 1: Stylized polling place



A single line forms in front of the check-in table, where there may be one or more stations at which a voter can be checked in. After checking in, if there is a vacancy at the voting booth(s), the voter immediately goes to an available booth and marks the ballot. If all the voting booths are occupied, the voter joins another line and waits for a booth to become vacant.

We focus here on the second queue, between the check-in table and the voting machines, and the process that gives rise to it. In the argot of queuing theory, this can be modeled as an M/M/c queuing system, where "M" denotes the nature of the arrival process and the distribution of the service time (Markovian, in this case) and "c" denotes the number of servers (the number of voting booths, 5 in this example).[1]

The service time we are interested in is the time when a voting booth is monopolized by a voter. This time can be decomposed into three parts. The first is the *ballot marking time,* which is the time that begins when the voter starts marking the ballot and ends when the voter completes the ballot. This is the quantity that is traditionally captured whenever ballot marking is measured in a laboratory or office environment. However, there are two other components of the service time. One starts when the voter begins to move toward the machine from the top of the queue (or the check-in table) and ends when the voter starts to mark the ballot. We will call this the "booth travel time." The other component starts when the voter has completed marking the ballot, but has yet to vacate the voting booth. We will call this the "booth vacating time." Both of these additional components of the service time consist of "business" the voter engages in while still monopolizing the voting booth, such as putting down and picking up a purse. This additional time is unlikely to be captured in laboratory methods, but should be accounted for if the purpose of the timing is to allocate resources effectively.

The total *voting service time* can be stated using the following accounting identity:

$$Voting\ service\ time = Booth\ travel\ time + Ballot\ marking\ time + Booth\ vacating\ time$$

How to measure these quantities? In observational studies, it is possible to instruct researchers to measure any or all of these times directly. Typically, there has been little intrinsic interest in the booth travel and vacating times, so observational studies have tended to measure either the total voting service time or the ballot marking time.

[1]Because entry into the voting booth queue is regulated by the process at the check-in station, arrivals may not in fact be Markovian, and may be more regular and autocorrelated than the Markovian process assumes. It is also possible that arrivals into the voting booth queue will be regulated by the check-in table, depending on the length of the voting booth queue. Because this paper is not about the complete dynamics of the voting booth queue, only the measure of the voting booth service times, we leave the implications of the voting machine queue dynamics to future research. The important thing here is that a queue forms when all the voting machines are occupied.

Using machine records, it may be possible to capture either the ballot marking time or the total voting service time, although this depends on the details of the machine being studied and (perhaps) on assumptions made about the queue.

If a voting machine log file records both the specific time the machine is engaged by a voter and the specific time the voter completed the transaction, then the machine log can be used to measure the ballot-marking time of each voter.[2] The ES&S ExpressVote Ballot Marking Device records both times, as well as the new voting system being developed by Los Angeles County.[3]

Furthermore, if there is a queue in front of the voting machines — that is, the machines are being used to capacity — then the time between successive ballot castings can be used to measure the total voting service time, but not the ballot marking time. If there is no queue, then the time between successive ballot castings will be contaminated by the amount of idle time a machine might (or might not) experience when the polling place's machines are used at less than capacity.

To clarify the situation, consider the following scenario. In this hypothetical, there is a polling place with eight iVotronic DRE machines. All the machines are being occupied with voters. A queue has formed to wait for machines to become vacant. Voter A casts her vote at time t_1 and immediately leaves the voting booth. The voter at the top of the voting machine queue, Voter B, goes to the vacated machine and starts voting. When finished, he casts his vote at time t_2. The total voting service time in this situation is simply $t_2 - t_1$. On the other hand, if Voter A casts her vote at time t_1 and leaves the voting booth at a moment when there is no queue waiting for a free machine, and then Voter B starts voting at some later time, the quantity $t_2 - t_1$ is no longer a measure of the total voting service time, but rather, the voting service time plus the idle time.

[2]Depending on whether the machine in question is a DRE or a ballot-marking device, the time interval may be more or less contaminated by non-marking time. We leave that consideration aside for the moment.

[3]This latter point has been verified by the authors through personal communication with the Program Manager of the Voting Solutions for All People (VSAP) program of the Los Angeles County Registrar-Recorder County Clerk.

The iVotronic machines used in South Carolina do not record when a voter begins voting on the machine, only when the ballot is cast. Therefore, South Carolina fits into the case where we are able to measure only the voting service time, and only able to measure it accurately if we know there is a queue waiting for access to machines.

The critical issue, then, is knowing when the machines are fully occupied — that is, when there is a queue.

Previous research has addressed the issue of knowing there is a queue by focusing on the end of the voting day, after the polls have closed, but voters in line are allowed to remain and eventually cast a ballot. In theory, the only reason voting should continue past the poll closing times is that there is a line of voters waiting to cast ballots. Because the polls close when all voters have cast a ballot, and poll workers have incentives to close the polls as early as possible (constrained by the law), it is reasonable to assume that all available machines are being utilized, and that slack time in the use of machines is as close to zero as practicable. In other words, it is reasonable to assume that if a voting machine is used after the poll-closing time, there is a queue to access the machines.

Buell (2013) used votes cast after the listed closing time in South Carolina in 2012 precisely in this fashion. Additionally Herron and Smith (2016) also used polling place closing times in Florida during the 2012 presidential election to study the predictors of long polling-place lines.

The logic associated with this strategy is solid, and yet comes with significant costs. The cost is related to the fact that measuring vote service times, and other voter queue dynamics, based on post-closing data significantly limits the number of precincts brought into the analysis, and may additionally bias the sample of precincts analyzed. In South Carolina in 2012, for instance, Buell (2013) was able to analyze data associated with 14,790 voters who cast ballots after 7pm, out of the 121,206 votes cast on Election Day throughout Richland County. In 2016, when wait times were much shorter in South Carolina, only 6,467 voters, or 0.40% of the 1,605,407 votes cast *statewide* on Election Day, cast their ballots after 7pm.

Furthermore, the interest fostered in polling place wait times after the 2012 election led to a series of studies that measured wait times more systematically and directly. This research tended to show that the greatest congestion in polling places occurred at the *beginning* of the day, not the end of the day. Polling places rarely have lines at the end of the day, even when average wait times for voters have been relatively high. In most elections, when a polling place has a long line at poll-closing time, something went wrong early in the voting day. This means that the sample of polling places studied after the polls have closed may be atypical of polling places in a particular jurisdiction.

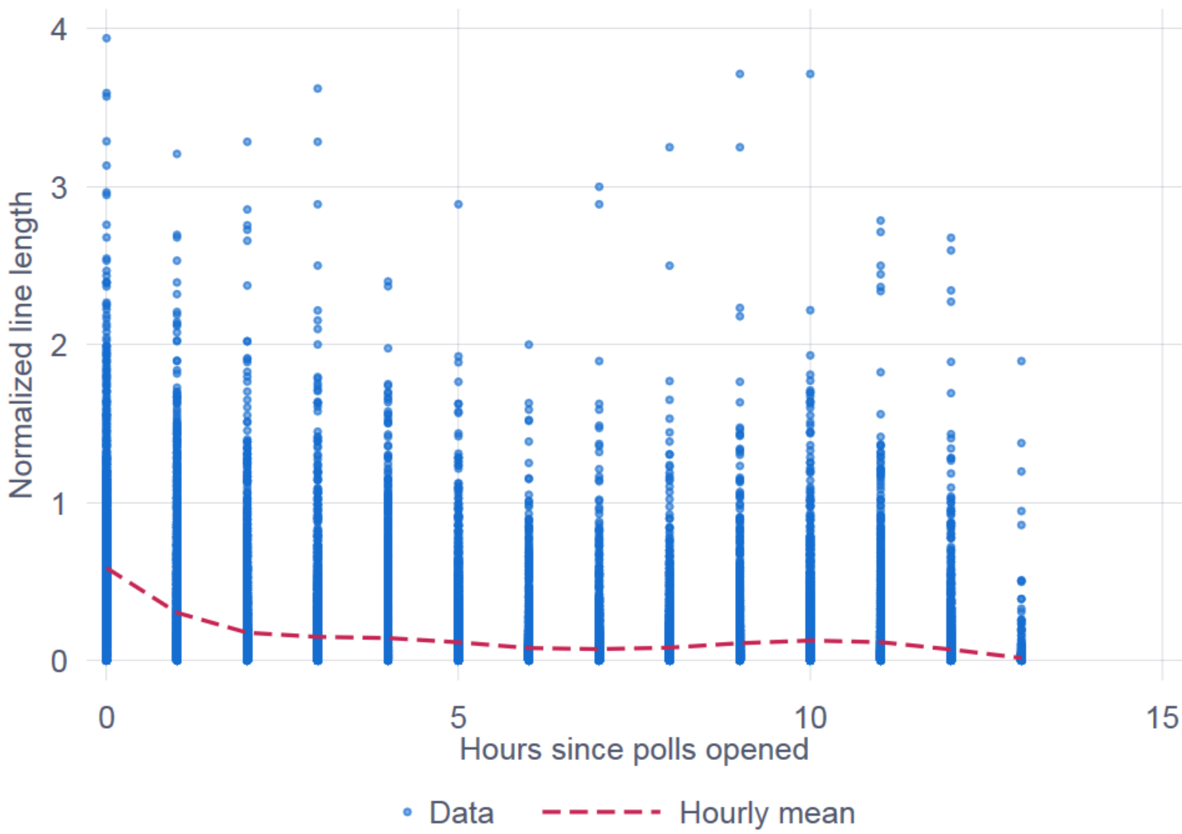
The prevalence of early morning congestion is shown in the following figures. First, research jointly conducted by the Bipartisan Policy Center and the Caltech/MIT Voting Technology Project enlisted the assistance of local election officials from 88 localities throughout the country in 2016, to count line lengths on an hourly basis in all polling places from the participating jurisdictions (Fortier et al; 2017). While this is not a random sample of polling places, it is broadly dispersed geographically.

