




ORIGINAL ARTICLE

# The Effect of Ballot Characteristics on the Likelihood of Voting Errors

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## Abstract

In the United States, people are asked to vote on a myriad of candidates, offices, and ballot questions. The result is lengthy ballots that are time intensive and complicated to fill out. In this paper, we utilize a new analytical technique harnessing ballot scanner data from a statewide midterm election to estimate the effects of ballot complexity on voting errors. We find that increases in ballot length, increases in the number of local ballot questions, and increases in the number of candidates listed for single offices significantly increase the odds of encountering ballot marking and scanning errors. Our findings indicate that ballots' characteristics can help election administrators make Election Day planning and resource allocation decisions that decrease ballot errors and associated wait times to vote while increasing the reliability of election results and voter confidence in the electoral process.

**Keywords:** voting machines; ballot errors; ballot length; optical scanners

## Introduction

Scholars and journalists have been investigating the role of the voting process in voter disenfranchisement since at least the 2000 election (e.g., California Institute of Technology and The Massachusetts Institute of Technology 2001; Sinclair et al. 2000). Events surrounding recent elections demonstrate that ongoing investigation is necessary, with continued focus on ballot characteristics (e.g., Bullock and Hood III 2002; Everett, Byrne, and Greene 2006; Greene, Byrne, and Goggin 2013; McCadney and Norden 2020). Voters who experience long wait times or machinery that breaks down may lose the opportunity to vote (Stein et al. 2019) or lose faith in the system (Alvarez, Hall, and Llewellyn 2008; Bracken, Eaton, and Throop 2020; Chen et al. 2020; Pettigrew 2017). Long wait times and voter confidence have been associated with administrator decision making (e.g., Pettigrew 2017), including the allocation of voting machines and poll workers—generally, more resources improve voters' experience, fewer resources lead to long lines and less confidence in the system. While scholars have paid significant attention to the administrative reasons for poor voter

experiences at the polls, such as the elimination of polling locations, ballots themselves may lead to inter-jurisdictional differences in the voter experience (Herrnson et al. 2008a, 2008b).

Paper ballots are popular because they give election officials the ability to conduct a hand recount of election results. An additional benefit of paper ballots is the voter's ability to witness their votes being processed when they feed it into an optical scanner and see that it is accepted. When ballots are collected for scanning later, voters may feel concerned that their votes will fail to be counted, particularly among voters with low trust in the system. The other benefit of scanning ballots on-site is the scanner can alert the voter that there is an error on their ballot and give the voter the chance to correct it. Common errors in paper-based voting systems include the selection of too many candidates (overvote) in an electoral contest and marks on the ballot that cannot be read by the optical scanner.<sup>1</sup> However, other machine errors include issues, such as feeding two pages at once or trying to feed a folded ballot into the machine.

As a result, when voters submit their ballots using an optical scanner at the polls, there is the potential for a negative impact on the in-person voting experience. While a major benefit is that the voter can correct any ballot mistakes, each scanning issue can increase the time it takes to vote both for the voter and those standing behind them. Lines grow when voters are detained at the optical scanner because of either a human or machine issue or because the scanner jams or breaks down. Both frustration and increased distrust of the process occurs when voters face technical problems casting their ballots. Additionally, voters are disenfranchised by long wait times and technical issues as people are more likely to give up on voting as the time to vote increases (Cassidy, Colleen Long, and Balsamo 2018; Jackson 2000; Levine 2008). This increase in the time to vote and, particularly, long lines also impact voter confidence. Both King (2020) and Claassen et al. (2013) identify negative effects on voter confidence when voters experience irregularities and processing delays while voting.

As of 2016, 47% of registered voters throughout the United States live in a precinct that utilizes optical or digital ballot scanners. An additional 19% of voters live in precincts that utilize mixed systems that include ballot scanning devices and other voting machine types (DeSilver 2016). Every state and all US territories contain at least one jurisdiction that utilizes optical scanning devices (Verified Voting 2019). Many states, including Alabama, Connecticut, Iowa, Maine, and Rhode Island, utilize paper ballots and digital ballot scanning devices exclusively.

From a research perspective, optical scanning logs allow for an assessment of ballot characteristics and the presence of ballot errors. These logs create the potential to use data to prepare for elections in ways that can decrease voter and machine errors and decrease the likelihood of long lines in polling locations or unpleasant voter experiences (Cassidy, Colleen Long, and Balsamo 2018; Jackson 2000; Levine 2008; Pettigrew 2017). In this analysis, we use data generated by optical ballot scanners to understand how ballot characteristics affect the likelihood of voters making ballot marking errors or experiencing a machine–voter interaction error.

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<sup>1</sup>Optical scanner errors can be corrected by the voter in real-time because the machine allows the voter to resubmit the ballot having fixed the issue or override the machine and submit without adjustment. For example, in the case of an overvote, the scanner will prompt the user to choose to submit without correction or to eject the ballot for correction.

The findings indicate that ballot complexity significantly increases the likelihood voters will either make errors on their ballot or experience issues while interacting with the ballot-scanning machine. These results indicate that election administrators need to consider the complexity of the ballots being used in different jurisdictions in addition to the demographics and size of the precinct when allocating scanners and making staffing decisions for Election Day(s). Jurisdictions with longer, more complicated ballots should receive additional staff and scanning machines as administrators should expect an increased number of scanner issues and delays as the ballot becomes more complex. Moreover, districts whose ballots are complex and whose voters have lower socioeconomic status, our results suggest, do particularly require additional resources.

### Ballot Characteristics and Voting Errors

Scholarship investigating the relationship between ballot characteristics and overvotes and undervotes (Acemyan et al. 2015; Acemyan and Kortum 2017; Alvarez, Beckett, and Stewart 2011; Ansolabehere and Stewart 2005; Brady 2000; Bullock and Hood III 2002; Herrnson, Hanmer, and Niemi 2012; Kimball and Kropf 2005; Knack and Kropf 2003; Reilly and Richey 2011; Shocket, Heighberger, and Brown 1992) often finds that ballot design can impact ballot marking behavior. However, other types of errors that voters experience during the voting process have received considerably less attention. While some errors can affect election outcomes, others result in longer lines, voter frustration, and decreased voter efficacy and trust, but not necessarily the election's result. As a result, limiting the opportunities for voter errors and, subsequently, the quantity of voter errors that occur is critical. For this analysis, we define voting errors as—errors that occur during ballot marking (marking errors), the submission process (human-machine interaction [HMI] errors), and ballot processing (machine errors).

Like voting errors, ballot characteristics have many definitions in the ballot design literature. Studies that investigate ballot characteristics consider the complexity of ballot questions (Milita 2017; Niemi and Herrnson 2003; Reilly and Richey 2011), graphic design principles (e.g., the use of bolding, shading, positioning of questions, and candidates; Kimball and Kropf 2005), and ballot format (e.g., bubble ballots, connect the arrow ballots, punch-card ballots, digital ballots; Herrnson, Hanmer, and Niemi 2012; Bullock and Hood III 2002; Alvarez, Beckett, and Stewart 2011; Ansolabehere and Stewart 2005; Shocket, Heighberger, and Brown 1992; Hamilton and Ladd 1996). Here, we consider ballot characteristics that are mainly beyond election administrators' ability to control—primarily the ballot content that leads to increased complexity and ballot length. Voters in the United States are asked to vote on more offices and on more topics than most other countries, which increases the cost of voting and particularly the cost of gathering information on different offices and ballot questions—a characteristic of US elections that has been attributed to low voter turnout (Lijphart 1997). Election administrators have little to no administrative discretion over ballot length and complexity, such as the number of offices on which a voter is asked to vote, the wording and length of ballot questions, and how many questions are on the ballot. However, election administrators can plan for variable circumstances and make resource allocations that consider how ballot complexity differs across polls.

