2019

QUANTIFICATION OF VOTING ERROR: THE 2018 RHODE ISLAND MIDTERMS

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QUANTIFICATION OF VOTING ERROR:
THE 2018 RHODE ISLAND MIDTERMS

BY
NICHOLAS D. BERNARDO

A THESIS SUBMITTED IN PARTIAL FULFILLMENT OF THE
REQUIREMENTS FOR THE DEGREE OF
MASTER OF SCIENCE
IN
SYSTEMS ENGINEERING

UNIVERSITY OF RHODE ISLAND

2019

MASTER OF SCIENCE THESIS

OF

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2019

Abstract

Studies pertaining to election systems have historically identified paper-based voting systems as better performing than most voting system alternatives. Despite this, there is a lack of literature exploring the use of paper ballots from an in-depth perspective. This study investigates different metrics of ballot length (i.e., words, questions, selections, pages, sheets, and bilingual) and how they impact voting errors (i.e., machine-based errors, human-machine interaction errors, and ballot marking errors) during the 2018 Midterm election in Rhode Island. Logistic regression models are developed to measure the relationship between ballot length and voting errors while controlling for municipal and precinct level demographics. The findings indicate that areas with longer ballots and urban areas significantly increase the odds of encountering voting errors. Among the most contributing measures are the number ballot pages, the number of local questions, and the number of candidate selections allowed on a ballot. These factors significantly increased the odds of experiencing voting errors, in some cases as high as 160%. The statewide impact of these errors is presented and opportunities for future work are shared.

Acknowledgement

I would like to give a special thanks to my academic advisor, Dr. Macht. Thanks to Dr. Macht and the SIS Lab, I have found a love for research and plan to continue conducting it into the foreseeable future. Keep changing the world, Dr. Macht, and continue to do it in *your* way.

Additionally, I would like to thank Rachel Bartels and James Houghton, my teammates throughout the RI VOTES project. Rachel played a critical role in supporting me as a student and person in the short time that we worked together. Without her encouragement, I would have never had the confidence to pursue a master's degree, let alone a PhD which I plan on pursuing in the near future. And of course, James has always been there to share his knowledge and expertise to help not only his teammates, but anyone he sees in need. Without his programming and statistics skills, the RI VOTES project would not have accomplished nearly what it has.

I would also like to thank my committee members, Dr. Sperdelozzi, Dr. Pearson-Merkowitz, and Dr. Shwartz for sharing their knowledge and feedback with me throughout the development of my thesis.

Another thanks belong to the Democracy Fund for funding my research as well as the Rhode Island Board of Elections for their willingness to share their expertise and data with the RI VOTES team.

And finally, I would like to thank my friends and family who were extraordinarily understanding when plans were cancelled, and my attention was elsewhere due to my studies. They were always in support of my decisions and encouraged me to follow my own path. Thank you all very much!

Preface

This thesis is written in a format for submission to the Journal of Electoral Studies. There is no strictly required format, so the Author's Guide states the following:

“Formatting requirements: There are no strict formatting requirements but all manuscripts must contain the essential elements needed to convey your manuscript, for example Abstract, Keywords, Introduction, Materials and Methods, Results, Conclusions, Artwork and Tables with Captions. If your article includes any Videos and/or other Supplementary material, this should be included in your initial submission for peer review purposes. Divide the article into clearly defined sections,” (Electoral Studies Author's Guide, 2019).

Therefore, this thesis follows a general manuscript format with page layout following that required by the URI Masters Thesis guide.

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Beginning of the Manuscript “Quantification of Voting Error: The 2018 Rhode Island Midterms”

This manuscript is prepared for submission to the Journal of Electoral Studies.

Introduction

Throughout the United States (U.S.), as of 2016, 47% of registered voters lived in a precinct that utilized optical or digital ballot scanners with an additional 19% of voters living in precincts that utilize both direct recording-electronics (DRE) and optical/digital ballot scanning devices (DeSilver, 2016). These statistics indicate that 74 million voters, in 2016, cast a ballot on an optical/digital ballot scanner while another 29.9 million used either a DRE or an optical/digital scanner (Census Bureau, 2018). These voting systems also continue to show prevalence as institutions encourage the development of Voter Verifiable Paper Audit Trail (VVPAT) compatible systems, of which paper-based ballot scanners show promise (Hall, 2006; Goggin, Byrne, Gilbert, Rogers, and McClendon, 2008). With such an overarching reach within the election system, optical/digital ballot scanners are a key piece of voting equipment to be investigated. These devices indicate when errors occur on a per-ballot sheet basis, indicating that a voter may have selected too many candidates (overvote), generated unreadable marks, or experienced difficulties when interacting with the ballot scanner, all of which have the potential of causing long lines within polling locations and disenfranchising voters. Having access to this error information allows for an assessment of the current state of election systems, as voting technology in recent history has been blamed for voter disenfranchisement and long lines in polling locations (Cassidy, Long, Balsamo, 2018; Jackson, 2000; Levine, 2008). Many states utilize paper ballots and digital ballot scanning devices, exclusively (e.g., Alabama, Connecticut, Iowa, Maine, Rhode Island); thus, with access to ballot scanner data (i.e., log files) and corresponding ballots (i.e., ballot characteristics), an investigation of voting errors associated with ballot scanning can occur.

This article presents an analysis that utilizes data generated by ballot scanners and ballot characteristics. Relationships between ballot length and voting errors are identified while controlling for *municipal level* and *precinct level* demographics, exploring the impact that ballot length has on voting errors in paper-based voting systems. To summarize the goals of this article, the following research questions are presented:

R1: Does ballot length impact the odds of encountering a voting error?

R2: If so, how does ballot length impact the odds of encountering a voting error?

Literature Review

Research on voting errors and ballot characteristics has been conducted from several perspectives throughout voting machine and ballot design literature, although the measure of voting error often differs between studies. Lacking a formal definition, “voting error” is classified in the literature as unrecorded votes (Kimball & Kropf, 2003; Kimball & Kropf, 2005; Acemyan, Kortum, Byrne, & Wallach, 2015), roll-off (Reilly & Richey, 2011), residual votes (Ansolabehere & Stewart, 2005; Alvarez, Beckett, & Stewart, 2011), unintentional undervotes and unintentional candidate selection (Herrnson, Hanmer, & Niemi, 2012; Brady, 2000), or purely undervotes (Schocket, Heighberger, & Brown, 1992; Bullock & Hood, 2002). One commonality between these definitions is that the errors are observed after the voting process takes place with no potential for correction, presenting a focus on the impact of errors on election results. A different perspective that goes largely unconsidered is the impact on voters themselves. Examining ballot scanner log files identifies that there are many more types of errors that can occur while marking and scanning a ballot that may not always impact election results but impact the time a voter spends in a polling location. Thus “voting error” in this paper is defined as errors that occur

during the ballot marking (i.e., marking) and scanning process (i.e., human-machine interaction and machine) as observed by the ballot scanner. While there are many potential causes of voting errors, the potential impact of many ballot characteristics has not been investigated.

Like voting errors, *ballot characteristics* have many definitions in ballot design literature. Studies that investigate *ballot characteristics* consider the complexity of ballot questions (Reilly & Richey, 2011; Milita, 2017), graphic design principles (e.g., the use of bolding, shading, positioning of questions and candidates) (Kimball & Kropf, 2005), and ballot format (e.g., bubble ballots, connect the arrow ballots, punch card ballots, digital ballots) (Herrnson, Hanmer, & Niemi, 2012; Bullock & Hood, 2002; Alvarez, Beckett, & Stewart, 2013; Ansolabehere & Stewart, 2005; Shocket, Heighberger, & Brown, 1992). Another ballot characteristic that has been investigated is ballot length (i.e., the number of questions on a ballot) which increased the variability of a voter's propensity to respond 'yes' or 'no' on Swiss referendums (Selb, 2008). While this study did not explicitly investigate voting error, an effect of ballot length was observed.

While ballot length has been theorized to impact nonresponse rates (i.e., undervotes and blank ballots) (Walker, 1966; Taebel, 1975), little is known about its effects on other types of voting errors (e.g., ballot scanner errors, marking errors). Anecdotally, Elections Officials consider ballot length to be a likely cause of voting errors and literature identifies some effect on voter response variability (Selb, 2008). Despite these implications, direct effects of ballot length on roll-off are found to be insignificant (Reilly & Richey, 2011). Limited studies investigate the impact of ballot length in real elections and those that do consider only a partial measure of ballot length (e.g., word count) (Reilly & Richey, 2011).