Figure 2 shows the average line length at the start of each hour of the voting day among the 1,719 precincts involved in this project for which there was complete line-length and check-in data. Because the precincts studied varied significantly in the number of voters who turned out at each, the y-axis has been normalized to the average number of voters who cast ballots in each precinct each hour during the day. The x-axis is also normalized, so that the "zero hour" is the hour when the polls opened at each jurisdiction.

Of the 1,719 precincts analyzed, 1,144, or 67%, had a queue when the polls opened or immediately developed one, and the average queue amounted to nearly 45 minutes worth of voters. After one hour, 60% of precincts still had a queue. After both twelve and thirteen hours of voting, which are the typical voting day lengths, only 1.2% and 0.12% of precincts, respectively, had queues.

Another perspective on when congestion is most likely to arise in polling places is offered by responses to the Survey of the Performance of American Elections (SPAE), which asked voters what time they went to vote, and how long they waited. As Figure

Figure 2: Length of polling place lines on Election Day 2016



Source: Fortier (2018).

3 suggests, morning is the preferred time for in-person voting on Election Day in both midterm and presidential elections. A majority of voters reported at least some queuing to vote at almost every hour of the day in 2016, although those numbers exceeded two-thirds in the hours before 10am. In 2014, there was a spike in the report of voters waiting in the late afternoon, but the overall amount of waiting was significantly lower than in 2016.

We do not have sufficient data in the SPAE to separate out wait-time patterns in South Carolina on an hourly basis. However, if we divide the voting day into quarters, we see a pattern that issues the nationwide result — arrivals are most likely to occur in the morning, and the overwhelming majority of morning voters experience at least a minimal wait (See Table 1).

Figure 3: Arrival times to vote, 2014 and 2016

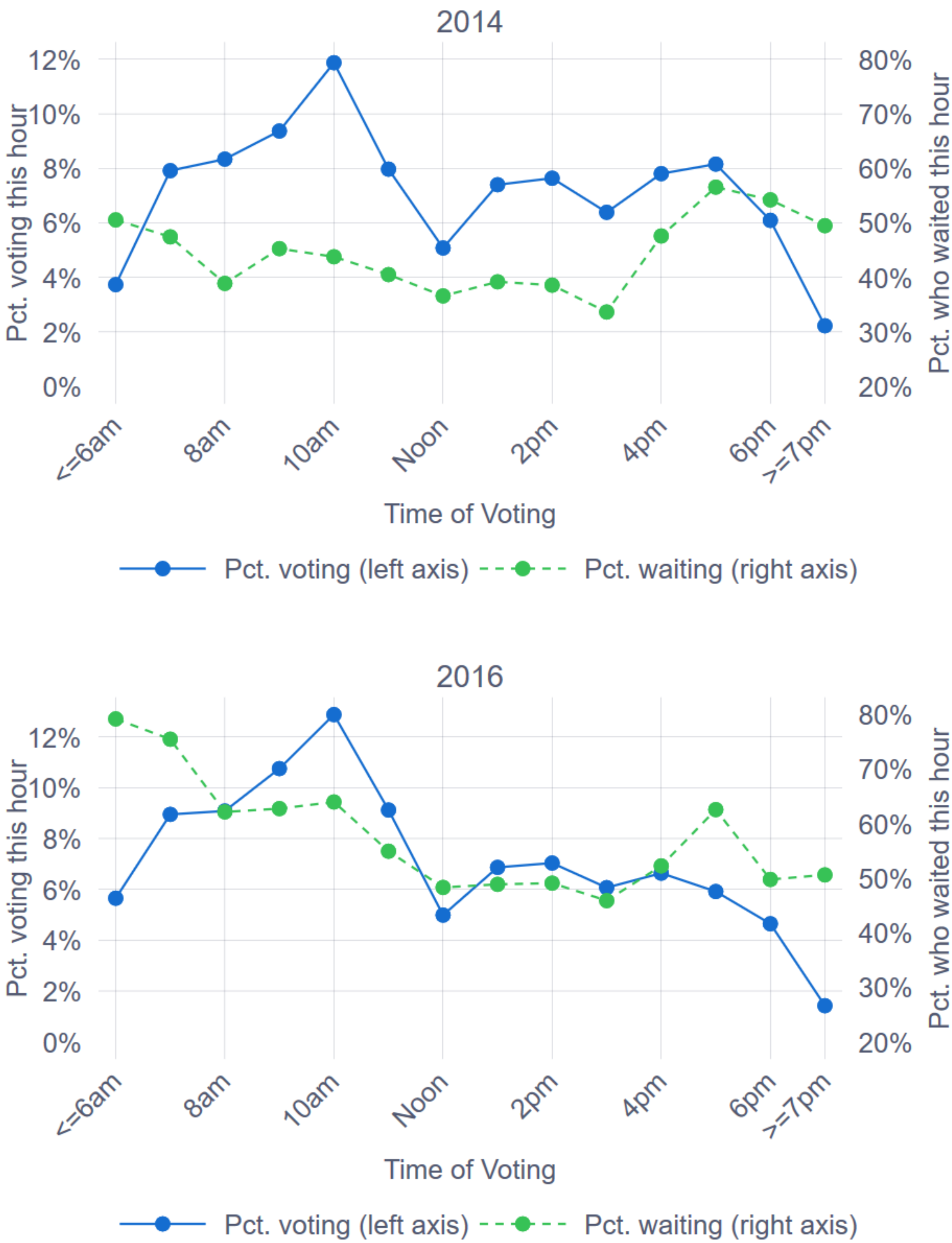


Table 1: South Carolina Voting and Arrival Patterns, 2016

Time period	Pct. voting	Ptc. who waited
6am-10am	32.6%	96.8%
10am-1pm	25.5%	83.7%
1pm-5pm	26.7%	56.8%
5pm-7pm	15.2%	69.5%

Source: Survey of the Performance of American Elections, 2016

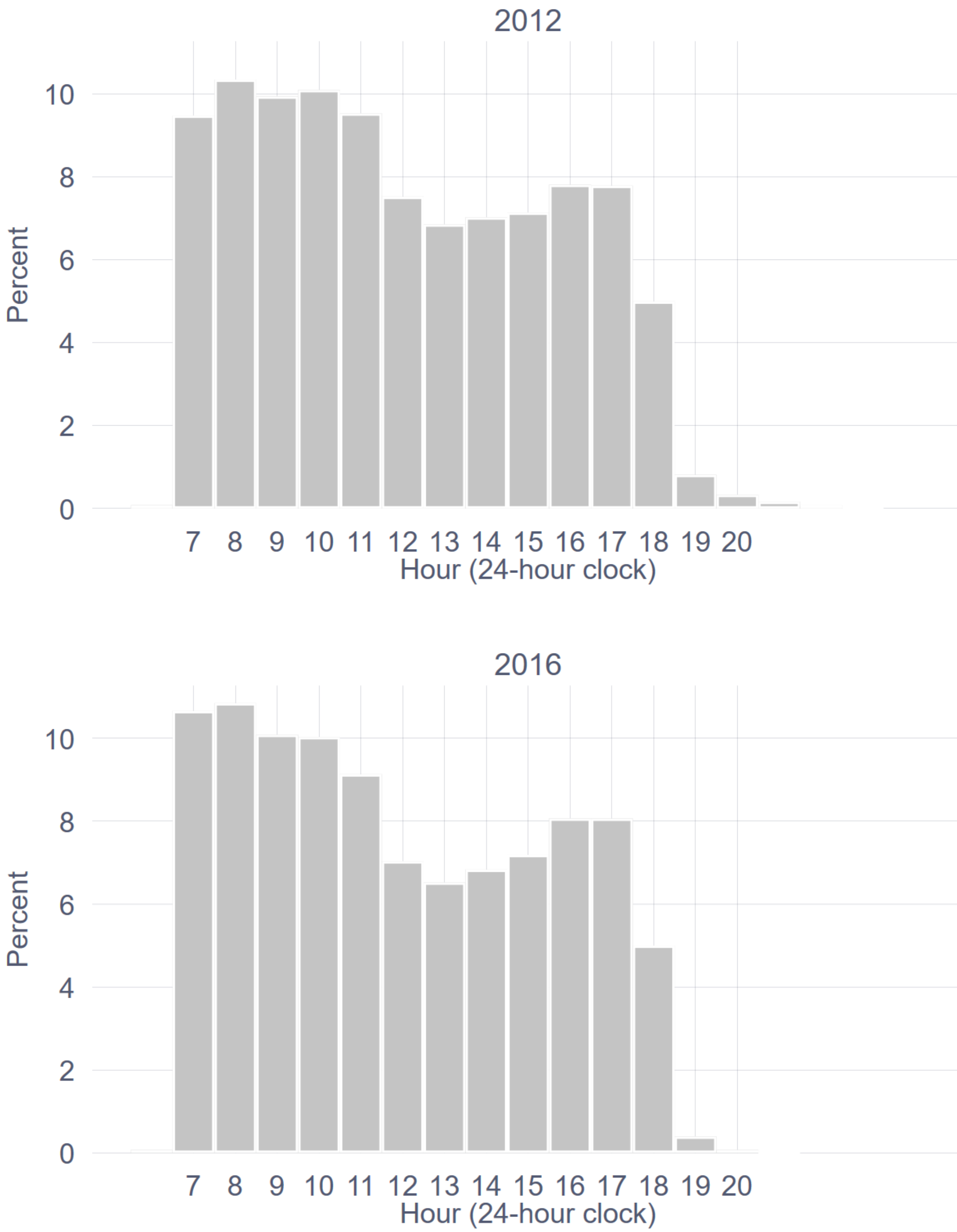
Finally, if we examine the times when ballots were cast in South Carolina, using the machine log files, it is clear that the number of early morning ballots swamp the number of post-closing ballots in the Palmetto State. This is illustrated in Figure 4, which shows the ballot-casting times from 2012 and 2016. An above-average number of ballots are cast in each of the morning hours, and a tiny number were cast after closing.