The complexity and length of a ballot are likely to lead to increases in errors for several reasons. The simplest reason is that the more questions asked or selections expected, the opportunities for voters to incorrectly mark a ballot or make some sort of error increases. While this is a likely explanation for voting errors, there are also implications regarding the psychological/physiological effects of long ballots on voting error. As Downs (1957) argues, the process of procuring, analyzing, and evaluating information carries a cost. The expected benefit of the time invested in reaching political decisions is minuscule compared with the benefits of spending one's time doing something more directly related to one's daily life. In the face of a lengthy and complicated ballot, voters may speed through and decrease the amount of time they spend reading carefully and making sure they select their choices correctly, particularly on races or questions they know little about or have little personal interest (Selb 2008).

Seib (2015) finds that "as the length of the ballot increases, voters become frantic, struggling to manage time and using different search and acquisition strategies" (p. 116) and that voters also spent significantly less time researching each candidate as the number of candidates increases. This indicates that the complexities of a ballot, both in length and question type, may also increase voting errors as voters attempt to hurry to get to the end of the ballot.

Survey research also finds the longer the survey, the fewer people complete the questionnaire, and, perhaps more importantly, questions that are positioned later in the survey are answered more quickly and more uniformly per participant (Galesic and Bosnjak 2009). The notion of "satisficing" was first introduced by Krosnick (1999). Krosnick proposed that respondents either devote considerable cognitive effort or little to no effort to answer survey questions. In the latter case, respondents may seek to generate answers quickly based on little thinking or minimal cognitive workload.

Higher education research finds mixed results of accuracy and exam length (Jensen, Berry, and Kummer 2013; Brunello, Crema, and Rocco 2018) in different circumstances. For example, Jensen, Berry, and Kummer (2013) find no effect in cognitive fatigue due to longer exams, but students perceive subjective fatigue the more prolonged the exam. We expect the process of casting ballots to be more similar to taking a survey than an exam or an incentivized survey due to the optional nature of the environment. Voters are not punished for making mistakes as they are in test environments, and there are no monetary or other external incentives for taking deliberate time to fill out the ballot. Instead, many people vote out of intrinsic motivation, such as civic duty or by a desire to vote on a single race, often at the top of the ticket. Therefore, the longer the ballot, the more likely voters will be asked to vote on issues and candidates they have never heard (Palfrey and Rosenthal 1983).

Regardless of the more complex interactions between ballot length and psychological effects on voters, ballot length is inherently expected to relate to voting errors due to the increase in opportunities for errors to occur as length increases (e.g., more questions mean more potential for errors). Despite this expectation or the reason for an increase in errors, the potential effects on the voting system remain; voting errors lead to delays in the ballot scanning process and, therefore, the potential for long voter wait times.

Finally, technical issues are also more likely to arise as the ballot's complexity and length increase simply because the process leads to more pages being entered into a machine. Thus, we expect that the longer the ballot, the more voters will experience errors when entering their ballots into the ballot-scanning machine.

1.	1004115,	10/17/2016,	09:33:40,	E,	0523022316061677,	P_LOG,	Vote Session Started
2.	3004101,	10/17/2016,	09:33:42,	E,	0523022316061677,	P_LOG,	IMR Log Characteristic Point Status Init 24 New 24
3.	1004111,	10/17/2016,	09:34:06,	E,	0523022316061677,	P_LOG,	Voter Accepted Overvoted Ballot
4.	1004107,	10/17/2016,	09:34:07,	E,	0523022316061677,	P_LOG,	Ballot images stored
5.	1004022,	10/17/2016,	09:34:07,	E,	0523022316061677,	P_LOG,	Voting session complete
6.	1004115,	10/17/2016,	09:34:30,	E,	0523022316061677,	P_LOG,	Vote Session Started
7.	3004101,	10/17/2016,	09:34:32,	E,	0523022316061677,	P_LOG,	IMR Log Characteristic Point Status Init 24 New 24
8.	1004107,	10/17/2016,	09:34:33,	E,	0523022316061677,	P_LOG,	Ballot images stored
9.	1004022,	10/17/2016,	09:34:33,	E,	0523022316061677,	P_LOG,	Voting session complete
10.	1004115,	10/17/2016,	10:57:08,	E,	0523022316061677,	P_LOG,	Vote Session Started
11.	3013001,	10/17/2016,	10:57:10,	E,	0523022316061677,	P_ERROR,	Ballot was removed during scanning. Please re-insert the ballot completely.
12.	1004115,	10/17/2016,	11:10:03,	E,	0523022316061677,	P_LOG,	Vote Session Started
13.	3004101,	10/17/2016,	11:10:05,	E,	0523022316061677,	P_LOG,	IMR Log Characteristic Point Status Init 15 New 15
14.	1004111,	10/17/2016,	11:10:10,	E,	0523022316061677,	P_LOG,	Voter Accepted Overvoted Ballot
15.	1004107,	10/17/2016,	11:10:11,	E,	0523022316061677,	P_LOG,	Ballot images stored
16.	1004022,	10/17/2016,	11:10:11,	E,	0523022316061677,	P_LOG,	Voting session complete

**Figure 1.** Excerpt raw DS200 ballot scanner log file.

*Note.* An error-free scanning observation is identified in Lines 6–9. Lines 10 and 11 identify an error that led to a returned ballot. Lines 1–5 indicate a scanning observation that contained an error but was accepted by the voter. The timestamps are used to calculate the duration of the corresponding observation.

## Data and Methods

Our data offer a unique and novel way to investigate ballot errors. These include three sources: (i) ballot scanner log files from in-person voting in each precinct in Rhode Island,<sup>2</sup> (ii) the characteristics of the ballot in each jurisdiction, and (iii) demographics from the 2016 five-year American Community Survey (ACS).

We attained the data on ballot errors from the Rhode Island Board of Elections (BOE). We utilize log files from ES&S DS200 optical scanners used in every precinct in Rhode Island for the 2018 RI Midterm election. The RI BOE distributed a total of 555 ballot scanners to 421 precincts statewide, and the RI BOE oversaw all precincts and voting machines.

DS200s record every action that the machine makes while in election mode and stores those actions in a transaction log. Figure 1 presents a sample DS200 log file for illustration purposes. Each data file per DS200 log contains an “event code” (i.e., an identification code that corresponds to an event type and description) for each attempt to use the machine. Each row of data directly corresponds to a recorded event within the machine. We cleaned the transaction log files and imported them into workable Comma Separated Variable (CSV) files from their raw log format for the analysis.