The distinct differences in these bodies of work indicate that there is a need for more investigation into the impacts of ballot length on elections, especially with respect to understanding voting error in a real election.

The literature investigating ballot length has conflicting findings regarding its impact on voting. The work of Selb (2008), being one of the few works focusing exclusively on ballot length, identifies that there is in fact some impact of ballot length on elections. However, the study performed in Selb (2008) focusses on Swiss elections and utilizes simulated results. To gain a better understanding of the impact of ballot length, a real Midterm election is investigated. Voting errors are utilized as a proxy for election impact, as they present a cause of delays and voter disenfranchisement in voting systems for individual voters.

H1: Longer ballots lead to an increase in the odds of voting error occurrences.

Methodology

The 2018 Rhode Island and Providence Plantations Midterm election was assessed on the *municipal level* and *precinct level* to explore the impact of ballot length on the odds of voting errors. Data collected from ballot scanner (DS200) log files, sample ballots, and the American Community Survey (ACS) was used to perform four logistic regression models (i.e., municipal level general model, precinct level general model, municipal level differentiated model, and precinct level differentiated model). Methods used to clean, process, and code the datasets are shared in this section. Statistical methods are described as used throughout the analysis including correlation testing, binary logistic regression, and multinomial logistic regression. These models are further articulated at the *municipal level* and *precinct level* in the following sections.

Data Collection and Processing

RI was selected for analysis due to the openness of the RI Board of Elections (BOE) to provide data, as well as due to their methods for running elections. RI is the smallest state across the U.S. although it is the second most densely populated (“U.S. States by Density 2019,” 2019). With its small physical size, the RI BOE is able to oversee elections within each municipality and even within each precinct. The 2018 RI Midterm experienced a turnout of 381,267 voters (48.4% of registered voters), the second highest turnout in the last five Midterm elections (AP News, 2018).

Election data were acquired from two sources in the U.S. 2018 Midterm in RI: (i) ballot scanner log files from digital scanners and (ii) sample ballots. The datasets were stripped of any potential identifying information prior to leaving the possession of the RI

BOE. In RI, as well as 32 other states as of 2018, DS200 ballot scanners are utilized to tabulate paper ballots (U.S. Election Assistance Commission, 2018). These digital scanning devices produce a transaction log file throughout their use which indicates and records every action that the machine (i.e., DS200) makes. Prior to the 2018 RI Midterm election, sample ballots were distributed for each precinct across RI, which closely resembled the official ballot on Election Day. Both DS200 log files and 2018 sample ballots were provided by the RI BOE and required preprocessing prior to analysis.

A total of 555 ballot scanners were distributed to the 421 precincts during the 2018 RI Midterm. To obtain information about error occurrences, the DS200 log files generated from the ballot scanners were exported into a CSV format and stripped of any identifiable voter information prior to custody. Using a Microsoft Excel package titled BOOTH Voting Package developed by the RI VOTES Project, the files were cleaned and imported into workable Excel files from their raw format.

A sample, compiled DS200 log file is presented in Figure 1 for illustration purposes of the raw data. The average number of lines the machine logged information per the 555 DS200 log files was 2354 with a standard deviation of 1079. Each data file per DS200 log contained the following information, as columns: an *event code* (an identification code that corresponds to an event type and description), a *date*, a *timestamp*, the *operating mode* (i.e., “E” was seen in all files due to it being activated for an election), a *scanner ID number* (consistent per log file), the *event type*, and an *event description*. Each row of data directly corresponds to a recorded event within the machine, although some rows were not necessary for the purposes of this analysis, such as the setup and

shutdown procedures, and were automatically detected and removed upon the importing of the data.

Utilizing the event codes, scanning observations (i.e., when a ballot is fully scanned and processed by the scanner) can be obtained. Successful scans (i.e., when a ballot is accepted by the scanner) are recorded 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 purple in Figure 1. By identifying the starting and ending codes of scanning observations, an event description was identified for each corresponding scanning observation, thus identifying if the scan was error free or otherwise. There are types of scanning observations that indicated two different types of identification of errors within the sequential lines of codes: (a) one that would be sandwiched within a “Voting Session Started” and a “Voting Session Complete” or (b) one that would keep iterating within the system until completed. Orange boxes in Figure 1 emphasize scanning observations that were accepted by the voter, meaning that their ballot was cast by them despite the error, and thus, would have a beginning event, an error event recorded, and an ending event. Green boxes in Figure 1 highlight scanning observations that contained an error which led to the ballot being returned to the voter with an error and would not result in the end of the interaction. The status of the scan was identified as ‘Unsuccessful’ if the ballot was returned to the voter (Green in Figure 1) or ‘Successful’ if the ballot was accepted by the scanner (Purple and Orange in Figure 1) (see Appendix A). Due to the anonymity of the scanning process, the DS200 does not record which sheet of a multi-sheet ballot is being

processed or where on the ballot errors occur. Ballot length values were therefore taken as a total per ballot.

1004115	11/08/2016	<u>07:17:22</u>	E	0523022316061493	P_LOG	Vote Session Started
3004101	11/08/2016	07:17:25	E	0523022316061493	P_LOG	IMR Log Characteristic Point Status Init 18 New 18
1004107	11/08/2016	07:17:25	E	0523022316061493	P_LOG	Ballot images stored
1004022	11/08/2016	<u>07:17:25</u>	E	0523022316061493	P_LOG	Voting session complete
1004115	11/08/2016	<u>07:17:31</u>	E	0523022316061493	P_LOG	Vote Session Started
3013001	11/08/2016	<u>07:17:32</u>	E	0523022316061493	P_ERROR	Ballot was removed during scanning. Please re-insert the ballot completely.
1004115	11/08/2016	07:17:43	E	0523022316061493	P_LOG	Vote Session Started
3004101	11/08/2016	07:17:46	E	0523022316061493	P_LOG	IMR Log Characteristic Point Status Init 18 New 18
1004107	11/08/2016	07:17:47	E	0523022316061493	P_LOG	Ballot images stored
1004022	11/08/2016	07:17:47	E	0523022316061493	P_LOG	Voting session complete
1004115	10/18/2016	<u>15:13:30</u>	E	0523022316061493	P_LOG	Vote Session Started
3004101	10/18/2016	15:13:32	E	0523022316061493	P_LOG	IMR Log Characteristic Point Status Init 24 New 24
1004111	10/18/2016	15:13:38	E	0523022316061493	P_LOG	Voter Accepted Overvoted Ballot
1004107	10/18/2016	15:13:39	E	0523022316061493	P_LOG	Ballot images stored
1004022	10/18/2016	<u>15:13:39</u>	E	0523022316061493	P_LOG	Voting session complete

Figure 1: Raw DS200 ballot scanner log file. An error free scanning observation is identified by the code in the purple boxes. The green boxes identify an error that led to a returned ballot. The orange boxes indicate a scanning observation that contained an error but was accepted by the voter. The underlined timestamps are used to calculate the duration of the corresponding observation.

The sample ballots used in this analysis were provided in PDF format for each of the 421 precincts in the 2018 RI Midterm (see Appendix B for a 2018 sample ballot). From these files, measurements of ballot length were determined for each precinct by counting: the number of sheets (i.e., total number of paper sheets) and pages (i.e., summed number of sides), the number of questions in total and type (i.e., national, state, local, candidate, multiple select, referendums), the required number of selections per question, the total number of words per ballot, and whether a ballot contained multiple language translations (see Appendix C for a sample compiled data table). Finally, the scanning observation data and sample ballot data were normalized into a single database by precinct (see Appendix D for a sample).

Demographic data were obtained from the 2017 5-year American Community Survey (ACS) at the *municipal level* across RI and from the 2016 5-year ACS at the *precinct level*. Within both the *precinct level* and *municipal level* data, the demographics collected were as follows: median income (‘Median Income’), percent of the population with a bachelor’s degree or greater (‘Percent College Educated’), and percent of the population

that are not white ('Percent Non-white'). The *municipal level* data also included information regarding the percent of the population living in an urban area ('Urbanicity'). When considering race and ethnicity, the percent of non-white persons was selected due to the large Spanish and Portuguese speaking community with a diverse racial composition in RI. This grouping is more representative of a voting population that may or may not receive a bilingual ballot format which is federally mandated via the Voting Rights Act if 5% or more of a municipality's population speaks a non-English language (U.S. Department of Justice, 2018).

Seven of the 421 active precincts during the 2018 Midterm election in RI were removed from the dataset. These seven precincts were changed or newly established after the 2016 elections, and therefore had no corresponding demographic data in the 2016 ACS.