Thus, if researchers are interested in using machine-log files during times of the day when the voting equipment is fully occupied, they would be well served by shifting their attention to the beginning of the day. However, once we do this, we can no longer rely on the assumption that all machines are fully occupied.

One assumption we could make is that all voting machines are fully occupied for the first n minutes after the polls open. Because most precincts nationwide open with a line out the door, this is a reasonable assumption, at least for reasonable value of n. Under this assumption, we could then capture all the vote-casting times on all voting machines used during this period, and then calculate voting service times for individual voters as simply the difference in the recorded times of sequential votes cast during the chosen period.

This is the strategy we employ. Before working through how this method works in the case of South Carolina, we must first discuss some details related to the data file.

Figure 4: Vote-casting times in South Carolina, 2012 and 2016



Data Files

The primary source for the data used here is the machine logs from the ES&S iVotronic voting machines used throughout South Carolina during the 2016 election. South Carolina uses these machines only for in-person voting (absentee voting is done with paper ballots and are beyond the scope of this paper). South Carolina reported 2,123,584 ballots cast in the 2016 election. Of these, 502,819 of were cast as absentee ballots, leaving 1,620,765 cast in person. The in-person ballots were cast in 1,719 precincts throughout the state. The number of iVotronics deployed to these precincts ranged from 1 machine to 23, as is reported in Table 2. The typical polling place had between four and six machines.

Table 2: Distribution of iVotronic Machines

Machines	Count	Machines	Count
1	2	11	18
2	155	12	16
3	273	13	11
4	317	14	7
5	342	15	3
6	229	16	3
7	162	17	1
8	126	18	6
9	64	20	1
10	48	23	1

One function of the machine logs is to serve as input into post-election audits that are conducted to confirm the fidelity of an election. A successful audit must be completed before each individual county can certify its election. After the certification, another audit is performed, either by the county or the state. Both audits are performed using ballots stored in each iVotronic machine separate from the tabulation records.[4]

The audits generate two machine files that are used in this paper. Examples of the files are attached as part of Appendix I.

[4]The absentee paper ballots are not done in such a way, and are instead separately scanned.

The first machine files are EL155 files, which are the Vote Image Logs, and contain a copy of each ballot cast on an iVotronic. This contains the precinct and machine number on which the ballot was cast, but does not indicate the time of casting or the voter. In other words, the EL155 records are completely randomized within the larger file.

The EL155 files were used to reconstruct the ballot styles associated with each precinct and to construct statistics associated with ballots, such as the fraction of ballots on which the straight party choice was made. A discussion of how the ballot styles were constructed is contained in Appendix II. To aid in discussion, we will refer to the EL155 files as the "cast-vote record" (CVR) or "ballot image file."

Table 3 reports basic statistics describing the typical ballot reconstructed from the CVRs. The average ballot contained 27.8 candidates running in 14.5 offices. Nearly 40% (39.5%) of ballots utilized the straight-ticket vote, and nearly one-quarter (24.7%) of offices on all the ballots went unmarked, that is, they were under-voted.

Table 3: Summary Statistics for Ballot Styles

Statistic	Mean	St. Dev.	Min	Max
Undervote pct.	0.247	0.091	0.036	0.581
Straight-ticket pct.	0.395	0.105	0.150	0.799
Offices on ballot	14.476	2.467	9	25
Candidates on ballot	27.773	5.475	14	55

The second machine files are the EL152 files, which are the iVotronic Event Logs. These files contain a detailed list of each event that occurred on each machine. It has the machine number, personal electronic ballot (PEB) used for the event, as well as the date and time, but not the precinct. The EL152 files contain the information necessary to calculate the voting times. To aid in discussion, we will refer to the EL152 files as the "machine log files."

These files are extremely useful, but they also present some major challenges. The only time record offered in the machine log file is the time at which the vote is actually cast. This does not give, for instance, the time when a poll worker opened the terminal so that the voter could cast their vote. As discussed above, the interval between the two sequential timings in the log file may not be the exact amount of time it takes to cast a ballot, both because of the travel time that surrounds the ballot marking and because machines may simply go idle. An important part of our method is ascertaining when a voting machine is being used by a non-stop sequence of voters.

There is another detail of the CVR files that must be dealt with in the following analysis. Once we have calculated the average voting service time for ballots cast in a precinct, we will conduct a series of analyses in which the service times are regressed on demographic characteristics of the precincts. In those cases where a polling place only houses a single precinct, there is no problem in merging demographic data with the timing data. However, in those cases in which a polling place hosts multiple precincts, it is not always possible to associate a ballot-marking time with the precinct of the voter.

In 2016, there were 11,343 total voting machines used throughout South Carolina, each identified by their unique voting machine number. Out of those 11,343 machines, 1,524 (13.4%) appear to be located in polling places that hosted multiple precincts. To avoid confusion and mistakes in the analysis that follows, records from these 1,524 scanners located in multi-precinct polling places are dropped.

Methodology for Ascertaining Polling Place Congestion

We now turn our attention to ascertaining when a polling place is likely to be congested. As noted previously, if we know for certain when there is a queue to gain access to a precinct's voting machines, then we can use the machine-log time-stamps as the basis for calculating service times. There is a strong argument to be made that queues are most likely to form at the beginning of the day, but what constitutes "the beginning of the day?" Although focusing on the beginning of the day gives us more data to work with than focusing on the period after the polls have closed, we also know there will be periods during the middle of the day when there are queues and the machines are being used to capacity. Are there ways to bring in observations from these periods later in the day?

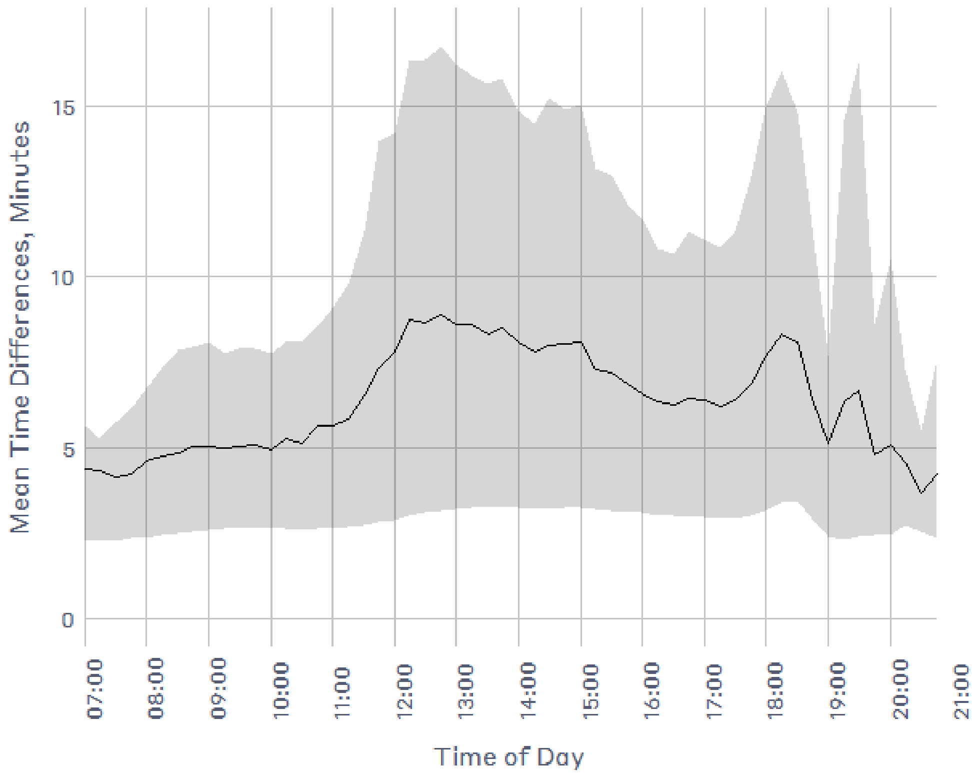
Honing in on the appropriate time period is an inductive process. How do we know the "right" time when we see it? To answer this question, we take a step back and ask another question: If we *knew* the starting and stopping time of each ballot-marking session, what would the distribution of calculated ballot-marking times look like? The answer is, it would probably have a right-skew, because ballot-marking times cannot be less than zero, and it is well-known that some voters simply take much longer to vote than others. This distribution would also have a mean, $\bar{m}$, and variance, s_m^2. If, as is actually the case, we only know the stopping time, but there is a queue to use the voting machines, the distribution of the voting times (calculated as the difference between the times when successive ballots were cast) would also be right-skewed. The mean of this distribution, $\bar{b}$, would be greater than the mean of the ballot-marking times, and the variance, s_b^2, would be greater, too. Finally, if there is no queue, then the calculated difference in ballot-casting times would the sum of the voting times and the average period between arrivals to each voting machine. This distribution would have a larger-still mean, $\bar{t}$, and a larger variance, s_t^2, compared to either of the distributions just discussed.

Thus, we can assume that $\bar{m} < \bar{b} < \bar{t}$ and $s_m^2 < s_b^2 < s_t^2$. At least conceptually, this suggests that the time of day with the most congestion will tend to have the lowest average voting-service times and the lowest variance of the service times, as well.

If we look at the data, the earliest voting service times in South Carolina in 2016 tend to fit this bill. Figure 5 graphs the average calculated voting service times on each voting machine in the state for fifteen-minute intervals throughout Election Day. The shaded interval represents the range between the 10th and 90th percentiles.

Leaving aside observations past 7:00pm, the fifteen-minute intervals with the lowest means and smallest variances are all before 8:00am. The smallest variance occurs between 7:15 and 7:30, and then begins to march steadily upward (we assume the first fifteen-minute interval has a larger variance because the start-up period right after

Figure 5: Estimating voting times, 15-minute bins, no machine restrictions



the polls open induces some additional variation into the voting behavior during this period). While we are certain that not all voting machines were occupied during the first 15 or 30 minutes of voting in every precinct, it is this early period of voting that behaves the most like things would if all machines *were* so occupied.