Log files record successful scans (i.e., when the scanner accepts a ballot) in the log files by identifying the beginning (i.e., “Vote Session Started”; ballot is inserted into the scanner) and end (i.e., “Voting Session Complete”; when the ballot is counted) of the interaction, as shown in Lines 6 and 9 in Figure 1, respectively. By identifying the starting and ending codes of scanning observations, we identified an event description for each corresponding scanning observation, thus identifying if the scan was error-free or not. Lines 1–5 in Figure 1 are an example of an observation that includes a ballot error. In the example, the voter accepted an overvote error, meaning that the voter was alerted to an overvote error on their ballot, but the voter chose to cast their ballot despite the error. Lines 10 and 11 in Figure 1 highlight an observation that

<sup>2</sup>Absentee ballots in Rhode Island are all processed by the State Board of Elections in a central processing center. As a result, our data do not include absentee ballots.

contained an error that resulted in the ballot being returned to the voter. In our analysis, the status of the ballot submission was identified as “Unsuccessful” if the scanner returned the ballot to the voter (Lines 10 and 11 in [Figure 1](#)) or “Successful” if the scanner accepted the ballot (Lines 1–5 and Lines 6–9 in [Figure 1](#)). A full breakdown of error types are provided in Supplementary Appendix A for all 555 DS200 logs with the number of observations and descriptive statistics on the durations of each observation. Supplementary Appendix B includes the amount of time errors held up the machine. These errors ranged from a single second on the lower bound to 80 minutes on the upper bound. The average delay with each error was 11 seconds. It is important to note that due to the scanning process’s anonymity, the DS200 does not record which sheet of a multi-sheet ballot is processed or where on the ballot the errors occurred. Thus, we cannot investigate if voters are more likely to make errors further along in the voting process (e.g., end of the ballot) or on specific questions, only if the occurrence of errors is correlated with length and complexity. Ballot length and complexity values are, therefore, total per ballot. With this limitation, we define the unit of analysis as the scanning event (i.e., the recorded interaction between the voter and the DS200) due to the lack of differentiation between a voter’s first attempt at scanning and their subsequent attempts in the presence of an error. This unit of analysis is expected to be larger than the number of ballots cast in the election due to the fact that some ballots are scanned more than once before a vote is completed. However, if this limitation affects the statistical analysis of these data, we expect it to bias our results away from finding evidence in favor of our hypothesis.

We used PDFs of the actual ballots for each of the 421 precincts to determine ballot length (an example is provided in Supplementary Appendix C). Finally, we normalized the scanning observation data and sample ballot data into a single database, resulting in the 416,657 scanning observations matched to precinct level ballot characteristics and voter demographics. A sample is available in Supplementary Appendix D. Since ballots are private, we do not have data on individual-level voter demographics; instead, we employ aggregate precinct-level voter demographics to account for variation between precincts that may affect the likelihood of ballot errors.<sup>3</sup> Demographics include median income (“Median Income”), the percent of the population with a bachelor’s degree or greater (“Percent College-educated”), and the percent of the population that do not identify as non-Hispanic White (“Percent non-White”).

### Coding of Ballot Length Measurements

Sample ballots contained a combination of four possible question types: state elected offices, local elected offices, state ballot questions, and local ballot questions. During the RI 2018 Midterm election, the ballots distributed resulted in 39 unique ballots, one for each jurisdiction.

We include several measures of ballot complexity and length, including the number of pages (i.e., sides of a ballot) with questions listed (“Pages”; ranging from

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<sup>3</sup>We obtained demographic data from the 2017 five-year ACS at the municipal level. At the precinct level, we used geo-referenced 2016 precinct voting location addresses in ArcGIS matched with census-tract level demographic statistics from the 2008–2012 ACS five-year estimates from (Prendergast et al. 2019). Only seven of the 421 active precincts in 2018 were different from those used in 2016. The BOE changed or newly established these seven after the 2016 election; resulting in the elimination of seven precincts in the models.



2 to 4 pages with an average of 2.31), the number of office-based questions (e.g., Senate, House, Governor, Statehouse, Town Council; “Office Questions”; ranging from 10 to 18 with an average of 12.30), and the number of local referendums (“Local Questions”; ranging from 0 to 10 with an average of 2.44). We also include the maximum number of candidates a voter is instructed to select (“Candidate Select”; ranging from 10 to 27 with an average from 16.36) to account for races, such as Town Council, in which voters are asked to vote for more than one candidate. We also include a binary variable for if the ballot included more than one language (“Bilingual”).<sup>4</sup> This is included as it directly impacts Rhode Island’s ballot length and complexity because bilingual ballots contain each question listed in English followed by the Spanish translation, which increases the total word count and total space used on a ballot without additional offices or questions. It also directly increases the complexity since questions appear twice and voters could become confused by this presentation.<sup>5</sup>

### Coding of Voting Error Types

We classified errors based on the system elements (i.e., the human and the machine) or their interactions (i.e., HMI) that cause the error to occur (Meadows and Wright 2015). To classify each DS200 error code, we evaluated the DS200 training manual (Election Systems and Software 2011, p. 7–8) and the observation description generated by the scanner log files. The category of “No Error” contains events that did not contain an error of any type. Any ballot scan that prompted voter interaction with the DS200 beyond the traditional submission process is considered an error due to its potential impact on the voting processes within a polling location (e.g., long lines, voter disenfranchisement, and distrust in the voting system). We classify physical errors that occurred while a voter was interacting with the machine as a “HMI” error, such as “multiple ballots detected” or “ballot was not inserted far enough” (e.g., Belton, Kortum, and Acemyan 2015). These HMI errors are based on the voter’s actions, for example, trying to insert two sheets together or inserting a folded ballot. We classify errors that occurred due to the programming of the machine or due to the device’s functionality as “Machine” errors (e.g., “ballot jam,” “error scanning ballot,” and “ballot could not be read”; Gautam and Singh 2015). The final classification is the “Marking” error, which contains events that were caused by inappropriate pen markings. “Marking” errors may be caused by voters creating marks on restricted areas of the ballot (i.e., “unreadable marks”), marking too many

<sup>4</sup>Based on the Voting Rights Act criteria (United States Department of Justice 2020) and ACS 2017 five-year survey data, three Rhode Island municipalities are required to distribute bilingual ballots: Providence, Pawtucket, and Central Falls. An additional municipality, Woonsocket, also distributes bilingual ballots due to special request (Office of the Secretary of State 2018).

<sup>5</sup>We also explored three other potential ways of measuring ballot complexity including a total questions variable and a total candidate selection variable. These variables included both the number of statewide questions and office questions added to the local number. These variables were correlated with local questions and local candidate selection variables at over 0.9. Since the local variation in ballot complexity is a product of the local questions and numbers of candidates, we include those only in the models. In addition, we ran municipality-level models. However, given our need to rely on aggregate demographics, the precinct level models are superior as they provide a higher degree of variability between precincts and this variability improves the model specifications. The municipal level modes are available upon request.

**Table 1.** Overall error rates by error type in the 2018 RI Midterm election

Error type	Error rate (%)	Odds of error	Number of observations
HMI	1.22	0.0123	4,983
Machine	1.57	0.0160	6,424
Marking	4.31	0.0451	17,612
No Error	92.90	13.076	379,455

*Note.* The number of observations are the number of scanning events. Scans with errors that are subsequently fixed are counted in both the applicable error category and in the No Error category.  
Abbreviation: HMI, human-machine interaction.

selections for a single question (e.g., “voter accepted/rejected an overvoted ballot”), or leaving the ballot blank (e.g., “voter accepted/rejected a blank ballot”). The total number of each type of error is included in Supplementary Appendix A.<sup>6</sup> Ballot characteristics are likely to have the most impact on human errors, here measured as HMI errors and Marking errors. However, we include Machine errors so that we do not exclude a potential area of errors and bias our models toward finding evidence of our hypotheses.