Coding of Ballot Length Measurements

To analyze the impact of ballot length on voting errors, measurements of ballot contents are first defined and gathered. Sample ballots contained a combination of three possible question types: candidate-based questions, state questions, and local questions (Figure 2).

Of these question types, state questions are consistent throughout RI, while only some candidate questions are consistent. The ballots distributed during the 2018 Midterm elections in RI resulted in 39 unique ballots, one for each municipality.

Moderator Two Year Term Vote for 1 ☐ Julia P. Califano DEMOCRAT ☐ Write-in	Local Questions QUESTIONS 4 - 6 AMENDMENTS TO THE BARRINGTON HOME RULE CHARTER 4. TOWN COUNCIL MEETINGS (Amends Section 2-1-9) Approved by the Town Council June 4, 2018 and amended and approved at the Town Council meeting held on July 30, 2018. Shall the elected Town Council determine the time of its first regularly scheduled Town Council meeting following the Town election and to meet regularly. ☐ Approve ☐ Reject	State Questions QUESTIONS 1 - 3 (Chapter 047 - Public Laws 2018) Shall the action of the General Assembly, by an act passed at the January 2018 session, authorizing the issuance of bonds, refunding bonds, and/or temporary notes of the State of Rhode Island for the capital projects and in the amount with respect to each such project listed below (Questions 1-3) be approved, and the issuance of bonds, refunding bonds, and/or temporary notes authorized in accordance with the provisions of said act? 1. RHODE ISLAND SCHOOL BUILDINGS - \$250,000,000 To provide state assistance to cities and towns for the construction of new public schools and renovation of existing public schools. ☐ Approve ☐ Reject
Town Council Four Year Term Vote for any 2 ☐ Jacob N. Brier DEMOCRAT ☐ Stephen B. Primiano REPUBLICAN ☐ Michael W. Carroll DEMOCRAT ☐ Write-in ☐ Write-in		

Figure 2: Sample ballot questions types: Candidate Questions (left), Local Question (middle), and State Question (right).

The definition of ballot lengths resulted in the following classifications: the number of pages and/or sides of a ballot with questions listed ('Pages'), the number of physical sheets of paper ('Sheets'), the number of candidate based questions ('Candidate Questions'), the number of local questions ('Local Questions'), the total number of questions ('Total Questions') (Selb, 2008), the maximum number of candidates to be selected ('Candidate Select'), the maximum total number of selections ('Total Select'), and the total word count of the ballot ('Total Words') (Reilly & Richey, 2011). An additional ballot characteristic, ballot language ('Bilingual'), is included as it directly impacts ballot length as they contain questions listed in English followed by the Spanish translation in RI municipalities which increases the total word count and total space used on a ballot (see Appendix B). The number of selections to be made on a ballot is differentiated between 'Candidate Select' and 'Total Select' due to some office races having several positions available (e.g., town councils, school committees, planning commissions) while other questions, such as

referendums, offer only one binary selection opportunity (i.e., approve or reject). The measure of ‘Total Questions’ is the summation of ‘Candidate Questions’, ‘Local Questions’, and the statewide questions (three in the 2018 RI Midterm).

To determine which of the proposed measures of ballot length and demographic control variables are included in the model, correlation tests were performed for all combinations of variables. The criterion for acceptance is a correlation coefficient less than 0.8 at a Bonferroni corrected alpha-value of 0.0003 (0.05/158 tests).

Independent Variable Selection

To identify which of the independent variables (i.e., ballot length and demographics) to include in the model, correlations tests were performed (Tables 1 and 2). Several ballot length variables were identified as significantly correlated, thus running into six instances of collinearity.

The measures of ‘Pages’ and ‘Sheets’ had a correlation coefficient of 0.961 (p-value = 0.000). ‘Pages’ was selected to remain in the models as it measures ballot length with more granularity than ‘Sheets’, as a single ‘Sheet’ can have either one or two ‘Pages’. ‘Total Words’ also shared a significant correlation coefficient of 0.905 with ‘Pages’. ‘Pages’ was chosen to remain in the model as the additional ballot pages corresponds with additional scanning observations per ballot.

‘Total Questions’ and ‘Local Questions’ are also highly correlated with a coefficient of 0.928, as expected, the number of ‘Local Questions’ varies between municipalities and plays a role in the total number of questions that appear on a ballot. ‘Local Questions’ was selected to remain in the model due to the exclusion of the number of statewide questions in its measurement. Another highly correlated pair of ballot length variables was ‘Total

Select’ and ‘Candidate Select’ (0.863). ‘Candidate Select’ is selected to remain in the models due to the potential for multiselect questions in the candidate-based portion of the ballot, and due to its lower correlation coefficients with the included variables (i.e., ‘Pages’, ‘Candidate Questions’, ‘Local Questions’, and ‘Bilingual’).

The remaining ballot length variables are ‘Candidate Questions’ and ‘Bilingual’. These variables are included in the model because ‘Candidate Questions’ accounts for the potential variation in candidate-based questions on ballots from municipality-to-municipality and ‘Bilingual’ ballots tend to be longer and present questions in a different format than single language ballots.

Performing the correlation tests for the control variables (i.e., demographic variables) at the *municipal level*, shown in Table 1, result in only one collinearity between *municipal level* demographics and ballot length variables. The collinearity present is between ‘Bilingual’ and ‘Percent Non-white’ at the *municipal level* (i.e., correlation coefficient = 0.895 and p-value = 0.000); ‘Percent Non-white’ is chosen to remain in the model over ‘Bilingual’. Among the *precinct level* demographics, shown in Table 2, no collinearities are present. Therefore, all *precinct level* variables are included in both the *general model* and the *differentiated model*.

Table 1: Correlation matrix for the independent variables measuring ballot length and *municipal level* demographic variables.

	Independent Variables												
	Pages	Sheets	Candidate Questions	Local Questions	Bilingual	Total Questions	Candidate Select	Total Select	Total Words	Percent College Educated	Median Income	Urbanicity	Percent Non-white
Pages	-												
Sheets	0.961	-											
Candidate Questions	0.059	0.040	-										
Local Questions	0.650	0.532	0.263	-									
Bilingual	0.585	0.634	-0.163	0.219	-								
Total Questions	0.559	0.455	0.605	0.928	0.118	-							
Candidate Select	0.365	0.415	0.471	0.315	0.046	0.443	-						
Total Select	0.599	0.572	0.468	0.751	0.149	0.801	0.863	-					
Total Words	0.905	0.816	-0.009	0.728	0.603	0.597	0.194	0.522	-				
Percent College Educated	-0.492	-0.537	-0.065	-0.190	-0.529	0.597	0.102	-0.030	-0.456	-			
Median Income	-0.389	-0.439	0.134	-0.079	-0.742	-0.013	0.180	0.083	-0.382	0.780	-		
Urbanicity	0.158	0.172	-0.321	0.153	0.277	0.002	-0.359	-0.168	0.162	-0.174	-0.421	-	
Percent Non-white	0.415	0.396	-0.160	0.187	0.895	0.093	-0.184	-0.029	0.485	-0.455	-0.760	0.364	-

All correlations are found to be significant with a p-value < 0.0003. Bolded observations are considered highly correlated ($\geq |0.8|$).

Table 2: Correlation matrix for the independent variables measuring ballot length and *precinct level* demographic variables.

	Independent Variables											
	Pages	Sheets	Candidate Questions	Local Questions	Bilingual	Total Questions	Candidate Select	Total Select	Total Words	Percent College Educated	Median Income	Percent Non-white
Pages	-											
Sheets	0.961	-										
Candidate Questions	0.059	0.040	-									
Local Questions	0.650	0.532	0.263	-								
Bilingual	0.585	0.634	-0.163	0.219	-							
Total Questions	0.559	0.455	0.605	0.928	0.118	-						
Candidate Select	0.365	0.415	0.471	0.315	0.046	0.443	-					
Total Select	0.599	0.572	0.468	0.751	0.149	0.801	0.863	-				
Total Words	0.905	0.816	-0.009	0.728	0.603	0.597	0.194	0.522	-			
Percent College Educated	-0.337	-0.375	-0.099	-0.124	-0.283	-0.140	0.026	-0.048	-0.285	-		
Median Income	-0.248	-0.284	0.097	-0.019	-0.492	0.022	0.105	0.063	-0.231	0.683	-	
Percent Non-white	0.290	0.278	-0.144	0.118	0.721	0.042	-0.195	-0.073	0.360	-0.421	-0.634	-

All correlations are found to be significant with a p-value < 0.0003. Bolded observations are considered highly correlated ($\geq |0.8|$).