Turning our attention to the end of the day, the period after 7:00pm does not reliably have the lowest average calculated vote times — sometimes it does and sometimes it does not — and for most fifteen-minute periods after 7:00pm, the measures are quite variable. Furthermore, the number of machines and precincts represented by the post-7:00pm period is quite small compared to the early-morning period. The data in Figure 5 is based on observations from 7,700 machines in 1,577 precincts during the 7:00 – 7:15*am* period, whereas this drops down to 322 machines from 123 precincts from 7:00 to 7:15*pm*.

We choose, at least preliminarily, to use the 7:15am – 7:30am period to estimate the ballot-marking times in each precinct. Although this is not the period with the lowest average ballot-marking times, it is the period with the least variance. We will, however, conduct sensitivity analyses of this decision.

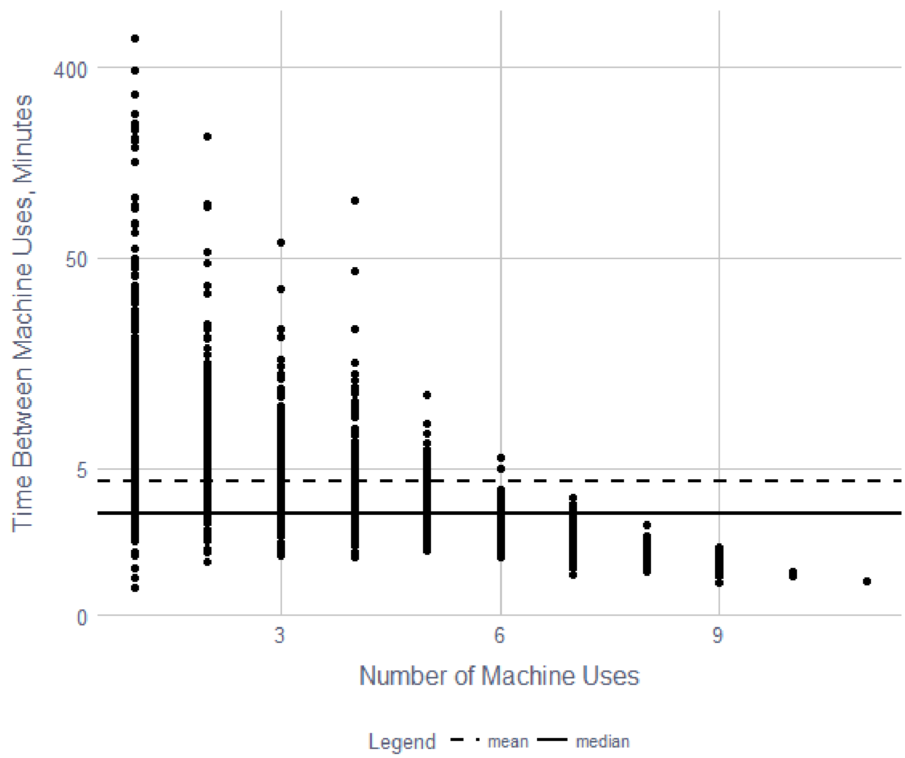
Before proceeding, we engage in two other forms of data trimming. The first helps us deal with a small detail pertaining to measured voting times at the end of the chosen time window. When we visually inspected the data, we discovered that there were a few cases where estimated service times within the time window were "reasonable," but that the time associated with the last interval was not. For instance, consider a machine with voting times as follows during the 7:15 – 7:30am window: 7:16:24, 7:19:37, 7:21:00, 7:24:27, 7:26:40, and 7:29:35. Using this data, we can estimate the voting service times with precision — 193, 83, 207, 133, and 175 seconds. What do we do with the next time stamp outside this window, or the one before it? Is the machine being used before 7:16:24 or after 7:29:35 or not?

In answering this question, we had to decide how far into the adjacent window to reach, to find the previous or next voting time. Here, we decide to reach only five minutes into the adjacent time bin. If the gap between the measurements within our time window and the next times outside the time window are less than some threshold, we keep the observations. If the gap is greater than the threshold, we delete the observation. Here, we use a five-minute trimming rule. In Appendix III, we explore different trimming rules. (It is sufficient here to report that different trimming rules do not affect the results substantively.) We choose the five-minute rule because it preserves the most data.

Another way we can be assured that we are mostly relying on vote timings from when the machines are at full capacity is by restricting our analysis to precincts in which at least four machines are being used during the fifteen-minute period of interest. When we visually inspected the data, it was clear that precincts in which fewer than four machines were being used typically had at least one idle machine during this period.

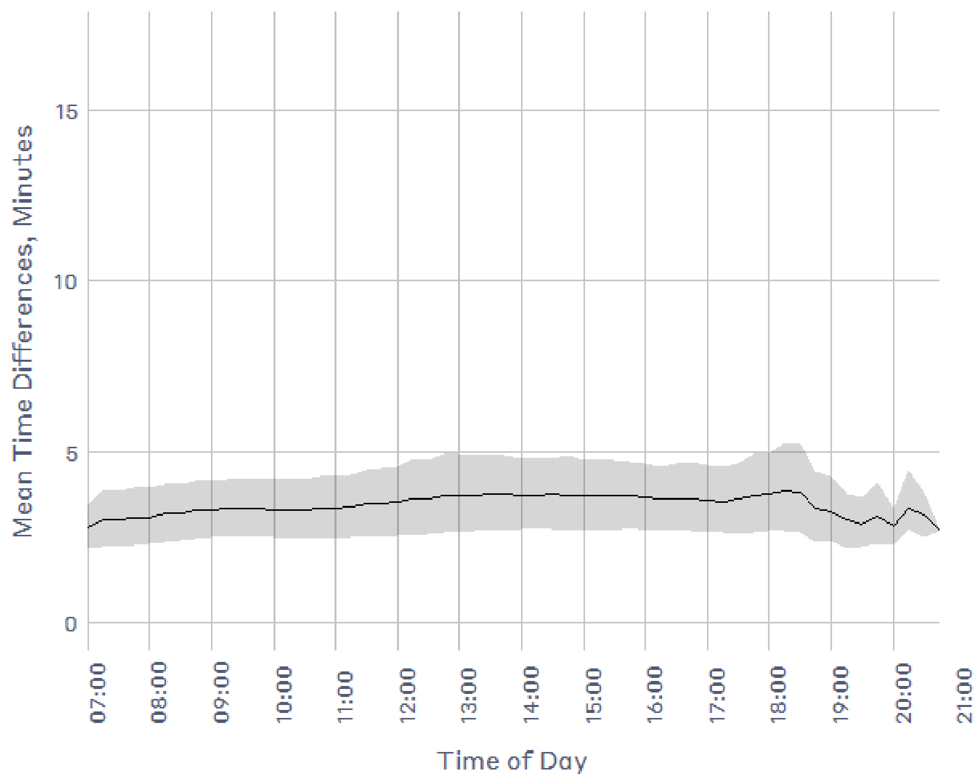
The effect of trimming the data in this way is illustrated in Figure 6. In that figure, we take the average estimated voting time for each precinct and plot it against the number of machines in use in that precinct during the 7:00am – 7:15am period. In the precincts with just one machine used during this period, the average estimated voting times range over 100 minutes. In these precincts, the single machine was used once, and then not used again for another hour or two. As more machines are used, the fewer extreme outliers there are. By the time we get to four machines, the distribution is fairly tight around an average of 3.11 minutes.

Figure 6: Number of machine uses and average difference, 7:15 - 7:30am, Log Scaling



With the four-machine restriction, the average time throughout the day flattens out, and the variance also decreases (see Figure 7). The variance does gradually grow throughout the day, peaking around noon, which suggests that it is wise to focus measurement on the early part of the day. Finally, it does appear that once we impose the four-machine restriction, the average calculated voting times for the period after 7:00pm return reliably to what we get if focus on the earliest time of the day, although the variance appears to be less stable, probably due to the tiny number of observations past 7:00pm.

Figure 7: Estimating voting time, 15-minute bins, 4-machine restriction



This combination of data-selection decisions presents us with a couple of options for how to proceed in calculating average voting service times. One is to focus on an early fifteen-minute period, augmented by the five-minute trimming and the four-machine restriction just described, in order to hone in on a period when we are the most assured of having queues and the full-capacity use of machines. Another is to abandon the fifteen-minute period, and rely entirely on the four-machine restriction and the five-minute trimming rule, while using data from the complete day. Going with this second option allows us to estimate average service times in each precinct with more data. However, it adds a risk that we are using more data from periods when the machines are not being used at capacity.

The risk and benefits are measured, in part, by the summary statistics associated with the various measures. With no data selection at all — that is, using all estimated service times throughout the day, without the four-machine restriction, the average estimated service time is 4.81 minutes ($s = 5.86$). Focusing on measurement taken only from the 7:15 – 7:30am period, and employing the four-machine restriction with the five-minute trimming rule, the average is 2.85 minutes ($s = 0.405$). Using data from the entire day, with the four-machine restriction and the five-minute trimming rule, the average is 3.10 minutes ($s = 0.242$). Thus, going from the early-morning 15-minute period to the full-day period increases the average estimated voting time by 15 seconds, but reduces the standard deviation of the measures nearly in half.