Utilizing these data, we test the following hypotheses:

H1: Longer ballots increase the odds of voting error occurrences.

H2: Ballots with more choices increase the odds of voting error occurrences.

## Results

Table 1 presents the error rates observed in the DS200 log files during the RI 2018 Midterm election. While over 90% of scans resulted in “No Error,” there are relatively large error rates (7.10%) given the context of events (29,019 observed errors). The most frequent errors are “Marking” errors (4.31%), followed by “Machine” (1.57%) and “HMI” (1.22%) errors.

Table 2 presents the bivariate relationship between the ballot characteristics and the different error types. The bivariate correlations suggest that our hypotheses are correct, in almost every case, our variables measuring the different elements of ballot complexity are positively correlated with ballot error, except in three cases: the number of pages, the number of Office Questions, and the number of candidate selections are negatively correlated with machine errors. To some extent, this is understandable as machine errors are those least likely to be associated with ballot characteristics. In addition, the negative relationship between pages and machine errors may be explained by the low probability of encountering ballot card related machine errors such as jams. This means that, in locations with multiple pages and ballot cards, the opportunity for encountering no error or other error types increases because the denominator increases so drastically.

<sup>6</sup>The different error types have different impacts on the time it takes to scan one’s vote. On average, votes submitted with no errors took an average of 2.89 seconds to process and ranged from 1 to 11 seconds with a standard deviation of 0.53 seconds. HMI errors caused delays of 2.46 seconds on average, ranging from 1 to 11 seconds with a standard deviation of 2.98 seconds. Machine errors caused the longest delays in machine use—with errors ranging from 1 second to 80 minutes, with an average delay of 13.27 seconds and a standard deviation of 139.27 seconds. Human marking errors had the second longest delays. These ranged from 2 seconds to 13.8 minutes with an average delay of 12.39 seconds and a standard deviation of 27.95 seconds.



**Table 2.** Effect of ballot characteristics on voting errors (correlation coefficients)

Variables	Any error	HMI	Machine	Marking
Ballot characteristics				
Pages	0.060***	0.086***	-0.012***	0.037***
Office questions	0.011***	0.003	-0.007***	0.016***
Local questions	0.043***	0.040***	8.51E-06	0.032***
Bilingual	0.054***	0.063***	0.001	0.033***
Candidate select	0.032***	0.040***	-0.028***	0.037***

Abbreviation: HMI, human-machine interaction.

\* $p < 0.0003$ .

\*\* $p < 0.00006$ .

\*\*\* $p < 0.000006$  (Bonferroni corrected).

**Table 3.** Effect of ballot characteristics on the logarithm of the odds of encountering voting errors (logistic regression models)

Variables	Any error	Type of error		
		HMI	Machine	Marking
Intercept	-3.293*** (0.061)	-6.857*** (0.169)	-3.168*** (0.129)	-3.790*** (0.075)
Ballot characteristics				
Pages	0.091*** (0.015)	0.981*** (0.045)	-0.189*** (0.031)	-0.049 (0.018)
Office questions	0.009 (0.005)	-0.014 (0.014)	0.024 (0.010)	0.006 (0.006)
Local questions	0.017*** (0.003)	-0.094*** (0.008)	0.048*** (0.006)	0.028*** (0.003)
Bilingual	0.318*** (0.018)	0.206*** (0.044)	0.137* (0.035)	0.356*** (0.023)
Candidate select	0.015*** (0.002)	0.024*** (0.005)	-0.059*** (0.004)	0.035*** (0.002)
Observations ( $n$ )	408,474	408,474	408,474	408,474
Pseudo $R^2$	0.008	0.016	0.016	0.016

Abbreviation: HMI, human-machine interaction.

\* $p < 0.0003$ .

\*\* $p < 0.00006$ .

\*\*\* $p < 0.000006$  (Bonferroni corrected).

Table 3 presents the models without demographic controls, and Table 4 presents the change in the odds of an error occurring for a one-unit increase in the independent variable to help translate the coefficients into meaningful statistics. Table 5 presents the models with the full set of demographic controls, and Table 6 presents the corresponding predicted change in odds. Tables 3 and 5 define the logistic regression model coefficients as well as the significance and standard error for each value. Effect significance is considered at a Bonferroni corrected  $\alpha$  of 0.0003.

Because our hypotheses are one-directional, we have no reason to expect an increase in ballot complexity to decrease errors, we focus here only on those items in which the models show a positive and statistically significant effect.

Within the models that do not include demographic variables (Tables 3 and 4), the models suggest that once accounting for the other types of ballot complexity characteristics, an increase in ballot pages results in an increased number of overall

**Table 4.** Effect of ballot characteristics in percent change of the odds of encountering voting errors (change in odds)

Variables	Any error	Type of error		
		HMI	Machine	Marking
Intercept	-96.287***	-99.895***	-95.792***	-97.741***
Ballot characteristics				
Pages	9.539***	166.813***	-17.222***	-4.819
Office questions	0.909	-1.416	2.468	0.555
Local questions	1.675***	-8.976***	4.943***	2.857***
Bilingual	37.461***	22.815***	14.712*	42.736***
Candidate select	1.560***	2.398***	-5.710***	3.599***
Observations (n)	408,474	408,474	408,474	408,474
Pseudo R <sup>2</sup>	0.008	0.016	0.016	0.016

Note. Coefficients represent the changes in odds for a one-unit increase in the variable. Change in odds is calculated by subtracting one from the exponentiated coefficients and then multiplying by 100 for the models in Table 2.

Abbreviation: HMI, human-machine interaction.

\*p < 0.0003.

\*\*p < 0.00006.

\*\*\*p < 0.000006 (Bonferroni corrected).

**Table 5.** Effect of ballot characteristics on the logarithm of the odds of encountering voting errors with demographic controls (logistic regression models)

Variables	Any error	Type of error		
		HMI	Machine	Marking
Intercept	-2.892*** (0.075)	-6.096*** (8.37E-06)	-3.213*** (6.61E-06)	-3.462*** (4.14E-06)
Ballot characteristics				
Pages	0.034 (0.016)	0.840*** (3.39E-05)	-0.186*** (1.84E-05)	-0.076*** (1.92E-05)
Office questions	-0.019* (0.005)	-0.036*** (1.02E-04)	0.014*** (7.46E-05)	-0.029*** (5.51E-05)
Local questions	0.02*** (0.003)	-0.073*** (5.75E-05)	0.046*** (1.97E-05)	0.028*** (4.54E-05)
Bilingual	0.114*** (0.026)	0.264*** (1.35E-05)	-0.035*** (9.70E-06)	-0.016*** (6.30E-06)
Candidate select	0.029*** (0.002)	0.028*** (1.55E-04)	-0.052*** (7.85E-05)	0.054*** (6.83E-05)
Demographics controls				
Percent college-educated	-0.009*** (0.001)	-0.011*** (2.49E-05)	-0.003*** (1.95E-05)	-0.010*** (7.15E-04)
Median income	1.54E-06*** (5.02E-07)	1.65E-06*** (3.09E-07)	1.72E-06*** (2.37E-07)	1.64E-06*** (3.82E-07)
Percent non-White	0.006 (0.001)	-0.004*** (5.96E-04)	0.006*** (5.47E-04)	0.010*** (3.29E-04)
Observations (n)	408,474	408,474	408,474	408,474
Pseudo R <sup>2</sup>	0.011	0.018	0.018	0.018

Abbreviation: HMI, human-machine interaction.