To demonstrate which variables are included in each model, Table 3 shows which of the discussed ballot length measurements and demographic variables are in the municipal level and precinct level models. An ‘X’ indicates that the corresponding variable is not included either due to collinearity or inapplicability given the model.

Table 3: Independent variables per model level

Independent Variables	Municipal Level	Precinct Level
Pages	✓	✓
Sheets	X	X
Candidate Questions	✓	✓
Local Questions	✓	✓
Bilingual	X	✓
Total Questions	X	X
Candidate Select	✓	✓
Total Select	X	X
Total Words	X	X
Percent College Educated	✓	✓
Median Income	✓	✓
Urbanicity	✓	X
Percent Non-white	✓	✓

Note: The checkmark indicates that the variable is included in the model. An ‘X’ indicates it was not included in the model.

Coding of Voting Error Types

In addition to the ballot length measurements, voting errors were defined and categorized. The categorization of error types follows an integrated approach of systems thinking and traditional ergonomics perspective. Errors are classified based on the system elements (i.e., the human and the machine) or their interactions (i.e., human-machine interaction) that cause the error occurrence (Meadows & Wright, 2015). In order to classify each DS200 error code, the DS200 training manual (Election Systems and Software, 2011, pp. 7-8) and the observation description generated by the scanner log files were considered based on the perspective of occurrence. The categories of ‘No

Error' contains events that did not result in an error of any type (purple highlighted in Figure 1). 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., due to long lines, voter disenfranchisement, distrust in the voting system). Physical errors that occurred while a voter was interacting with the machine are classified as a 'Human-Machine Interaction' (HMI) error, such as "multiple ballots detected" or "ballot was not inserted far enough" (Gautam & Singh, 2015). Errors that occur due to the programming of the machine or due to the device's functionality are classified as 'Machine' errors (e.g., "ballot jam", "error scanning ballot", "ballot could not be read") (Gautam & Singh, 2015). The final classification is 'Marking' error which contains events that were caused by inappropriate pen markings made or ballot accepted/rejected by the voters. 'Marking' errors may be caused by creating marks on restricted areas of the ballot (unreadable marks), marking too many selections for a single question (e.g., voter accepted/rejected overvoted ballot), or leaving the ballot blank (e.g., voter accepted/rejected blank ballot) (see Appendix E). From an ergonomics perspective, 'Marking' errors are considered physical or cognitive shortfalls between the voter and the ballot or between the voter and the method of marking.

It is important to note that the 2018 RI Midterm DS200 logs were not programmed to retain information regarding undervotes, thus this error was unable to be included in this study given this dataset.

Statistical Methods

Two steps were used in performing this analysis: 1) Pearson's correlation tests and 2) logistic regression modeling. The correlation testing was used to select which of the possible ballot length and demographic variables were included in the models. Two logistic regression models (i.e., binary response and multinomial unordered response) are described at two geographic levels (i.e., municipal and precinct) as they were used throughout the analysis of voting error. For each model type at each level of analysis, independent variables and dependent variables are classified.

Pearson's correlation testing was performed within and between all ballot length variables and *municipal level* demographic variables, as well as within and between all ballot length variables and *precinct level* demographic variables. Variables were considered highly correlated if their correlation coefficient was equal to or exceeded 0.8. The maximum alpha value allowed to reject the null hypothesis for the Pearson's correlation test was 0.0003. This value was adjusted using the Bonferroni correction method with the original alpha being 0.05 and a total of 158 test performed ($0.05/158 = 0.0003$).

To investigate the relationship between ballot length and voting errors, regression analyses are conducted once the data cleaning and correlation tests were performed. Literature in voting research exploring voting errors has used several forms of regression models to explore independent variable effects on continuous dependent variables (Milita, 2017; Kimball & Kropf, 2005; Hermson, Hanmer, & Niemi, 2012; Hamilton & Ladd, 1996). In this paper, two approaches are used to measure the response: binary (i.e., no error and error) and categorical (i.e., whether errors occur and what types of errors occur),

indicating the need for multiple logistic regression models. These models are used strictly to explore the relationship between ballot length metrics and voting errors as they occurred in the 2018 RI Midterm elections at the *municipal level* and *precinct level*. This combination of two types of dependent variable classification (i.e., binary and categorical) and geographic level (i.e., municipality and precinct) will result in four logistic regression models and eight unique regression equations with controls for voter demographics.

Each model quantifies the impact of ballot length (i.e., independent variables) on the odds of encountering a voting error (i.e., dependent variable) at different levels of granularity. First, the *general models* were created considering the dependent variable as a binary response where the occurrence of any type of voting error is considered an event (1) and ‘No Error’ observations are considered non-events (0). *Differentiated models* were created representing events in a multinomial, unordered manner where the error types (i.e., ‘Machine’, and ‘Marking’, and ‘HMI’) are treated independently and compared against the non-event (i.e., ‘No Error’) observations. The two *differentiated models* each resulted in three regression equations, one for each error type, using the non-event (i.e., ‘No Error’) observations as a reference model (Wang, 2005). Additional, aggregated voter demographics are controlled for in both models at the *municipal level* and *precinct level*.

The *general* and *differentiated models* were created in R-Studio using the ‘glm’ function from the ‘stats’ package and the ‘multinom’ function from the ‘nnet’ package, respectively. The resulting coefficients (i.e., the log odds) of the multiple logistic regression models are converted into the percent change in the odds of an event (i.e., a voting error) occurring to express the impact of each variable. Variables were considered significant if their p-values exceeded a Bonferroni corrected alpha value of 0.0003.

Results

Overview of Voting Error Rates

The error rates observed in the DS200 log files during the 2018 Midterm election in RI are presented in Table 4. While over 90% of scans resulted in ‘No Error’, there are relatively large rates of error (7.06%) given the context of events. ‘Marking’ errors are the most frequently occurring of the error types at 4.29%, with ‘HMI’ and ‘Machine’ errors each representing 1.21% and 1.56% of the total scanning events, respectively.

Table 4: Overall error rates by error type in the 2018 RI Midterm election

Error Type	Error Rate
HMI	1.21%
Machine	1.56%
Marking	4.29%
No Error	92.94%

Analysis of the *General Models*

The *general models* were applied to the data using the binary response for voting error first analyzing at the *municipal level* (Table 5) and then at the *precinct level* (Table 6).

Municipal Level General Model

Table 5 presents the results of the *municipal level general model*, indicating the significant ballot length variables as ‘Pages’ (p-value = 3.92e-07), ‘Local Questions’ (p-value = 4.14e-09) and ‘Candidate Select’ (p-value = 0.000). ‘Pages’, ‘Local Questions’, and ‘Candidate Select’ in the *precinct level general model* demonstrate an increase in the odds of error as their metrics increase by one unit, thus an increase of one page increases the odds of an error by 8.590%, an increase of one ‘Local Question’ increases the odds of an error by 1.609%, whereas an additional ‘Candidate Select’ opportunity increases the

odds of error by 2.893%. Of the demographic variables in the *municipal level general model*, ‘Median Income’ (p-value = 1.92e-07) and ‘Urbanicity’ (p-value = 8.08e-10) are significant. The results show that as ‘Median Income’ increases by one dollar, the odds of error are reduced by 0.0005%. As ‘Urbanicity’ is increased by one percent, the odds of error are increased by 26.838%. The remaining ballot length variable ‘Candidate Questions’ and the remaining *municipal level* demographic variables ‘Percent College Educated’ and ‘Percent Non-white’ are not significant in the *municipal level general model*.

Table 5: *Municipal level general model* results

Variable	Coefficient Estimate	Percent Change in Odds	Standard Error	Z value	p-value	
Intercept	-2.998	-95.010	0.104	-28.756	0.000	***
Pages	0.082	8.590	0.016	5.073	3.92e-07	***
Candidate Questions	0.004	-0.418	0.005	-0.772	0.440	
Local Questions	0.016	1.609	0.003	5.878	4.14e-09	***
Candidate Select	0.029	2.893	0.002	13.114	0.000	***
Percent College Educated	-0.004	-0.396	0.001	-3.404	6.63e-4	
Median Income	-5.04e-06	-5.04e-04	9.67e-07	-5.207	1.92e-07	***
Urbanicity	0.238	26.838	0.039	6.143	8.08e-10	***
Percent Non-white	0.000	0.025	0.001	0.310	0.757	

Significance Codes: p-value < 0.0003 (*); p-value < 0.00006 (**); p-value < 0.000006 (***) (Bonferroni corrected)

The results of both the *municipal level* and *precinct level general models* are used to test hypotheses *H1* independently. In the *municipal level general model*, the ballot length variables ‘Pages’, ‘Local Questions’, and ‘Candidate Select’ reject the null hypothesis (i.e., increasing measures of ballot length increase the odds of voting errors). The remaining ballot length variable in the model (i.e., ‘Candidate Questions’) fails to reject the null

hypothesis as it demonstrates no significant impact on the odds of voting errors at the *municipal level*.