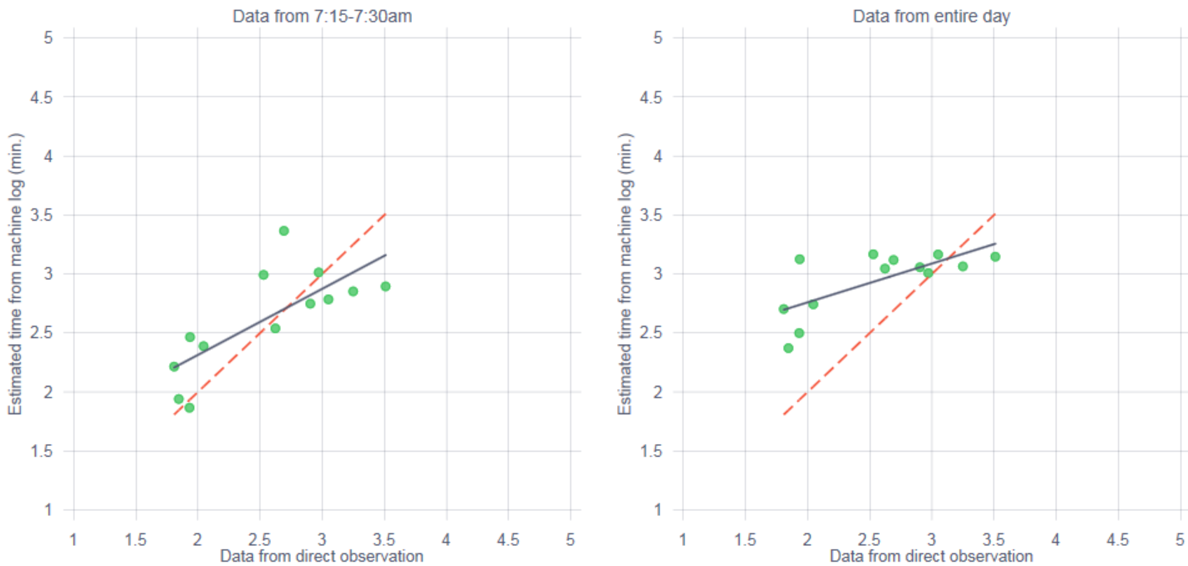
For the rest of this paper, we will keep voting-time estimates from the two extreme methods of restricting the data, for the sake of comparison.

To help validate these measures, we relied on the fact that a team of student researchers from the University of South Carolina participated in a multi-campus research project during the 2016 general election, in which they actually observed voters marking their ballots in Richland County (Columbia), South Carolina (Stein et al., 2017). That observation included hand-timing voters as they cast ballots in 14 different precincts in Richland County.

Figure 8 presents two scatterplots of the calculated voting times (y-axis) against the observed ballot-marking times (x-axis) from each of these 14 precincts. The left-hand plot uses data from 7:15 – 7:30 am, while the right-hand plot uses data from the entire day. The red dashed line represents the line of equality between the two measures, while the grey solid line represents the best-fit line from a linear regression.

There is mixed news in these comparisons. If all had gone according to our expectations, the voting service times calculated from the machine logs would generally be greater than the observed ballot-marking times. That is because the directly observed measures did not include the voting booth travel time, whereas the measures

Figure 8: Estimating voting time from machine logs vs. direct observation



from the machine logs did.[5] In addition, we expected that the times calculated from the machine logs would parallel the observed time, with the difference in the two times interpretable as the booth vacating time.

Instead, we see that both measures derived from the machine logs are correlated with the observed times, although they do not follow the patterns described in the previous paragraph. The correlation between the time estimated from early morning observations and the observed observations is strong ($r = .743$). That's the good news. The bad news is that the mean of the time calculated from the machine log is virtually the same as the mean derived from direct observation (2.62 vs. 2.55 minutes) and the slope of the best-fit line is significantly less than 1 ($b =$ 0.560, s.e. = 0.152).

The correlation between the time estimated from the entire day's observations and the directly-observed data is actually a little less than the alternative machine-log measure ($r = .709$), but still fairly strong. The mean estimated voting time is higher

[5]The coding instructions asked the student researchers to start timing when the voter arrived at the booth, and to stop when the voter left the booth. Thus, it does not include the booth travel time, but it does include the booth vacating time.

than that derived from direct observation (2.94 vs. 2.55), but again the slope of the best-fit line is significantly less than 1 ($b = 0.329$, s.e. $= 0.098$).

This attempt to validate the machine-log methods with independent observation meets mixed results. On the one hand, the two types of measures are strongly correlated with the measures that were derived from direct observation. On the other hand, the differences between the estimated derived by the two measures is not what we expected a priori. Of course, one reason for the disappointing results here may be due to the limited number of precincts for which we have direct observations, and the limited amount of time spent by coders at each precinct.[6] However, another possibility is that the machine methods are significantly less reliable than methods based on direct observation.

For now, we treat these validation results as follows. Because the machine-derived voting measures are strongly correlated with the measures based on direct observation, we feel comfortable using the machine-derived voting measures as dependent variables as we explore correlations between independent variables and voting times in precincts. However, because the machine-derived voting measures do not reliably over-estimate the voting times compared to direct observation, we are less comfortable using the measures to derive practical advice to election administrators about how long they should expect ballot-marking times to be, given the structure of the ballot and the demographics of the voters.

Findings

In this section, we explore the degree to which demographic and election administration factors influence the voting times we calculated. The basic set-up is a simple multiple regression with the unit of analysis being the precinct. The regression includes county-level fixed effects, clustering the standard errors at the county level as well.

[6] Coders only spent two hours at each precinct, timing an average of 21 voters in each precincts. (The range was from 14 to 29).

The first set of independent variables are related to election-administration factors. From a purely queue-theoretical perspective, voting times should be greatest where the ballots are the longest. We operationalize ballot length with two variables. The first, *number of offices*, is simply the number of offices or races on the ballot in a particular precinct. For instance, if is a presidential race, a senate race, two house races, two referenda, and three municipal races, the number of offices is seven. The second measure of ballot length is *total candidates*, which is the total number of candidates who appear on each ballot. In the above example, if each office has two candidates and each referendum has two choices, that equals 28 total candidates. If one of the offices is uncontested, then that makes 27 candidates.

Calculating the number of choices available on each ballot took some doing, since the CVR file is a "choices-only" file. That is, each ballot is represented by a list of candidates and questions the voter voted *for*, but does not list others on the ballot who did not receive a vote from that voter. To reconstruct a precinct's ballot, we had to append together all of the choices represented on all the ballots in a particular precinct, and then construct the super-set that encompassed all the offices that appeared on at least one ballot, and all the candidates who received at least one vote. We also had to take into account the fact that many precincts used several ballot styles, which were also indicated on the CVR file.

The number of offices on the ballots ranged from 9 to 25, with the number of candidates ranging from 14 to 55 (the respective means were 14.0 ($s = 2.47$) and 27.78 ($s = 5.48$). Of course the correlation between the two measures is high, but surprisingly less than 1 ($r = .65$). Four precincts in Berkeley County tied for having the fewest number of offices, with 9. The ballot of one of those precincts, Bethera, had the U.S. President (4 candidates), U.S. Senate (3 candidates), U.S. House (4 candidates), state senate (1 candidate), state house (2 candidates), solicitor and auditor (both 1 candidate), county treasurer (1 candidate on the ballot and one write-in), and soil and water district commission (5 write-in candidates not on the ballot).[7]

Deer Park 3 precinct in Charleston County had the most offices, with 25. This precinct had the usual races such as President, Senator, Representative, but also multiple municipal races, such as sanitation board and school board.

The third election-administration factor we considered was the percentage of voters who vote "straight ticket" at the top of the ballot. Choosing to vote straight ticket would obviate the need to vote for all the federal and state candidates of a particular party (if that was the voter's intent), but would still require the voter to vote in (non-partisan) local elections and on ballot questions. Overall, 39.5% of the ballots in our study voted straight ticket, ranging from 15.0% in Richland County Ward 3 to 79.9% in in Soluda County's Holstons Precinct.[8] We hypothesize that the greater the percentage of straight-ticket voters in a precinct, the shorter the ballot-marking time.

In addition, *ballot roll-off* is another ballot-related factor that could affect calculated voting times. We hypothesize that as the roll-off, or undervote rate goes up, voting service time will go down, all things considered.

We analyzed each ballot to see how many offices failed to receive a vote, taking into account the fact that voters selecting the straight-party choice should not be considered to have under-voted federal or state races. For each ballot, we calculated the total number of possible selections on that ballot and the number of selections the voter *failed* to make. For an individual ballot, the roll-off rate was the number of failed selections divided by the number of possible selections. This quantity was averaged across all ballots in a precinct to create the measure used here. The roll-off rate averaged 25.1%, ranging from 3.6% to 58.1%. Not surprisingly, there was a moderate correlation between the under-vote rate and the number of offices and candidates on the ballot ($r = .497$ and .484, respectively). Taking into account ballot length, straight

[7] In future revisions of this paper, we will explore whether write-in candidates have a separate influence on voting times.

[8] Among the variables examined here, the straight-ticket choice was most strongly correlated with the percentage of non-white voters in a precinct, at $r = .445$.

ticket and undervoting also appear to be correlated. This may be because they can both be thought of as time-saving measures; on longer ballots voters are less likely to fill in the non-partisan races after voting straight party.

Our final administration-related factor was the number of voters per machine. The number of voters per machine was considered a proxy for how crowded a polling place would seem to a voter casting a ballot. A polling place full of unused voting machines is likely to be less of a spur to get through the voting process quickly than a polling place with many voters, given the equipment available. The number of voters per machine averaged 181.3, ranging from 5.7 in the New Hope Precinct in Fairfield County to 664 in Charleston Precinct 2 in Charleston County.[9]

We focused on two demographic variables, both of which were available from the state board of elections on a precinct basis. The first was the percentage of registered voters who were 65 years of age and older. We hypothesized that there would be a positive relationship between this measure and ballot marking times. The first reason is the obvious one of older voters moving slower than younger voters. In this study, some portion of the dependent variable is taken up by the voter walking to the voting machine and then moving away from it. The effects of aging could very well have an affect on this.

The second demographic variable was the percentage of voters in a precinct that are non-white. We hypothesize a positive relationship between this variable and the voting time, as well, for many reasons. Some of these reasons may have to do with political interest and engagement of African American voters in South Carolina, which is not directly measured in this study. Greater engagement could lead to a voter spending greater time with the ballot, thus leading to longer voting times. However, the primary reason percentage non-white and voting times are likely to be positively correlated has to do with the effects of education, income, and health, none of which are directly measured in this study – at least not yet. Previous research has shown that African

[9]Because the average of this independent variable is two-to-three orders of magnitude larger than the other independent variables in the analysis, we also divide the number of voters per machine by 1,000, so that it range from 0.0057 to 0.664.