\*p < 0.0003.

\*\*p < 0.00006.

\*\*\*p < 0.000006 (Bonferroni corrected).

**Table 6.** Effect of ballot characteristics in percent change of the odds of encountering voting errors with demographic controls (change in odds)

Variables	Any error	Type of error		
		HMI	Machine	Marking
Intercept	−94.451***	−99.775***	−95.977***	−96.864***
Ballot characteristics				
Pages	3.416	131.748***	−16.990***	−7.321***
Office questions	−1.898*	−3.541***	1.394***	−2.843***
Local questions	2.024***	−7.013***	4.702***	2.828***
Bilingual	12.114***	30.174***	−3.431***	−1.610***
Candidate select	2.932**	2.876***	−5.038***	5.564***
Demographic controls				
Percent college-educated	−0.886***	−1.135***	−0.312***	−0.987***
Median income	1.54E-04***	1.65E-04***	1.72E-04***	1.64E-04**
Percent non-White	0.583	−0.353***	0.649***	1.012***
Observations ( <i>n</i> )	408,474	408,474	408,474	408,474
Pseudo <i>R</i> <sup>2</sup>	0.011	0.018	0.018	0.018

Note. Coefficients represent the changes in odds for a one-unit increase in the variable. Change in odds is calculated by subtracting one from the exponentiated coefficients and then multiplying by 100 for the models in Table 2.

Abbreviation: HMI, human-machine interaction.

\**p* < 0.0003.

\*\**p* < 0.00006.

\*\*\**p* < 0.000006 (Bonferroni corrected).

errors. In addition, an increase in the number of pages also increases the number of HMI errors. An additional ballot page has no significant effect on the probability of marking errors.

Likewise, once we consider the other elements of ballot complexity, additional office questions have no significant effect in any of the models. The addition of local ballot questions is significantly and positively related to an increase in the odds of encountering any error, machine errors, and marking errors. The effect of an additional candidate selection is significant and positively related to the likelihood of any error, specifically HMI and marking errors. Lastly, bilingual ballots are associated with increased errors across error types.

Table 4 helps us understand the magnitude of the results presented in Table 3. The results align with intuition: the number of pages of a ballot greatly increases the odds of experiencing an HMI error,<sup>7</sup> whereas having a ballot with two languages where questions are repeated dramatically increases the number of marking errors. Some of these increases are quite large: a single page increases the odds of an HMI error by 166%, and a bilingual ballot increases the likelihood of a marking error by 43%. Others are smaller; for example, adding a single local question to the ballot increases the likelihood of experiencing a marking error by 3% and a machine error by 5%.<sup>8</sup> Likewise, a one-unit increase in the number of candidates a voter is asked to select results in a 2% increase in the odds of experiencing an HMI error and a 4% increase in the odds of experiencing a

<sup>7</sup>There is a negative relationship between the number of pages and the likelihood of Machine errors, despite the positive relationship between pages and HMI errors.

<sup>8</sup>Despite the positive relationship between local questions and Marking and Machine errors, there is a negative relationship between local questions and HMI errors.

marking error.<sup>9</sup> While these numbers may appear small, they are compounded as a ballot adds more local questions or candidate selections. So far, our models suggest that different ballot characteristics have more/less effects on the likelihood of experiencing an error. These somewhat inconsistent and sometimes negative results make sense when one takes the model as a whole: the number of pages is intuitively more likely to increase the rate at which a ballot is incorrectly inserted than the likelihood of making a marking error when controlling for the other elements of the ballot (such as the number of questions and selections). Likewise, the presence of a second language should increase the rate of marking errors more than the likelihood of a machine error when controlling for the number of pages being processed.

Tables 5 and 6 add in our demographic controls to see if any probability of errors based on the ballot characteristics is still present when controlling for population-level variables. This is particularly important for our bilingual ballot variable: since bilingual ballots are only available in areas with larger non-English speaking populations, this coefficient could simply be a product of the population and not the ballot. Similarly, our models could be influenced by voter education levels and income.

Despite the addition of these controls, our models remain relatively consistent.<sup>10</sup> An increase in the number of pages is positively correlated with HMI errors. Additional local questions are positively associated with an increase in machine errors and marking errors. An increase in candidate selections is positively associated with HMI and marking errors. Finally, bilingual ballots remain significant for HMI errors. However, once we account for population demographics, bilingual ballots no longer have significant correlations with machine or marking errors. Overall, the introduction of controls helps clarify that some errors are more likely in towns with high levels of non-White voters, and higher population-level education is correlated with fewer errors. However, even once we account for these demographic controls, ballot characteristics remain a source of increased scanning errors.

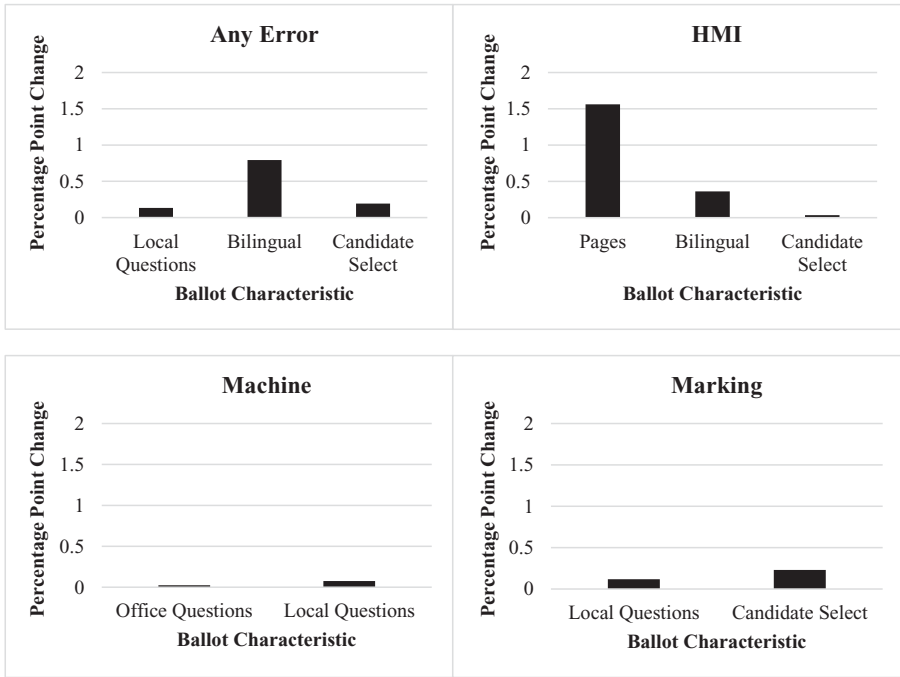
To understand the substantive effect of our findings, from here on we focus only on the results of the model that includes demographic controls (Tables 5 and 6). Figure 2 presents the percentage point increases in errors for a one-unit increase in the significant ballot characteristics compared to the observed percent error (Table 1). We focus here only on those that have a significant increase in the number of errors since we have a one-directional hypothesis, and there is no reason that we would expect a decrease in errors with more ballot complexity.