Precinct Level General Model

Table 6 presents the results of the *precinct level general model*, indicating the significant ballot length variables are ‘Candidate Questions’ (p-value = 2.28e-04), ‘Local Questions’ (p-value = 0.000), ‘Bilingual’ (p-value = 1.34e-05), and ‘Candidate Select’ (p-value = 0.000). The significant ballot length variables, aside from ‘Candidate Questions’, demonstrate an increase in the odds of error as their metrics increase by one unit. The variable ‘Candidate Questions’ demonstrates a decrease in the odds of error as its measure increases by one unit. As the number of candidate question increases by one, the odds of an error decrease by 1.898%. An increase of one local question increases the odds of an error by 2.024%. A ballot that is distributed in a ‘Bilingual’ format increases the odds of error by 12.114%. An additional ‘Candidate Select’ opportunity increases the odds of error by 2.932%. Of the demographic variables in the *precinct level general model*, ‘Percent College Educated’ (p-value = 0.000) and ‘Median Income’ (p-value = 0.000) are significant. The results show that as ‘Percent College Educated’ increases by one unit, the odds of error are reduced by 0.886%. As ‘Median Income’ is increased by one dollar, the odds of error are increased by 0.00015%. The remaining variables ‘Pages’ and ‘Percent Non-white’ are not significant in the *precinct level general model*.

Table 6: *Precinct level general model results*

Variable	Coefficient Estimate	Percent Change in Odds	Standard Error	Z value	p-value	
Intercept	-2.892	-94.451	0.075	-38.489	0.000	***
Pages	0.036	3.416	0.016	2.081	0.037	
Candidate Questions	-0.019	-1.898	0.005	-3.685	2.28e-04	*
Local Questions	0.020	2.024	0.003	7.413	0.000	***
Bilingual	0.114	12.114	0.026	4.354	1.34e-05	***
Candidate Select	0.020	2.932	0.002	14.836	0.000	**
Percent College Educated	-0.009	-0.886	0.001	-14.616	0.000	***
Median Income	1.54e-06	1.54e-04	5.02e-07	3.063	0.000	***
Percent Non-white	0.006	0.583	0.001	9.357	0.002	

Significance Codes: p-value < 0.0003 (*); p-value < 0.00006 (**); p-value < 0.000006 (****) (Bonferroni corrected)

At the *precinct level*, hypothesis *H1* is tested for all ballot length variables. The significant ballot length variables ‘Local Questions’, ‘Bilingual’, and ‘Candidate Select’ reject the null hypothesis as an increase of one unit in each measure increases the odds of experiencing voting errors (Table 6). The variables ‘Pages’ and ‘Candidate Questions’ fail to reject the null hypothesis, as ‘Pages’ demonstrates no significant impact on the odds of voting error and ‘Candidate Questions’ reduces the odds of error as its measure increases.

Analysis of the Differentiated Model

Within the *differentiated models*, effects are separated by error type (i.e., Marking, Machine, and HMI) with the ‘No Error’ observations as a reference event. Table 7 and

Table 9 present the results of the differentiated model at the *municipal level* and the results of the *precinct level*, respectively.

Municipal Level Differentiated Model

The *municipal level differentiated model*, shown in Table 7, identifies that all ballot length variables and *municipal level* demographic variables significantly impact the odds of ‘HMI’ errors occurring (all p-values = 0.000). Of the ballot length variables, an increase of one page increases the odds of ‘HMI’ errors by 160.862%, an additional candidate-based question reduces the odds of ‘HMI’ errors by 0.773%, an additional local question reduces the odds of ‘HMI’ errors by 7.087%, and an additional ‘Candidate Select’ opportunity increases the odds of ‘HMI’ errors by 2.832%. Of the *municipal level* demographic variables, an increase in the ‘Percent College Educated’ of one percent increases the odds of ‘HMI’ errors by 0.214%, an increase in ‘Median Income’ of one dollar reduces the odds of ‘HMI’ errors by 0.001%, an increase in ‘Urbanicity’ of one percent increases the odds of ‘HMI’ errors by 36.680%, and an increase in ‘Percent Non-white’ of one percent reduces the odds of ‘HMI’ errors by 1.321%.

The *municipal level differentiated model* results indicate that all ballot length variables significantly impact ‘Machine’ errors (all with p-value = 0.000). Of these variables, an increase of one page reduces the odds of ‘Machine’ errors by 5.261%, an increase of one candidate-based question increases the odds of ‘Machine’ errors by 4.501%, an increase of one local question increases the odds of ‘Machine’ errors by 4.440%, and an increase of one ‘Candidate Select’ opportunity reduces the odds of ‘Machine’ errors by 6.669%. Of the *municipal level* demographic variables, ‘Percent College Educated’, ‘Median Income’, and ‘Urbanicity’ are significant with equal p-values of 0.000. The demographic variable

‘Percent Non-white’ is not significant in the model ($p\text{-value} = 3.82e-04$). The model identifies that an increase in ‘Percent College Educated’ by one percent increases the odds of ‘Machine’ errors by 1.343%, an increase in ‘Median Income’ of one dollar decreases the odds of ‘Machine’ error by 0.00078%, and an increase in ‘Urbanicity’ of one percent increases the odds of ‘Machine’ errors by 0.147%.

Within the *municipal level differentiated model*, the odds of ‘Marking’ errors occurring are significantly impacted by all ballot length variables with equal $p\text{-values}$ of 0.000. Within this regression, an increase of one page reduces the odds of ‘Marking’ errors by 9.462%, an increase of one candidate-based question reduces the odds of ‘Marking’ errors by 1.532%, an increase of one local question increases the odds of ‘Marking’ errors by 2.747%, and an additional ‘Candidate Select’ opportunity increases the odds of ‘Marking’ errors by 5.456%. Of the municipal level demographic variables included in this differentiated model, the variables ‘Percent College Educated’, ‘Median Income’, ‘Urbanicity’, and ‘Percent Non-white’ are all significant with $p\text{-values}$ of 0.000. An increase in ‘Percent College Educated’ by one percent reduces the odds of ‘Marking’ errors by 0.882%, an increase in ‘Median Income’ of one dollar reduces the odds of ‘Marking’ errors by 0.000025%, an increase in ‘Urbanicity’ of one percent increases the odds of ‘Marking’ errors by 24.853%, and an increase in ‘Percent Non-white’ of one percent increases the odds of ‘Marking’ errors by 0.371%.

Table 7: *Municipal level differentiated model* results.

Variable	HMI Error			Machine Error			Marking Error		
	Percent Change in Odds	p-value		Percent Change in Odds	p-value		Percent Change in Odds	p-value	
Intercept	-99.785	0.000	***	-96.706	0.000	***	-96.720	0.000	***
Pages	160.862	0.000	***	-5.261	0.000	***	-9.462	0.000	***
Candidate Questions	-0.773	0.000	***	4.501	0.000	***	-1.532	0.000	***
Local Questions	-7.087	0.000	***	4.440	0.000	***	2.747	0.000	***
Candidate Select	2.832	0.000	***	-6.669	0.000	***	5.456	0.000	***
Percent College Educated	0.214	0.000	***	1.343	0.000	***	-0.882	0.000	***
Median Income	-0.001	0.000	***	-7.80e-04	0.000	***	-2.50e-5	0.000	***
Urbanicity	36.680	0.000	***	0.147	0.000	***	24.853	0.000	***
Percent Non-white	-1.321	0.000	***	-0.219	3.82e-04		0.371	0.000	***

Significance Codes: p-value < 0.0003 (*); p-value < 0.00006 (**); p-value < 0.000006 (****) (Bonferroni corrected)

Hypothesis *H1* is assessed for the *municipal level differentiated model*. Within each error type's regression in this model, *H1* is assessed by variable, as no regression demonstrates a unanimous increase in the odds of voting errors with an increase in ballot length. Table 8 displays the direction of the impact on the odds of error for each regression within the *municipal level differentiated model*.

Table 8: Directionality of *municipal level differentiated model* effects.

Variable	HMI	Machine	Marking
Intercept	-	-	-
Pages	+	-	-
Candidate Questions	-	+	-
Local Questions	-	+	+
Candidate Select	+	-	+
Percent College Educated	+	+	-
Median Income	-	-	-
Urbanicity	+	+	+
Percent Non-white	-	N/A	+

Note: (+) increase in the odds of error, (-) decrease in the odds of error, (N/A) variable not significant.