Americans in South Carolina have significantly lower education and income levels than whites (Stewart, 2013). Lower educational levels are especially likely to increase voting times. We would prefer to measure the effects of income and education directly, and we are exploring ways to get precinct-level measures of these variables for future research.

The dependent variable examined in this section is the average voting service time calculated from the machine logs, using the observations from the 7:15 – 7:30 time period. At the end of this section, we compare the results using the dependent variable calculated using data from the entire day. The Appendix IV contains comparisons of results using different time periods and trimming methods to construct the dependent variable.

We begin by examining the ballot variables alone, since they are the most closely associated with the task involved, and the most relevant to the election administration issues at the core of this analysis. Table reports the results. In the bivariate regressions, both the number of offices and the number of candidates on the ballot show positive effects on voting times. The estimated influence of adding an additional office on the ballot is 0.058 minutes of voting time, or 3.48 seconds; adding an additional candidate on the ballot adds an additional 0.030 minutes, or 1.8 seconds. Of course, adding an additional office on a ballot most typically adds two additional candidates, so it is assuring that the estimated effect of adding an office is very close to the effect of adding two candidates (some races have even more).

When we include both the number of offices and candidates together into the multiple regression, the coefficients around both variables decrease. This is likely because of the moderately high correlation between the number of offices and candidates on the ballot mentioned before.

It is useful to pause and think about what the results in the final column of Table mean. Keep in mind that, as always, the coefficients report the estimated change in the dependent variable from a one-unit change in the independent variable, holding the other variable(s) constant. This interpretation leads to an obvious intuitive interpretation in the case of the coefficient for the candidates on the ballot. If there

Table 4: Effect of ballot features on voting service times

Offices on Ballot	0.058***		0.025***
	(0.009)		(0.008)
Candidates on Ballot		0.030***	0.023***
		(0.003)	(0.005)
Constant	2.030***	1.994***	1.831***
	(0.142)	(0.089)	(0.133)
Observations	1,432	1,432	1,432
R^2	0.179	0.194	0.199

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

is already a fixed number of candidates on a ballot, and an additional one is added, we can expect it to take 0.023 more minutes (1.5 seconds), on average, to complete the ballot. Thinking about the addition of another office on the ballot without adding a candidate takes a little bit of mental gymnastics. It does appears that some of the offices on ballots in South Carolina in fact had no candidates, and were only filled through write-ins. Thus, it may be useful to think about this coefficient in terms of those races. Many voters just skip such races, adding virtually no additional time to the voting time. A few people pause and write in a name, which increases the mean voting time by a small amount overall.

To consider the practical implications of these findings, consider the shortest ballot in our sample, with 9 offices and 17 candidates. The point estimate for the average voting time for this ballot, using the results of the multivariate analysis, is 2.447 minutes. If another office with two candidates were added to the ballot, we would estimate that it would take an additional 0.071 minutes, or 4.2 seconds, to complete the ballot.

We note that the R^2 of the regressions is relatively low, and the standard errors of the estimates are substantively non-trivial. For instance, the 95% confidence interval for the number of candidates on the ballot in the multivariate regression ranges from

0.013 to 0.033 minutes, or between 0.78 and 1.99 seconds. If the estimates from this regression were to be used for planning purposes, it would probably be wise for an election official to use the upper end of the confidence interval in estimating what the effect of adding another set of candidates to a ballot will be, rather than hoping that the effect will be average.

We now turn our attention to other election administration factors that might affect ballot marking, which are the number of voters per machine, the amount of under-voting, and the frequency of the use of the straight-party choice. The results are in Table 5.

Table 5: Regression of vote times on administrative factors

	(1)	(2)	(3)	(4)	(5)
Thou. voters/machine	-1.182^{***}			-0.781^{**}	-0.879^{***}
	(0.348)			(0.348)	(0.338)
Undervote pct		1.014^{***}		0.924^{***}	0.046
		(0.118)		(0.109)	(0.252)
Straight-ticket pct.			0.513^{***}	0.222	0.414^{**}
			(0.162)	(0.185)	(0.179)
Candidates on ballot					0.024^{***}
					(0.007)
Offices on ballot					0.023^{***}
					(0.008)
Constant	3.146^{***}	2.602^{***}	2.732^{***}	2.701^{***}	1.848^{***}
	(0.067)	(0.037)	(0.058)	(0.120)	(0.216)
Observations	1,432	1,432	1,432	1,432	1,432
R^2	0.146	0.172	0.144	0.182	0.219

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

First, these results imply that the greater the number of voters per machine, the less the average ballot marking time is, confirming that when a polling place is more crowded, voters speed through the process faster. The effect can be interpreted this way: If we move from one standard deviation below the mean (129 voters per machine) to one standard deviation above the mean (234), the average amount of voting time declines by 0.124 minutes (7.46 seconds) in the bivariate case and 0.093 minutes (5.56 seconds) in the multivariate case. This is the equivalent of adding 4 candidates to a ballot in the multivariate analysis.

In addition, the results reported in Table 5 suggest that a higher undervote rate is associated with longer voting times. This is contrary to expectations. However, once we control for the length of the ballot (recall that undervotes are correlated with ballot length), the effect of undervoting goes to zero.

The effect of straight-ticket voting also demonstrates a counter-intuitive pattern in Table 5, both in the bivariate and multivariate regressions. The effect becomes statistically insignificant when the other administrative factors are included as controls, and then becomes significant again when the ballot-length variables are re-introduced. We defer addressing the effect of this variable further until we discuss the influence of the demographic factors.

The results of the regressions that introduce demographics are in Table 6. In the bivariate regressions, both the variables measuring the population older than 65 and the percentage non-white perform as expected. Once the two demographic variables control for each other, the effect of non-white population remains virtually unchanged, whereas the effect of having an older population on voting times becomes statistically indistinguishable from zero.

In the final column of the table, where all of the previous independent variables are returned as controls, the percentage of the population that is non-white remains statistically significant, as do the two variables we have been using to measure ballot length. We note that in the presence of the demographic controls, the effect of having more straight-ticket votes, which had a surprising *positive* effect on voting times, now has a *negative* effect.

Table 6: Regression of vote times on demographic

	(1)	(2)	(3)	(4)
Pct. pop. > 65	-0.342^{***}		-0.063	0.024
	(0.111)		(0.116)	(0.111)
Pct. pop. non-white		0.495^{***}	0.489^{***}	0.479^{***}
		(0.057)	(0.064)	(0.072)
Thousand voters/machine				-0.893^{***}
				(0.340)
Undervote pct.				-0.125
				(0.199)
Straight-ticket pct.				-0.260^{*}
				(0.144)
Offices on ballot				0.026^{***}
				(0.008)
Candidates on ballot				0.021^{***}
				(0.005)
Constant	3.017^{***}	2.774^{***}	2.794^{***}	2.038^{***}
	(0.032)	(0.017)	(0.048)	(0.142)
Observations	1,432	1,432	1,432	1,432
R^2	0.137	0.191	0.191	0.251

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Before concluding this section, we return to the issue of how to measure the dependent variable by asking if the results just described change if we measure voting time using data from the entire Election Day. Table 7 reports the results.

Table 7: Comparison of regression results with different measures of dependent variable

Time period of timing	7:15-7:30am	All day
Pct. pop. > 65	0.0471	0.100*
	(0.113)	(0.0468)
Pct. pop. non-white	0.485***	0.409***
	(0.0706)	(0.0382)
Thousand voters/machine	-0.891*	-1.802***
	(0.339)	(0.221)
Undervote pct.	-0.162	-0.0775
	(0.210)	(0.124)
Straight-ticket pct.	-0.234	-0.531***
	(0.143)	(0.150)
Offices on ballot	0.0279*	0.0218***
	(0.0129)	(0.00612)
Candidates on ballot	0.0208***	0.0118***
	(0.00480)	(0.00171)
Constant	1.933***	2.838***
	(0.165)	(0.114)
Observations	1432	1552
R^2	0.251	0.536
rmse	0.357	0.167

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The regression results using this alternative measurement strategy for the dependent variable produces results that by-and-large reinforce the previously-reported results, while making the coefficients more precisely estimated. The core independent variables in this study that measure ballot length remain significant and very precisely estimated. It is notable that the sizes of these coefficients are reduced somewhat, especially the coefficient associated with the number of candidates on the ballot. We return to this point below.

Because the coefficients are now much more precisely estimated, some of the effects that had previously been statistically insignificant are now significant. The effect of having more elderly voters in a precinct on voting times now has the hypothesized positive effect, while the effect of straight-ticket voting has the predicted negative effect. The only variable that is statistically insignificant is the extent of under-voting.

As with any political science paper that explores alternative specifications and alternative measurement strategies, there are concerns about p-hacking as we compare the results in the two columns of Table 7. Choosing the methods of data trimming or the algorithm for determining ballot marking times is vulnerable to exploitation. However, in this paper we have been careful to place bounds on the rules that govern our selection of possible measurement strategies for our dependent variable. As a consequence, while we have to be careful about favoring any one specification or measurement strategy over the other, we are confident that we have identified the space in which the "correct" estimates would be found, if we knew for sure when the periods of complete congestion occurred in each precinct in the state.

We close this section by engaging in a couple of exercises to illustrate the substantive impact of the independent variables on estimated voting service times, using both measurement strategies for the dependent variable. First, we show that estimated voting service times as we vary values of each independent variable, from the minimum to the maximum, while holding all other independent variables at their means. Second, we focus on the ballot-length variables specifically, showing how average voting times are expected to change as both the number of offices on a ballot increases, and as more of the offices are contested.