Overall, we find that there would be an increase in the percent of any errors occurring by 0.13 percentage points for a single additional local question,<sup>11</sup> 0.79

<sup>9</sup>The number of candidate selections has a negative relationship with Machine errors, demonstrating an opposite directionality compared to Marking and HMI errors.

<sup>10</sup>In the models with demographic controls, the number of Office Questions gains significance exhibiting a negative relationship with Any Error, HMI errors, and Marking errors. Office Questions, however, increases the likelihood of Machine errors.

<sup>11</sup>Percentage point change in expected errors is calculated by first generating the expected odds from the estimated percent change in odds. These expected odds are converted into an expected percent of errors. Finally, we take the difference between the expected percent of errors and the actual percent of errors (Table 1) to determine the percentage point change. For example, the odds of any error are 0.0765. The expected odds with a unit increase in local question are 0.0780 (i.e.,  $0.0765 + 0.0765 \times 2.024\%$ ). Converting this into an estimated percent results in an any error rate of 7.24% (i.e.,  $0.0780/[0.0780 + 1]$ ). Compared to the actual percent errors (i.e., 7.10%) the expected percent errors is larger by 0.13 percentage points.



**Figure 2.** Effect of ballot length increase on ballot Errors.

*Note.* Graphs present the change in the percent of errors, out of the total scanning observations, expected with an additional unit of ballot length (and distributing a bilingual ballot as opposed to a monolingual ballot).

percentage points if there is a bilingual ballot, and 0.19 percentage points for an additional candidate selection. Substantively, in our sample, an increase of about 545 errors would result for each additional local ballot question, 3,238 more errors when there is a bilingual ballot, and 789 more errors for each additional candidate selection.

Looking specifically at the types of errors, we find that the percent of expected HMI errors increases by 1.56 percentage points for each additional page, which in our data equates to an additional 6,383 HMI errors. Likewise, for an additional candidate selection listed on the ballot, we find a 0.03 increase in the expected percent of HMI errors. Again, in our sample, that would be approximately 142 additional HMI errors. Finally, bilingual ballots increase the percentage of HMI errors by 0.36 percentage points (or an increase of 1,480 errors given our  $N$ ).

Machine errors increase by 0.02 percentage points for an additional office question on the ballot. Again, using our data, that would be an expected increase of 89 additional machine errors. Furthermore, there is an increase of 0.08 percentage points in the expected percent of machine errors (i.e., an increase of 298 errors) with an additional local question. Finally, marking errors go up by 0.12 percentage points with each additional local question and 0.23 percentage points with each additional

candidate selection. In our data, this corresponds to an additional 477 and 936 additional errors, respectively.

While the percentage point changes may appear small, given the number of voters who vote in an election, the percentage point increases are substantively meaningful. Particularly given that errors result in voters having to take between 1 second and 80 minutes longer to vote.<sup>12</sup> This means that an increase of a few hundred errors can drastically increase the amount of time a voter (and those behind them in line) spends casting their ballot and a meaningful difference in how a voter experiences voting.

## Discussion

In this paper, we find that measures of ballot length affect specific types of voting errors (i.e., HMI, Machine, and Marking). Our findings generally align with Selb (2008), even though we approached the research differently: ballot length and complexity affect voting error rates.

The models presented demonstrate that ballot length and ballot complexity affect the odds of experiencing voting errors. The additional significance of demographic variables indicates that, in general, areas of lower educational attainment and median income experienced more voting errors. Communities with larger percentages of non-White voters experienced increases in the odds of machine and marking errors. This information alone is important from a resource planning and voter education perspective. These findings can help identify areas that require additional voter education material, extra personnel to assist voters through the voting processes, and precincts that may benefit from more resources, such as additional scanners. For example, machine errors, such as ballot jams, were correlated with lower education and more non-White voters. These areas may require additional machines and resources so that there are alternative ways to process a ballot when one is out of use due to a machine error.

Further, these findings identify that resource allocation plans should be adjusted to equitably accommodate voters and poll workers at the precinct-level rather than treating all precincts as equal. The number of poll workers and voting equipment are determined frequently only by the number of expected voters. Nevertheless, our models show that in elections with more complex ballots, dealing with machine jams, human-machine errors, and marking errors are likely to cause delays indicating the need for election officials to consider both ballot complexity and precinct-level demographics when preparing for elections. Likewise, and more to the point, with respect to ballot characteristics, our models indicate that increases in the number of ballot pages, local ballot questions, and the number of candidate selection opportunities increase the odds of voting errors. Considering the error rates in Table 1, 1.22% of Rhode Island scans contained a “HMI” error. The models imply that adding a single ballot page across all precincts would increase the odds of “HMI” errors by

<sup>12</sup>HMI Errors: Min. Scan Time (Min. ST) = 1 second, Average Scan Time (AST) = 2.46 seconds, Max. Scan Time (Max. ST) = 11 seconds; Machine Errors: Min. Scan Time = 1 second, AST = 13.27 seconds, Max. ST = 4782 seconds (79.7 minutes); Marking Errors: Min. ST = 2 seconds, AST = 12.39 seconds, Max. ST = 826 seconds (13.9 minutes).

131.75%—an increase in the error rate to 2.78% (or an increase of 6,383 errors with 11,366 total “HMI” errors).

Using these data, election officials in jurisdictions that utilize paper ballots can use the characteristics of their ballots to help determine the number of poll workers and machines needed to run Election Day(s) smoothly and efficiently, decrease the amount of time voters spend casting their ballots, and increase the reliability of the results. Signage can be implemented to remind people of how many pages there are and how to fill in a multiple language ballot correctly in locations with complicated ballots. Additionally, the number of poll workers and the amount of voting equipment can be increased to decrease the wait time for those who would otherwise be held up by someone who has made an error on their ballot or jammed the machine.

As with all research, our data had several limitations that future research could improve. Since our data source is an anonymous account of ballot scanning events, it is impossible to determine a voter’s intention. Thus, this methodology considers all blank ballots as errors, regardless of voter intention. Future research could employ experimental designs to investigate and elaborate on this finding further, however, the proportion of this Marking error was relatively small (i.e., 14.4% of Marking errors and <1% of all observations) minimizing the effect of this limitation. Specific voter characteristics, such as their level of experience with the ballot type or ballot scanner, cannot be captured from anonymous data. These factors may affect the odds of experiencing voting errors, although they must be observed via controlled experimentation to protect voter anonymity. Another limitation within this analysis is that the undervote voting error (i.e., when some questions on a ballot are not marked while others are) is unable to be addressed because the scanner does not log a single skipped question as an error.<sup>13</sup> Future research should assess how a ballot affects the odds of voting errors from a more holistic perspective. Additional research can also be conducted for different types of elections (e.g., midterm elections and primary elections). Additional scanning or ballot marking devices should be included and statistically controlled to further improve this model’s robustness. Including other state/county specific variables would allow for the assessment of a broader range of ballots.

Furthermore, our dataset only contains observations from in-person ballot scanning. Marking errors pose a particular issue to alternative voting methods, such as vote-by-mail and absentee voting, in which ballots are centrally scanned and counted. While an in-person voter has the opportunity to correct errors on their ballot, assuming they cast their ballot into a scanner themselves, a centrally counted ballot with marking errors has little to no opportunity to be corrected (Alvarez, Beckett, and Stewart 2011). Given the push toward vote-by-mail/absentee ballots during the 2020 General Election due to the Coronavirus Pandemic (Sepulveda and Jacobson 2020), the impact of a voter’s inability to correct ballot errors must be better understood. These research methods can be applied to alternative voting systems, such as central cast (e.g., vote-by-mail and absentee voting), to quantify the effect of errors in an environment where voters do not have the ability to address them.