With respect to ‘HMI’ errors, the variables ‘Pages’ and ‘Candidate Select’ reject the null hypothesis, as they increase the odds of ‘HMI’ errors when each variable’s value increases. The variables ‘Candidate Questions’ and ‘Local Questions’ fail to reject the null hypothesis as they do not increase the odds of ‘HMI’ errors as their values increase.

For ‘Machine’ errors in the *municipal level differentiated model*, the null hypothesis is rejected for the variables ‘Candidate Questions’ and ‘Local Questions’. The ballot length variables ‘Pages’ and ‘Candidate Select’ fail to reject the null hypothesis as they decrease the odds of error as their values increase.

Within the ‘Marking’ error regression, the ballot length variables ‘Local Questions’ and ‘Candidate Select’ reject the null hypothesis due to their increase in the odds of ‘Marking’ errors as their values increase. The variables ‘Pages’ and ‘Candidate Questions’ fail to reject the null hypothesis due to their decrease in the odds of ‘Marking’ errors as their values increase.

Precinct Level Differentiated Model

The *precinct level differentiated model* shown in Table 9 identifies the impact of ballot length and *precinct level* demographics on ‘HMI’, ‘Machine’, and ‘Marking’ errors, independently.

With respect to ‘HMI’ errors in the *precinct level differentiated model*, all ballot length variables are significant (p-values = 0.000). Of the significant ballot length variables, an increase of one page increases the odds of ‘HMI’ errors by 125.650%, an increase of one candidate-based question reduces the odds of ‘HMI’ errors by 4.676%, an additional local question reduces the odds of ‘HMI’ errors by 6.293%, a ‘Bilingual’ formatted ballot increases the odds of ‘HMI’ errors by 26.954%, and an increase of one ‘Candidate Select’ opportunity increases the odds of ‘HMI’ errors by 3.346%. Of the significant *precinct level* demographic variables, an increase in ‘Percent College Educated’ of one percent reduces the odds of ‘HMI’ errors by 1.299%, an increase in ‘Median Income’ of one dollar increases the odds of ‘HMI’ errors by 0.000198%, and an increase in ‘Percent Non-white’ of one percent reduces the odds of ‘HMI’ errors by 0.342%.

With respect to ‘Machine’ errors, the *precinct level differentiated model* indicates that all ballot length variables are significant (p-values = 0.000). Of the significant ballot length variables, an increase of one page reduces the odds of ‘Machine’ errors by 16.067%, an increase of one candidate-based question increases the odds of ‘Machine’ errors by 0.588%, an increase of one local question increases the odds of ‘Machine’ errors by 5.003%, a ‘Bilingual’ formatted ballot reduces the odds of ‘Machine’ errors by 6.698%, and an additional ‘Candidate Select’ opportunity reduces the odds of ‘Machine’ errors by 4.696%. Of the included *precinct level* demographic variables, ‘Percent College Educated’

and ‘Percent Non-white’ are significant with equal p-values of 0.000 and ‘Median Income’ is significant with a p-value of 5.66e-08. As demonstrated in Table 9, an increase in ‘Percent College Educated’ of one percent reduces the odds of ‘Machine’ errors by 0.263%, an increase in ‘Median Income’ of one dollar increases the odds of ‘Machine’ errors by 0.000129%, and an increase in ‘Percent Non-white’ of one percent increases the odds of ‘Machine’ errors by 0.681%.

Investigating ‘Marking’ errors in the *precinct level differentiated model* indicates that all ballot length variables are significant in the model (p-values = 0.000). Among the significant ballot length variables, an increase of one page reduces the odds of ‘Marking’ errors by 7.220%, an increase of one candidate-based question reduces the odds of ‘Marking’ errors by 3.226%, an increase of one local question increases the odds of ‘Marking’ errors by 2.718%, a ‘Bilingual’ formatted ballot reduces the odds of ‘Marking’ errors by 2.401%, and an additional ‘Candidate Select’ opportunity increases the odds of ‘Marking’ errors by 5.620%. Of the *precinct level* demographic variables, all but ‘Median Income’ are significant with p-values of 0.000. An increase in ‘Percent College Educated’ of one percent reduces the odds of ‘Marking’ errors by 0.926%, an increase in ‘Percent Non-white’ of one percent increases the odds of ‘Marking’ errors by 1.027%.

Table 9: *Precinct level differentiated model results.*

Variable	HMI Error			Machine Error			Marking Error		
	Percent Change in Odds	p-value		Percent Change in Odds	p-value		Percent Change in Odds	p-value	
Intercept	-99.739	0.000	***	-95.879	0.000	***	-96.708	0.000	***
Pages	125.650	0.000	***	-16.067	0.000	***	-7.220	0.000	***
Candidate Questions	-4.676	0.000	***	0.588	0.000	***	-3.226	0.000	***
Local Questions	-6.293	0.000	***	5.003	0.000	***	2.718	0.000	***
Bilingual	26.954	0.000	***	-6.698	0.000	***	-2.401	0.000	***
Candidate Select	3.346	0.000	***	-4.696	0.000	***	5.620	0.000	***
Percent College Educated	-1.299	0.000	***	-0.263	0.000	***	-0.926	0.000	***
Median Income	1.98e-4	1.56e-10	***	1.29e-4	5.66e-08	***	1.20e-4	0.002	
Percent Non-white	-0.342	8.76e-09	***	0.681	0.000	***	1.027	0.000	***

Significance Codes: p-value < 0.0003 (**); p-value < 0.00006 (***); p-value < 0.000006 (****) (Bonferroni corrected)

Within each error type's regression in the *precinct level differentiated model*, *H1* is assessed per variable, as no regression demonstrates a unanimous increase in the odds of voting errors with an increase in ballot length. Table 10 displays the direction of the impact on the odds of error for each regression within the model.

Table 10: Directionality of *precinct level differentiated model* effects.

Variable	HMI	Machine	Marking
Intercept	-	-	-
Pages	+	-	-
Candidate Questions	-	+	-
Local Questions	-	+	+
Bilingual	+	-	-
Candidate Select	+	-	+
Percent College Educated	-	-	-
Median Income	+	+	N/A
Percent Non-white	-	+	+

Note: (+) increase in the odds of error, (-) decrease in the odds of error, (N/A) variable not significant.

The variables ‘Pages’, ‘Bilingual’, and ‘Candidate Select’ reject the null hypothesis for the ‘HMI’ error regression. The variables ‘Candidate Questions’ and ‘Local Questions’ fail to reject the null hypothesis for the ‘HMI’ regression as an increase in their measure demonstrated a decrease in the odds of ‘HMI’ errors.

Within the ‘Machine’ error regression, the variables ‘Candidate Questions’ and ‘Local Questions’ reject the null hypothesis. For each of these variables, an increase in their measure results in an increase in the odds of ‘Machine’ errors. The variables ‘Pages’, ‘Bilingual’, and ‘Candidate Select’ fail to reject the null hypothesis.

Within the ‘Marking’ error regression, the variables ‘Local Questions’ and ‘Candidate Select’ reject the null hypothesis. The variables ‘Pages’, ‘Candidate Questions’, and ‘Bilingual’ fail to reject the null hypothesis for the ‘Marking’ regression in the *precinct level differentiated model*.

Discussion

Measures of ballot length impact specific types of voting errors (i.e., HMI, Machine, Marking), although the directionality and magnitude of these effects vary. These findings agree with the general implication of Selb (2008) which indicate that ballot length impacts voting systems. While research question one (*R1*) is answered, that ballot length does indeed impact voting errors, research question two (*R2*) must be addressed per model (i.e., the *general model* and *differentiated model*) at both the *municipal* and *precinct levels*.

The findings that some elements of ballot length increase the odds of voting error are consistent, providing insight into answering research question *R1*. These models demonstrate that ballot length does impact the odds of experiencing voting errors. Additionally, the directionality and magnitude of ballot length effects are determined from a general perspective, thus partially addressing research question *R2*. However, there are differences between the *municipal level* and *precinct level general models* regarding these impact magnitudes and direction. Where the models agree is in their significance and direction of some demographic variables. This indicates that, in general, areas with demographics that corresponded with commonly under-resourced communities (i.e., low percent college educated, low median income, and high urbanicity) experienced more voting errors regardless of ballot length during the 2018 RI Midterm election. With this information, resource allocation by election officials can be adjusted to provide additional personnel and equipment to municipalities that might require it in future elections.