We start with the analysis of the effects of all the independent variables, showing the results in Table 8. Here, we see that the effects of the independent variables that were statistically significant show moderate influences on the voting service times across the extremes of their ranges.

Table 8: Estimated effects of independent variables

Variable	Min.	25th ptile	Median	75th ptile	max
a. Time period: 7:15-7:30am					
Pct. pop > 65	2.84	2.85	2.85	2.85	2.88
Pct. pop. non-white	2.71	2.76	2.83	2.95	3.19
Thou. voters/mch	3.02	2.89	2.86	2.84	2.43
Undervote pct.	2.89	2.86	2.85	2.84	2.80
Straight ticket pct.	2.90	2.86	2.85	2.83	2.75
Offices on ballot	2.66	2.79	2.84	2.87	2.87
Candidates on ballot	2.49	2.74	2.80	2.89	3.67
b. Time period: All day					
Pct. pop > 65	3.08	3.10	3.10	3.11	3.16
Pct. pop. non-white	2.98	3.02	3.08	3.18	3.39
Thou. voters/mch	3.44	3.18	3.12	3.07	2.26
Undervote pct.	3.12	3.11	3.10	3.10	3.08
Straight ticket pct.	3.22	3.13	3.10	3.06	2.88
Offices on ballot	2.97	3.05	3.10	3.12	3.12
Candidates on ballot	2.90	3.04	3.08	3.12	3.39

From the narrow perspective of planning for election day, Table 9 helps to illustrate how estimated voting service times vary as the length of the ballot varies. Here, we have chosen ballots with three different numbers of offices — 8, 14, and 25. Then, for each, we have specified whether the ballot consists of (1) only uncontested races, (2) 50% uncontested and 50% two-candidate races, and (3) all two-candidate races.

Table 9: Estimated effects of different ballot lengths

	Time period: 7:15-7:30am			Time period: All day		
	Degree of contest			Degree of contest		
Num. of offices	None	Half	All	None	Half	All
8	2.52	2.79	3.05	2.88	3.03	3.18
14	2.69	2.95	3.21	3.01	3.16	3.31
25	3.00	3.26	3.52	3.25	3.40	3.55

For the shortest ballot, with only 8 offices and none of them contested, the estimated voting service time is 2.52 minutes when the voting time is measured only at the beginning of the day, and 2.88 minutes when measured all day long. If all the races are contested, the averages jump to 3.05 and 3.18 minutes, respectively. Thus, on a short ballot like this, the effect of moving from all uncontested to all contested races is an additional half minute to the ballot marking time. This has roughly the same effect as moving from the ballot with the fewest number of offices to the most offices.

It might be said that the effects describes here — only about 30 seconds of voting time at the extremes — are trivial. However, as queuing models show, a small increase in service time can move a precinct from having no lines at all to being in the "elbow of death," that is, in the region in which the capacity of the system cannot process arrivals into it. For instance, using the M/M/c modeling tool available on the Caltech/MIT Voting Technology website,[10] a small precinct with 100 arrivals per minute and 6 voting machines could easily manage this load if voting times were 3.0 minutes, which is the estimating voting time for an eight-race ballot with all the races contested by two candidates. The average wait-time to vote would be only 1.8 minutes. If the ballot went up to fourteen fully contested races, which is the median for the state, ballot-completion time would rise to 3.2 minutes, and the wait time would also rise to 3.2 minutes. And if the ballot went up to 25 fully contested offices, the voting time would rise to 3.52 minutes, but the average wait would skyrocket to 19 minutes, and 5% of voters would wait more than an hour.

Thus, although the marginal effects of the various independent variables on wait times may seem modest, in the context of South Carolina's election administration, under the right circumstances, relatively common changes to the ballot can lead to significant inconveniences on Election Day.

Finally, a word should be said about the fixed effects estimated in the regressions explored in this section. In this analysis, the fixed effects coefficients are not merely nuisance coefficients, but rather, estimates of the voting time variation across counties that cannot be accounted for by the ballot, election administration, and demographic factors included in the regressions. In the first set of regressions we explored — those using the dependent variable measured only at the beginning of the day, the value of these coefficients range from -0.429 (Cherokee County) to 0.369 (Berkeley County).

[10] http://web.mit.edu/vtp/

This difference, 0.825 minutes, is nearly 50 seconds, and represents a larger range of effects than any of the independent variables we explored in this section. If we look at the regressions based on the dependent variable measured throughout the day, the fixed effects coefficients range from -0.157 (Richland County) to 0.254 (Orangeburg County). This is a 0.411-minute difference, or 25 seconds.[11] While smaller in magnitude, it is still a large effect compared to the estimated effects from the independent variables in the regressions.

These results related to the fixed effects coefficients suggest that there are still important county-specific factors related to voting times that we still must explore.

Therefore, the results reported in this section are an important first step in showing that voting machine logs can be used to measure voting service times, and that these times can be related back to features of the ballot. However, it is also important to note that some of the factors shown to be related to voting times, such as demographics, are beyond the control of election administrators. Other factors, such as roll-off and perhaps straight-party voting, can only be estimated after an election. Therefore, although the analysis performed here is useful for understanding important factors that lead to variation in voting times, not all of these factors are subject to pre-election planning efforts.

Conclusions and Discussion

The purpose of this paper is to propose a method to estimate voting service times using voting machine log files and then to estimate the effects of voting behavior, election administration, and demographics on service times. The results presented here are promising, though further work clearly needs to be done.

If the iVotronic EL152 files contained time stamps for both the initiation and termination of a voter's voting session, the measurement methodology would be far more straightforward. Without a clear starting and stopping time, we must introduce

[11]The correlation between the two sets of fixed effects coefficient is r=.71, when weighted by the number of precincts in each county.

the problem of estimating when a precinct is congested. That estimation process introduces error and the possibility of subjective judgment interfering with the method. We believe that the approach we have followed avoids using wishful thinking as we trimmed the observations down to those most likely deriving from fully utilized voting machines. Nonetheless, as we show, employing different data selection criteria results in slightly different results. These results may be "close enough for social science," but it is not clear whether they are close enough for use by election administrators.

Our research shows the importance of relying on as much data as possible to estimate service times in polling stations. Previous research that has focused solely on post-closing times allows the utilization of only a tiny amount of the available data. A method such as our should, once fully developed, have advantages precisely because it utilizes so much of the available data.[12]

We should note that our results suggest a larger effect of adding candidates to the ballot for voting times than found by Stein et al (2017). For instance, they found that the addition of one candidate was associated with an additional 2.7 seconds of voting time across all the precincts in their nationwide study, compared to our estimates of between 6 and 12 seconds depending on the specification. Whether this difference is due to different methods or our focus on DREs, compared to a study that primarily studied marking paper ballots, awaits further research.

On the other hand, data gathered by the Center for Democracy and Civic Life for the purposes of creating an app to estimate ballot-marking times suggests that each additional contested office on the ballot increases voting time by 4.8 seconds.[13] In any event, further work will need to be done to see whether differences across jurisdictions are due to differences in methodology, or differences due to geography.

[12]We acknowledge that one important comparison is missing from this paper: comparing the method we have developed with results that rely only on data that come from the period after the polls have closed. This is a task for the next round of research.

[13]The data were supplied to the authors by Mark Pelczarski, the lead developer on the project. We are grateful for CDCL's sharing of the data. The analysis here is our own, and not the responsibility of CDCL or Pelczarski.

Appendix I: Machine timing and CVR files

The EL152 log files provide information about all the "events" that are logged by the computer unit that constitutes the iVotronics election system. Each iVotronics machine produces a separate log, which is downloaded following elections in South Carolina and then posted on the website of the South Carolina Board of Elections.

Figure A1 shows a snippet of the first few lines of an EL152 file from a machine in South Carolina. The file consists of six columns of data on each row.[14] The first column of data identifies the iVotronics machine in question. The second column identifies the personalized electionic ballot (PEB) associated with the events logged to the right. Note that neither the iVotronic identification number nor the PEB identification number is updated until the number changes. Therefore, in analysis done with the EL152, these two numbers must be filled in to lower rows without those numbers, so that the proper machine and PEB are associated with the relevant events.

Figure A1. Example of EL152

5101642	117461	SUP	11/08/2016 07:13:32	0002400	PEB access failed
		SUP	11/08/2016 07:13:32	0000706	Failed to retrieve EQC from PEB
		SUP	11/08/2016 07:13:32	0001635	Terminal shutdown - IPS exit
		SUP	11/08/2016 07:23:52	0001633	Terminal shutdown
	139456	SUP	11/08/2016 07:27:00	0001510	Vote cast by voter
		SUP	11/08/2016 07:30:39	0001510	Vote cast by voter
	0	UNK	11/08/2016 07:30:47	0002400	PEB access failed
		UNK	11/08/2016 07:30:47	0002400	PEB access failed
		UNK	11/08/2016 07:30:59	0002400	PEB access failed
		UNK	11/08/2016 07:30:59	0000706	Failed to retrieve EQC from PEB
		UNK	11/08/2016 07:30:59	0001635	Terminal shutdown - IPS exit
	139456	SUP	11/08/2016 07:35:52	0001510	Vote cast by voter
		SUP	11/08/2016 07:38:25	0001510	Vote cast by voter
		SUP	11/08/2016 07:41:17	0001510	Vote cast by voter
		SUP	11/08/2016 07:44:35	0001510	Vote cast by voter
		SUP	11/08/2016 07:48:33	0001510	Vote cast by voter
		SUP	11/08/2016 07:52:46	0001510	Vote cast by voter

The third column identifies the type of PEB that has been associated with an event. Next comes the time and date stamp. Finally, there is a numerical code for the event, followed by a brief verbal description of the code.

[14] Very little documentation is available in the public domain to help with the decoding of the iVotronic files. One very useful paper is Baxter (nd).

Note that code 0001510 is associated with the event "Vote cast by voter." The timing calculations performed in this paper are focused on extracting these entries, along with the time-stamp data. Note, too, that a number of entries in this example are associated with event 0002400, "PEB access failed." This is the most common error code, and is typically associated with a voter (or poll worker) putting a PEB in the machine incorrectly.