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<sup>13</sup>DS200s do include the option to track undervotes, however, election administrators do not use this function over concerns regarding the number of errors flagged and the subsequent increase in delays in the voting process. The associated increase in ballot scanning time would require additional resources (e.g., scanning machines and election workers) for the operation of an election.



Overall, however, the “big data” available in ballot scanning logs, such as the 555 logs we utilize here totaling 1,306,378 lines of code, may prove to be a good source for future research on these questions.

## Conclusions

Through our analysis, we find further support that there is an effect of ballot length and ballot complexity on voting error. While more complex ballots increase the voter’s ability to participate in democratic governance, one of the consequences is an increase in voting errors, which can lead to long wait times and voter disenfranchisement, and low voter confidence (Ansolabehere and Shaw 2016; Everett, Byrne, and Greene 2006).

Additionally, we have provided a methodology for processing and analyzing ballot-scanning machine log files and applied statistical methods to assess ballot-scanning and marking errors that others may use in future studies to test these effects under other conditions in different contexts. From a data perspective, we demonstrate the value of log files generated from voting equipment. While difficult to obtain, voting equipment log data provide insight into voting systems, voter behavior, and voter disenfranchisement that would otherwise be challenging or impossible to holistically capture, let alone in observations. Finally, our results suggest that assessing the ballots distributed to voters *before* an election can provide insight into estimated marking and scanning error behavior, which could assist with effective election preparation.

**Supplementary Materials.** To view supplementary material for this article, please visit <http://doi.org/10.1017/spq.2021.24>.

**Data Availability Statement.** Replication materials are available on SPPQ Dataverse at <https://doi.org/10.15139/S3/SlAZLY> (Pearson-Merkowitz et al. 2021).

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## References

- Acemyan, Claudia Z., and Philip Kortum. 2017. “Assessing the Usability of the Hart InterCivic ESlate During the 2016 Presidential election.” *Proceedings of the Human Factors and Ergonomics Society Annual Meeting* 61: 1404–8. <https://doi.org/10.1177/1541931213601835>.
- Acemyan, Claudia Z., Philip Kortum, Michael D. Byrne, and Dan S. Wallach. 2015. “From Error to Error: Why Voters Could Not Cast a Ballot and Verify Their Vote with Helios, Prêt à Voter, and Scantegrity II.” *Journal of Election Technology and Systems (JETS)* 3 (2) 1–25.
- Alvarez, R. Michael, Dustin Beckett, and Charles Stewart III. 2011. “Voting Technology, Vote-by-Mail, and Residual Votes in California, 1990–2010.” *Political Research Quarterly* 66 (3): 658–70.

- Alvarez, R. Michael, Thad E. Hall, and Morgan H. Llewellyn. 2008. "Are Americans Confident Their Ballots are Counted?" *Journal of Politics* 70 (3): 754–66.
- Ansolabehere, Stephen, and Daron Shaw. 2016. "Assessing (and Fixing?) Election Day lines: Evidence from a survey of local election officials." *Electoral Studies* 41: 1–11. <https://doi.org/10.1016/j.electstud.2015.10.010>.
- Ansolabehere, Stephen, and Charles Stewart III. 2005. "Residual Votes Attributable to Technology." *The Journal of Politics* 67: 365–89. <https://doi.org/10.1111/j.1468-2508.2005.00321.x>.
- Belton, M. Grant, Philip Kortum, and Claudia Acemyan. 2015. "How Hard Can It Be to Place a Ballot into a Ballot Box? Usability of Ballot Boxes in Tamper Resistant Voting Systems." *Journal of Usability Studies* 10 (4): 129–39.
- Bracken, Kassie, Alexandra Eaton, and Noah Throop. 2020. "Why Voting in This U.S. Election Will Not Be Equal" (video). *The New York Times*, September 27, 2020. <https://www.nytimes.com/video/us/elections/10000006810942/voter-suppression-georgia.html>.
- Brady, Henry E. 2000. *Report on Voting and Ballot Form in Palm Beach County*. Berkeley: University of California. <http://www.skirsch.com/politics/election2000/brady.pdf>.
- Brunello, Giorgio, Angela Crema, and Lorenzo Rocco. 2018. "Testing at Length If It Is Cognitive or Non-Cognitive." IZA Discussion Paper No. 11603. <https://ssrn.com/abstract=3205890>.
- Bullock III, Charles S., and M. V. Hood III. 2002. "One Person—No Vote; One Vote; Two Votes: Voting Methods, Ballot Types, and Undervote Frequency in the 2000 Presidential Election." *Social Science Quarterly* 83 (4): 981–93.
- California Institute of Technology and The Massachusetts Institute of Technology. 2001. "Voting – What Is, What Could Be." Report. California Institute of Technology and the Massachusetts Institute of Technology Corporation. <http://vote.caltech.edu/reports/1>.
- Cassidy, Christina A., Colleen Long, C., and Michael Balsamo. 2018. "Long Lines, Machine Breakdowns Mar Vote on Election Day." *Providence Journal*, November 7, 2018. <https://www.providencejournal.com/news/20181106/long-lines-machine-breakdowns-mar-vote-on-election-day>.
- Chen, M. Keith, Kareem Haggag, Devin G. Pope, and Ryne Rohla. 2020. "Racial Disparities in Voting Wait Times: Evidence from Smartphone Data." Working Paper 26487. NBER Working Paper Series.
- Claassen, Ryan L., David B. Magleby, J. Quin Monson, and Kelly D. Patterson. 2013. "Voter Confidence and the Election-Day Voting Experience." *Political Behavior* 35: 215–35.
- DeSilver, Drew. 2016. "Most U.S. Voters Use Electronic or Optical-Scan Ballots." *Pew Research Center*, November 8. [www.pewresearch.org/fact-tank/2016/11/08/on-election-day-most-voters-use-electronic-or-optical-scan-ballots/](http://www.pewresearch.org/fact-tank/2016/11/08/on-election-day-most-voters-use-electronic-or-optical-scan-ballots/).
- Downs, Anthony. 1957. "An Economic Theory of Political Action in a Democracy." *Journal of Political Economy* 65 (2): 135–150.
- Election Systems and Software. 2011. *DS200 Precinct Ballot Scanner Election Day Training Manual*. [https://sos.idaho.gov/elect/clerk/DS200%20Procedures/U3400\\_TRN00\\_DS200\\_Election.pdf](https://sos.idaho.gov/elect/clerk/DS200%20Procedures/U3400_TRN00_DS200_Election.pdf).
- Everett, Sarah P., Michael D. Byrne, and Kristen K. Greene. 2006. "Measuring the Usability of Paper Ballots: Efficiency, Effectiveness, and Satisfaction." *Proceedings of the Human Factors and Ergonomics Society* 50: 2547–2551.
- Galesic, Mirna, and Michael Bosnjak. 2009. "Effects of Questionnaire Length on Participation and Indicators of Response Quality in a Web Survey." *Public Opinion Quarterly* 73 (2): 349–60. <https://doi.org/10.1093/poq/nfp031>.
- Gautam, Ritu, and P. Singh. 2015. "Human Machine Interaction." *International Journal of Science, Technology & Management* 4 (1): 188–93.
- Greene, Kristen K., Michael D. Byrne, and Stephen N. Goggin. 2013. "How To Build an Undervoting Machine: Lessons from an Alternative Ballot Design." *Journal of Election Technology and Systems (JETS)* 1: 38–52.
- Hamilton, James T., and Helen F. Ladd. 1996. "Biased Ballots? The Impact of Ballot Structure on North Carolina Elections in 1992." *Public Choice* 87: 259–80. <https://doi.org/10.1007/bf00118648>.
- Herrnson, Paul, Richard G. Niemi, Michael J. Hanmer, Benjamin B. Bederson, Frederick G. Conrad, and Michael W. Traugott. 2008b. *Voting Technology: The Not-So-Simple Act of Casting a Ballot*. Washington, DC: Brookings Institution Press.
- Herrnson, Paul S., Michael J. Hanmer, and Richard G. Niemi. 2012. "The Impact of Ballot Type on Voter Errors." *American Journal of Political Science* 56 (3): 716–30.