With respect to ballot length, the *municipal level general model* results specifically indicate that increases in ‘Pages’, ‘Local Questions’, and/or ‘Candidate Select’ opportunities increase the odds of voting errors. Considering the error rates in Table 4,

approximately 7.06% of scans in RI contained an error. The *municipal level general model* implies that the addition of a single ballot page across RI would increase the odds of voting errors by 8.590%, indicating an increase in error rate to 7.666%. The impact on the odds of voting errors in the *municipal level general model* from ‘Urbanicity’ would increase the error rate from 7.06% to 8.955% with an additional ‘Urbanicity’ percentage point. This model suggests that municipalities that have highly populated urban areas and municipalities that distributed longer ballots, with respect to the number of pages, local questions, and candidate selections, experienced significantly higher odds of voting errors during the 2018 RI Midterm election. Considering this investigation focused on a RI election, the high population density of the state may explain the large impact of ‘Urbanicity’. With up to 3,000 voters assigned to a single polling location in RI, areas that are more densely populated/have higher ‘Urbanicity’ experience more heavily used equipment and more opportunities for error (i.e., more users of the system). To avoid potential delays caused by these errors in future elections, additional resources (i.e., poll workers and voting equipment) may be allocated to municipalities with long ballots and high urbanicity. However, future research should explore whether urbanicity is truly a function of population density when investigating voting error or if the impact is caused by the number of voters per piece of voting equipment. In order to explore urbanicity more in depth, cross-state and cross-election investigations must be performed.

The issue with this recommendation becomes that the overall capacity and layout planning that is or is not able to accommodate increases in resource allocation. As more poll workers and more voting equipment are allocated to a municipality, additional physical space is required which, in turn, could require more polling locations within a municipality.

Locating available space for more polling locations within urban areas continues to be a challenge that confronts election officials across the U.S. with various options being electronic voting (i.e., eliminating polling locations all together, which continues to be a very unpopular idea), voting centers (i.e., central, larger locations where resources can be vast and effectively used while serving larger active voter populations), vote by mail, or even universal polling locations in which any voter can cast a ballot at any polling location within a particular state. Essentially, this has a two-fold meaning. First, that using ‘Rules of Thumb’ that are developed statewide are not applicable to every municipality or precinct and models that decisions are being made from must continue to consider all variables together in a robust manner in a continuous improvement perspective. And second, that data from technology can be utilized as valuable inputs into these decision-making processes and resource allocation models to eliminate the need for ineffective proxies of polling place performance and resource needs.

An interesting component of this outcome is the fact that these are errors at only one station of the voting system on a specific type of voting equipment (i.e., digital ballot scanners). There are multitudes of opportunities to use data to directly feed into the decision-making loop to continuously improve the models through every election in order to advance these models, such as incorporating data generated by electronic poll books or DREs. Additional research must explore resource allocation models and their current effectiveness, as well as the impact of incorporating other input variables, such as those described in this research, based on reducing errors.

Within the *precinct level general model*, the ballot length variables ‘Local Questions’ and ‘Candidate Select’ increase the odds of voting errors as their measures increase.

Additionally, 'Bilingual' ballots led to higher odds of error than single language ballots. The 'Local Questions' and 'Candidate Select' variables represent opportunities for voters to mark the ballot. As more voter interaction is required with the ballot, the odds that an error will occur are expected to increase. Interestingly in this model, despite controlling for the non-white population, 'Bilingual' ballots have a large impact on the odds of voting errors by a 12.114% increase. Bilingual ballots (Appendix B), on average, tend to be quite long by several measures of ballot length when compared to single language ballots. In the 2018 RI Midterm election, the average number of words on a bilingual ballot was 1942 compared to the average number of words on a single language ballot of 860. Additionally, the average number of pages for bilingual ballots was 2.98 compared to an average of 2.07 pages for single language ballots. These longer ballot properties that are associated with bilingual ballots may have caused the increased odds of errors during the 2018 RI Midterm election. Additionally, bilingual ballots are distributed in areas with higher non-English speaking populations. This may indicate a population that is less experienced with the voting process, which may also lead to increased odds of voting errors.

Other potential reasons for the impact of bilingual ballots could be the translation accuracy, the complex and legalese language use in many ballot measures and this interaction with non-English languages, or education about bilingual ballots in general. The impact of bilingual ballots on voting errors presents a critical point of focus as bilingual and multilingual ballots are mandated by law. If more municipalities begin to exceed the threshold for single language ballots, then these errors have the potential to propagate and lead to more serious issues; though, not necessarily due to multilingual ballots themselves, but the properties that are associated with them. Within ballot design research, focusses

have been on the format of a ballot (e.g., selection method, paper ballot, digital ballot) (Hamilton & Ladd, 1996; Everett, Byrne, & Greene, 2006), the layout of the ballot (e.g., the order of candidates, the order of questions, where instructions are on the page) (Kimball & Kropf, 2003; Kimball & Kropf, 2005), and the design of the ballot (e.g., bolding of words, language complexity) (Redish, Chisnell, Laskowski, & Lowry, 2010). The results of the *precinct level general model* indicate the need to also focus on methods of presenting information in multiple languages, such as using bilingual ballots and facsimile ballots, to determine which formats mitigate effects on voting error rates.

At the *precinct level*, the length of the ballot significantly increased the odds of voting errors after controlling for *precinct level* demographics during the 2018 RI Midterm election. With this information, precincts that distribute longer ballots, with respect to the number of ‘Local Questions’ and ‘Candidate Select’ opportunities as well as ballots in a ‘Bilingual’ format may consider performing narrower investigations into the design of ballots. Techniques for survey design may be a helpful resource to accommodate the large amount of information often presented on Midterm and General election ballots. Additional resource allocation techniques may be required that consider traditionally unincluded factors or that more scientifically assess the traditionally included factors. Another component that must be considered is the level of experience that voters have with elections, in general, as well as with a specific ballot design/format or voting equipment.

Assessing both the *municipal level* and *precinct level differentiated models* generates insight regarding research questions *R1*. The *general models*’ findings: ballot length does significantly impact the odds of experiencing voting errors. The *differentiated models* also provide more specific answers to research question *R2*: depending on the error type and

the measure of ballot length, the odds of voting errors may be increased or decreased. Comparing the *municipal level* and *precinct level differentiated models* indicates that the odds of ‘HMI’ errors are consistently increased by measures of ballot length (i.e., the number of pages and the number of candidate select opportunities). Additionally, the *municipal level* model indicates that ‘Urbanicity’ contributes to increases in voting errors of all types. In both models, as certain measures of ballot length increase, the odds of experiencing errors are reduced. These effects may be explained by external variables (e.g., voter behavior, level of voting experience, equipment maintenance frequency, other unincluded demographic data).

Within the *municipal level differentiated model*, error types (i.e., ‘HMI’, ‘Machine’, and ‘Marking’) are investigated independently while controlling for *municipal level* demographics. The model identifies that the odds of ‘HMI’ errors are increased by increases in ‘Pages’ (a 160.862% increase in the odds of ‘HMI’ error), ‘Candidate Select’ opportunities (a 2.832% increase in the odds of ‘HMI’ error), and ‘Urbanicity’ (a 36.680% increase in the odds of ‘HMI’ error). In other words, areas that distributed ballots with several pages, more candidate selection opportunities, and/or had high urbanicity experienced more errors when voters attempted to insert their ballot into the DS200. Assessing this impact in terms of the overall 2018 RI Midterm election, the experienced ‘HMI’ error rate (i.e., 1.21%) (Table 4) would increase to 3.16%, more than doubling the number of affected voters, if an additional page is added to each ballot. With a single additional percentage point of ‘Urbanicity’, the state wide ‘HMI’ error rate would increase from 1.21% to 1.65%. ‘Local Questions’ also has a large impact on ‘HMI’ errors, reducing their odds by 7.087% when an additional ‘Local Questions’ is listed on the ballot. On its

own, there is not much meaning behind this effect, although municipalities that distributed ballots with many local questions during the 2018 RI Midterm election may have shared a trait that confounds the ‘Local Questions’ variable (e.g., a more voting involved/experienced population).

These findings indicate that the number of ballot pages and the urbanicity of an area impact the odds of ‘HMI’ errors and therefore require special consideration when preparing for elections. This impact on ‘HMI’ error may indicate insufficient voter education materials regarding how to use the ballot scanner. Studies can be conducted in areas that have high rates of ‘HMI’ errors and areas that have several ballot pages and high urbanicity to better understand their underlying relationship. Feedback from voters may also provide insight into why these errors occur.