Figure A2 shows the first few lines of data from the EL155 file, also known as the cast-vote record (CVR) or ballot image file. The file includes header information that records the time when the report was run, along with the precinct associated with the report.

The core of the file includes the choices made by every voter on each machine. The first column is the iVotronics machine on which the vote was cast, and can be used to help associate voting machines with precincts (it is impossible to associate *voters* with ballots, because the ordering of the ballots in the EL155 is random). The "B/I" column corresponds with the ballot style the voter used. Following that, an asterisk appears every so often. An asterisk indicates the beginning of a voter's choices (in other words, a voter's choices are all the votes recorded right after an asterisk appears, to the record right before the next asterisk). The next three columns record a candidate number, which is unique for that ballot style in that precinct, a candidate's name, and a plain text identification of the office of the candidate chosen. Note that a candidate name preceded with "W/I" is a write-in vote.

Not shown in this example is a case of a voter who activated the voting machine, but who cast his or her ballot without voting for any candidates. A separate notation is made for those cases where no choices were made on a ballot.

Figure A2. Example of EL155

```
RUN DATE:11/08/16 09:56 PM                        PRECINCT    1 - Abbeville No. 1

VOTR.    B/I     CANDIDATES RECEIVING A VOTE

5120096    4 *   10 Hillary Rodham Clinton                  President and Vice President
5120096    4     19 Thomas Dixon                            U S Senate
5120096    4     27 Hosea Cleveland                         CONG003 President District 3
5120096    4     31 Floyd Nicholson                         SEN0010 State Senate District 10
5120096    4     35 Craig Gagnon                            HOUS011 State House of Representatives D
5120096    4     38 David Stumbo                            Solicitor District 8
5120096    4     42 W/I CALLAHAN                            Sheriff
5120096    4     44 Emily Yeargin McMahan                   Clerk of Court
5120096    4     47 Ronnie Ashley                           Coroner
5120096    4     50 Charles H Goodwin                       CNCL003 County Council District 3
5120096    4     65 Susie K New                             Soil and Water District Commission
5120096    4     71 Harold McNeill                          MUNABBE Mayor
5120096    4     79 Jim Grant                               CTY0008 City Council District 8
5120096    4     82 Yes                                     Sales and Use Tax Referendum
5120096    5 *   14 Donald J Trump                          President and Vice President
5120096    5     22 Tim Scott                               U S Senate
5120096    5     28 Jeff Duncan                             CONG003 President District 3
5120096    5     32 J Bryan Hope                            SEN0010 State Senate District 10
5120096    5     35 Craig Gagnon                            HOUS011 State House of Representatives D
5120096    5     38 David Stumbo                            Solicitor District 8
5120096    5     41 Ray Watson                              Sheriff
5120096    5     44 Emily Yeargin McMahan                   Clerk of Court
5120096    5     47 Ronnie Ashley                           Coroner
5120096    5     53 Billy Norris                            CNCL004 County Council District 4
5120096    5     65 Susie K New                             Soil and Water District Commission
5120096    5     71 Harold McNeill                          MUNABBE Mayor
5120096    5     76 Joshua Bryan Baughman                   CTY0007 City Council District 7
5120096    5     83 No                                      Sales and Use Tax Referendum
5120096    9 *   12 Evan McMullin                           President and Vice President
5120096    9     22 Tim Scott                               U S Senate
5120096    9     28 Jeff Duncan                             CONG003 President District 3
5120096    9     31 Floyd Nicholson                         SEN0010 State Senate District 10
5120096    9     35 Craig Gagnon                            HOUS011 State House of Representatives D
5120096    9     38 David Stumbo                            Solicitor District 8
5120096    9     41 Ray Watson                              Sheriff
5120096    9     44 Emily Yeargin McMahan                   Clerk of Court
5120096    9     47 Ronnie Ashley                           Coroner
5120096    9     50 Charles H Goodwin                       CNCL003 County Council District 3
5120096    9     65 Susie K New                             Soil and Water District Commission
5120096    9     71 Harold McNeill                          MUNABBE Mayor
5120096    9     76 Joshua Bryan Baughman                   CTY0007 City Council District 7
5120096    9     82 Yes                                     Sales and Use Tax Referendum
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Appendix II: Ballot Style Construction

For this paper, the quantity of interest is the time required to send one person through a voting booth. Previously, what a voter actually does in the voting booth has not been addressed. The voter enters the booth, and for each issue on the ballot the voter reads the issue at hand, chooses one or multiple options if allowed or elects not to vote in that contest, and does that for every race on the ballot. Alternatively, the option of "straight ticket" voting is available throughout South Carolina, in which the voter selects a political party and the machine automatically votes the relevant party for the races in which a candidate running is nominated by that party. This gives a strong idea of what factors on the ballot may affect ballot marking times. The number of races on the ballot, the number of candidates to choose between on the ballot, the number of races in which voters did not select a voter, and the number of times a voter chose the "straight ticket" option would all be relevant to ballot marking times.

Those pieces of information are gathered through the cast vote records (also referred to as the ballot images). These records contain every vote cast in a precinct. Since write-ins and individual races are specifically marked, by listing every unique race on the ballot found in the EL155 form for a precinct, we have a record of how many races each voter is asked to vote in. This assumes, of course, that each office on a ballot received at least one vote. By counting the number of unique non-write-in candidates, it is also possible to identify the candidates who are listed to be chosen from on the ballot, per precinct. As a final assumption, this also assumes that every candidate on the ballot receives at least one vote in each precinct.

Straight ticket votes are also specially marked, so counting them is relatively straight forward. For each race, recording the most candidates any voter voted for in a precinct for a specific race gives the number of legal votes it is possible to cast in that race. For most races, such as President or member of Congress, this will only ever be one, but for some races such as school board, more than one vote is possible per race. By subtracting the number of selections made per ballot from this hypothetical maximum, it is possible to determine the rate of undervoting.

Appendix III: Alternative Data Selection Rules

The body of the paper notes different decision rules that were employed for the inclusion and exclusion of vote-cast time stamps that were used to calculate voting service times. Below, in Table A3, we list the results of the regressions performed on dependent variables calculated using decision criteria not explored in the paper.

These alternative data-choice methods are distinguished by two parameters: (1) the period of time in which the time stamps are gathered and (2) the trimming performed to account for time stamps immediately adjacent to the target time period. The target time periods were 7:00-7:15am, 7:15-7:30am, and all day. The trimming periods were 5, 10, and 30 minutes.

Note that the results displayed in Appendix A3 are very similar to those reported in the body of the table. As a general matter, the regression coefficients grow slightly larger as the amount of time defining the target grows. The standard errors also tend to shrink as the target time window grows, too, as the R^2 tends to grow.

Table A3. Comparison of multivariate regression results for different datasets

Time period	7-7:15am	7-7:15am	7-7:15am	7:15-7:30am	7:15-7:30am	7-7:30am	7-7:30am	7-7:30am	All day	All day
Trimming cut-off (min.)	5	10	30	10	30	5	10	30	10	30
Pct. pop. > 65	0.161	0.220	0.248	0.125	0.299	0.0709	0.114	0.236	0.143*	0.233**
	(0.143)	(0.133)	(0.127)	(0.135)	(0.221)	(0.110)	(0.124)	(0.154)	(0.0546)	(0.0836)
Pct. pop. non-white	0.293***	0.330***	0.339**	0.630***	0.773***	0.435***	0.555***	0.651***	0.527***	0.691***
	(0.0766)	(0.0919)	(0.0984)	(0.0815)	(0.0944)	(0.0629)	(0.0709)	(0.0777)	(0.0357)	(0.0491)
Thou. voters/machine	-0.962**	-1.415***	-1.526***	-1.008*	-1.458**	-0.845*	-1.053*	-1.472**	-2.345***	-3.494***
	(0.348)	(0.362)	(0.395)	(0.439)	(0.511)	(0.344)	(0.425)	(0.498)	(0.253)	(0.291)
Undervote pct.	0.120	0.107	0.0824	-0.239	-0.230	-0.0430	-0.0981	-0.0885	-0.0678	-0.0982
	(0.209)	(0.219)	(0.235)	(0.234)	(0.260)	(0.193)	(0.201)	(0.229)	(0.116)	(0.119)
Straight-ticket pct.	-0.348**	-0.314*	-0.384**	-0.224	-0.467*	-0.245*	-0.195	-0.386*	-0.622***	-0.788***
	(0.118)	(0.129)	(0.138)	(0.172)	(0.226)	(0.119)	(0.143)	(0.178)	(0.168)	(0.184)
Offices on ballot	0.0174	0.0236*	0.0249*	0.0283	0.0229	0.0243*	0.0251	0.0217	0.0241**	0.0347***
	(0.0106)	(0.00983)	(0.00942)	(0.0173)	(0.0204)	(0.0107)	(0.0134)	(0.0152)	(0.00702)	(0.00722)
Candidates on ballot	0.0215*	0.0220**	0.0207*	0.0228***	0.0212**	0.0196***	0.0213***	0.0191**	0.0106***	0.00243
	(0.00829)	(0.00768)	(0.00897)	(0.00628)	(0.00674)	(0.00493)	(0.00586)	(0.00665)	(0.00177)	(0.00300)
Constant	1.969***	1.974***	2.054***	1.926***	2.179***	1.976***	1.981***	2.223***	3.098***	3.546***
	(0.227)	(0.247)	(0.262)	(0.203)	(0.248)	(0.153)	(0.180)	(0.215)	(0.121)	(0.151)
Observations	1144	1144	1144	1432	1432	1474	1474	1474	1552	1552
R^2	0.221	0.213	0.200	0.249	0.231	0.282	0.284	0.252	0.568	0.599
rmse	0.340	0.381	0.408	0.413	0.476	0.317	0.362	0.414	0.192	0.234

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

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