- Herrnson, Paul S., Richard G. Niemi, Michael J. Hanmer, Peter L. Francia, Benjamin B. Bederson, Frederick G. Conrad, and Michael W. Traugott. 2008a. "Voters' Evaluations of Electronic Voting Systems." *American Politics Research* 36 (4): 580–611.
- Jackson, Brooks. 2000. "Punch-Card Ballots Notorious for Inaccuracies." *Cable News Network*, November 15, 2000. <http://www.cnn.com/2000/ALLPOLITICS/stories/11/15/jackson.punchcards/>.
- Jensen, Jamie L., Dane A. Berry, and Tyler A. Kummer. 2013. "Investigating the Effects of Exam Length on Performance and Cognitive Fatigue." *PLoS ONE* 8 (8): 1–9. <https://doi.org/10.1371/journal.pone.0070270>.
- Kimball, David C., and Martha Kropf. 2005. "Ballot Design and Unrecorded Votes on Paper-Based Ballots." *Public Opinion Quarterly* 69: 508–29. <https://doi.org/10.1093/poq/nfi054>.
- King, Bridgett A. 2020. "Waiting to Vote: The Effect of Administrative Irregularities at Polling Locations and Voter Confidence." *Policy Studies* 41 (2–3): 230–48. <https://doi.org/10.1080/01442872.2019.1694652>.
- Knack, Stephen, and Martha Kropf. 2003. "Roll-Off at the Top of the Ballot: International Undervoting in American Presidential Elections." *Politics & Policy* 31 (4): 575–94.
- Krosnick, Jon A. 1999. "Survey Research." *Annual Review of Psychology* 50: 537–567.
- Levine, Samantha. 2008. "Hanging Chads: As the Florida Recount Implodes, the Supreme Court Decides Bush v. Gore." *U.S. News & World Report*, January 17, 2008. [www.usnews.com/news/articles/2008/01/17/the-legacy-of-hanging-chads](http://www.usnews.com/news/articles/2008/01/17/the-legacy-of-hanging-chads).
- McCadney, Andrea C. and Lawrence Norden. 2020. "Georgia Ballot Design Problems and What to Do About Them." *Brennan Center for Justice*, September 30. <https://www.brennancenter.org/our-work/research-reports/georgia-ballot-design-problems-and-what-do-about-them>.
- Lijphart, Arend. 1997. "Unequal Participation: Democracy's Unresolved Dilemma." *American Political Science Review* 91 (1): 1–14. <https://doi.org/10.2307/2952255>.
- Meadows, Donella H., and Diana Wright. 2015. *Thinking in Systems: A Primer*. Hartford, VT: Chelsea Green Publishing.
- Milita, Kerri. 2017. "Beyond Roll-off: Individual-Level Abstention on Ballot Measure Voting." *Journal of Elections, Public Opinion and Parties* 27 (4): 448–65.
- Niemi, Richard G., and Paul S. Herrnson. 2003. "Beyond the Butterfly: The Complexity of U.S. Ballots." *Perspective on Politics* 1: 317–26. <https://doi.org/10.1017/s1537592703000239>.
- Office of the Secretary of State. 2018. "Press Releases: Bilingual Ballots to Be Used in Woonsocket." *RI.gov*, October 19, 2018. [ri.gov/press/view/34462](http://ri.gov/press/view/34462).
- Palfrey, Thomas R., and Howard Rosenthal. 1983. "A Strategic Calculus of Voting." *Public Choice* 41: 7–53.
- Pearson-Merkowitz, Shanna; Bernardo, Nicholas D.; Macht, Gretchen, 2021, "Replication Data for "The Effect of Ballot Characteristics on the Likelihood of Voting Errors." UNC Dataverse. Dataset. <https://doi.org/10.15139/S3/SIAZLY>.
- Pettigrew, Stephen. 2017. "The Racial Gap in Wait Times: Why Minority Precincts Are Underserved by Local Election Officials." *Political Science Quarterly* 132 (3): 527–47.
- Prendergast, P., S. Pearson-Merkowitz, and C. Lang. 2019. "The Individual Determinants of Support for Open Space Bond Referendums." *Land Use Policy* 82: 258–268.
- Reilly, Shauna, and Sean Richey. 2011. "Ballot Question Readability and Roll-off: The Impact of Language Complexity." *Political Research Quarterly* 64 (1): 59–67.
- Seib, J. Drew. 2015. "Coping with Lengthy Ballots." *Electoral Studies* 43: 115–23. <https://doi.org/10.1016/j.electstud.2016.05.011>.
- Selb, Peter. 2008. "Supersized Votes: Ballot Length, Uncertainty, and Choice in Direct Legislation Elections." *Public Choice* 135: 319–36. <https://doi.org/10.1007/s11127-007-9265-7>.
- Sepulveda, José, and Lindsey Jacobson. 2020. "Lawmakers Push for Vote by Mail in Response to Coronavirus Pandemic." *CNBC*, April 6, 2020. <https://www.cnbc.com/2020/04/06/coronavirus-election-lawmakers-push-for-vote-by-mail.html>.
- Shocket, Peter A., Neil R. Heighberger, and Clyde Brown. 1992. "The Effect of Voting Technology on Voting Behavior in a Simulated Multi-Candidate City Council Election: A Political Experiment of Ballot Transparency." *Political Research Quarterly* 45 (2): 521–37.
- Sinclair, Robert C., Melvin M. Mark, Sean E. Moore, Carrie A. Lavis, and Alexander S. Soldat. 2000. "An Electoral Butterfly Effect." *Nature* 408: 665–6. <https://doi.org/10.1038/35047160>.

- Stein, Robert M., Christopher Mann, Charles Stewart III, Zachary Birenbaum, Anson Fung, Jed Greenberg, Farhan Kawsar, *et al.* 2019. "Waiting to Vote in the 2016 Presidential Election: Evidence from a Multi-County Study." *Political Research Quarterly* 73 (2): 439–53.
- United States Department of Justice. 2020. "About Language Minority Voting Rights." *The United States Department of Justice*, March 11, 2020. <https://www.justice.gov/crt/about-language-minority-voting-rights>.
- Verified Voting. 2019. "The Verifier—Polling Place Equipment—November 2020." <https://www.verifiedvoting.org/verifier/#>.

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