With respect to ‘Machine’ errors in the *municipal level differentiated model*, ‘Candidate Questions’ and ‘Local Questions’ have the largest impacts (a 4.501% increase and 4.440% increase, respectively). In addition to ballot length, all *municipal level* demographics, excluding ‘Percent Non-white’, present significant impacts on the odds of ‘Machine’ errors. These findings indicate the need to investigate the ballot scanners in active use during real elections. There may be issues with equipment maintenance or an inherent sensitivity to longer ballots that lead to ‘Machine’ errors. In depth testing of these devices should be performed and compared to test results reported by device manufacturers as well as testing facilities employed by the U.S. Election Assistance Commission. Other investigation should be performed to compare the equipment distributed to different types of areas throughout a region to ensure that the level of maintenance and accuracy of the devices is consistent regardless of area specific demographics.

Within the ‘Marking’ error regression, the ballot length variables ‘Local Questions’ and ‘Candidate Select’ increase the odds of ‘Marking’ errors as their measures increase. However, increases in ‘Pages’ and ‘Candidate Questions’ significantly reduce the odds of ‘Marking’ errors. Within this model, ‘Urbanicity’ increases the odds of ‘Marking’ errors by 24.853% as ‘Urbanicity’ increases by one percentage point. The increase in the odds of ‘Marking’ errors due to ‘Local Questions’ and ‘Candidate Select’ indicates that as voters interact with a ballot more, their odds of mismarking a ballot increase. Additional causes may be from confusion with the wording of local questions, which often include more legalese than candidate questions (Reilly & Richey, 2011; Milita, 2017), and/or from confusion from the instructions for multiselect candidate questions. Within several candidate-based questions on a ballot, the voter can select more than one candidate whereas on other candidate-based and local questions, marking more than one selection is considered an error. This contradictory instruction may be a source of confusion for voters. Additional research can assist with identifying specific sources of ‘Marking’ error. This error type is one of the most concerning as it implies the possibility that voters are not able to accurately portray their intentions on the ballot (Redish, Chisnell, Laskowski, & Lowry, 2010; Herrnson, Hanmer, & Niemi, 2012).

The *municipal level differentiated model* demonstrates that variables impacted different types of errors uniquely. The model indicates that municipalities with several pages and municipalities with a large percent of the population living in urban areas experienced higher odds of encountering ‘HMI’ errors during the 2018 RI Midterm election. The effects of these variables may indicate a need for revised resource allocation techniques and voter education materials to ensure that areas with several page ballots and higher urbanicity can

cast votes as equally as other areas. ‘Machine’ errors were more likely to occur in areas with more ballot questions as well as areas with lower median incomes. These findings may indicate that additional maintenance and testing methods for voting equipment may be required for areas distributing longer ballots or in low income regions. Within the ‘Marking’ error regression, demographic variables such as ‘Urbanicity’ and ‘Median Income’ significantly impacted the odds of experiencing ‘Marking’ errors during the 2018 RI Midterm election as well as the number of ‘Local Questions’ and ‘Candidate Select’ opportunities. These factors indicate that more research should be performed on the effectiveness of voter education materials and the instructions provided on the ballot itself. Other research may be performed on the level of assistance that is provided to voters that may not understand how to properly mark a ballot or to investigate how often voters seek assistance when marking a ballot.

Within the *precinct level differentiated model*, error types (i.e., ‘HMI’, ‘Machine’, and ‘Marking’) are investigated independently while controlling for *precinct level* demographics. The model identifies that ‘HMI’ errors are increased by ‘Pages’ (a 125.650% increase in the odds of ‘HMI’ error), the ‘Bilingual’ ballot format (a 26.954% increase in the odds of ‘HMI’ error), and ‘Candidate Select’ opportunities (a 3.346% increase in the odds of ‘HMI’ error). As the number of ballot pages increase, voters must feed additional ballot sheets into the scanner, providing more opportunities to incorrectly insert the ballot. ‘Bilingual’ ballots also cause several ballot length measurements to increase (i.e., questions are listed once in English and once in Spanish in the case of RI) potentially leading to additional opportunities for ‘HMI’ errors. Assessing this impact with

respect to 2018 RI Midterm error rates, presented in Table 4, the 1.21% statewide ‘HMI’ error rate would increase to 2.73% if an additional page is added to each distributed ballot.

These impacts on the odds of ‘HMI’ errors indicates the tradeoff between longer ballots and the rate of ‘HMI’ error. Despite longer ballots allowing for increased voter participation, more voting errors may occur. While ‘HMI’ errors can be resolved by either reinserting the ballot or remarking a new ballot, there is still the potential to disenfranchise the voter and cause delays or lines in a polling location. Additional research is required to determine the effectiveness of distributed instructions regarding how to properly scan a ballot. During the 2018 RI Midterm elections, additional personnel was stationed at the ballot scanning station in every precinct, however these errors are still present indicating that voters may not be seeking help.

All ballot length variables also significantly impacted the odds of ‘Machine’ errors, however only the variable ‘Local Questions’ largely increased the odds of ‘Machine’ errors (a 5.003% increase). Considering the results of the *precinct level differentiated model*, there may be an element of the scanning process that is uncaptured in the model, such as the general capabilities of the DS200.

The ‘Marking’ error regression in the *precinct level differentiated model* indicated that ‘Local Questions’, ‘Candidate Select’ opportunities, and ‘Percent Non-white’ significantly increased the odds of ‘Marking’ errors as their measures increase, agreeing with the findings of the *municipal level differentiated model*. An interesting finding in this model is that ‘Bilingual’ formatted ballots led to a decrease in the odds of ‘Marking’ errors by 2.401%, demonstrating the benefit of language accessible ballots. This effect of bilingual ballots further indicates that additional research should investigate their design and use in

elections. While their importance in the democratic process is clear, there may be unnoticed complications with the current methods of designing and/or implementing language accessible ballots. A study into the format, design, and translation accuracy of bilingual and multilingual ballots can provide insight into how to better accommodate low English proficiency voters, as well as mitigate any effect these ballots may have on voting errors in general.

The results of the *precinct level differentiated model* indicated that longer ballots distributed during the election had the largest effect on the odds of ‘HMI’ errors. The remaining error categories (i.e., ‘Machine’ and ‘Marking’) had their odds both increase and decrease by different measures of ballot length which may indicate that these errors may have had additional causes that must be considered in future analyses, such as equipment specific characteristics, level of voter experience with a voting method, and/or the extent and effectiveness of election education materials.

Conclusion

The implications of these findings are that in the 2018 RI Midterm elections, voters in municipalities with high urbanicity or in municipalities that distributed lengthy ballots had larger odds of experiencing voting errors, specifically more human-machine interaction (HMI) errors. Providing longer ballots increases the voter's ability to participate in democracy, although the consequence is an increase in voting errors which can lead to long wait times and voter disenfranchisement (Everett, Byrne, & Greene, 2006; Ansolabehere & Shaw, 2016). This investigation into the 2018 RI Midterm election indicates that, in areas with long ballots and high urbanicity, measures of ballot length should be used to influence strategies in election preparation and resource allocation techniques (e.g., polling places receive advanced voter education materials, additional poll workers, and voting equipment). This research provides an initial understanding of how ballot length impacted voting errors during the 2018 RI Midterm elections, stating that there is evidence that ballot length increases the odds of experiencing voting errors, regardless of location specific demographic. Although more work is required to fully understand how voting errors occur and their impacts are on the voting system.

A limitation in this study is the method by which voting error is defined. Due to the data source being an anonymous account of ballot scanning events, it is impossible to determine a voter's intention. For this reason, all overvotes and blank ballots were considered voting errors regardless of voter intention. This limitation could be resolved by performing controlled experiments in which participants are interviewed during or after the scanning process to identify their intentions throughout the marking process. Additionally, specific voter characteristics such as their level of experience with the ballot type or ballot

scanner cannot be captured from the anonymous data. These factors may impact the odds of experiencing voting errors, although 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) was uncaptured by the DS200 for the 2018 RI Midterms. The method of data collection also presents a limitation, as the election considered was a Midterm election. Therefore, the results cannot be assumed to imply anything about other elections (e.g., General, Primary, Special) as each election type has several points of variation (e.g., turnout, perceived question importance, public awareness of the election).

With these limitations in mind, there is a plethora of future work that can build from the analysis in this research article. By simply including additional variables regarding ballot design and ballot measure information (i.e., the topic and information provided in a question), additional models can be developed to assess how a ballot impacts the odds of voting errors from a more holistic perspective. Additional research can also be conducted for different types of elections as well as in controlled environments. By assessing and comparing different election types, the most impactful errors across elections in general can be identified. Controlled experiments allow for the collection of participant demographic information which can also be recorded on a per participant basis and matched with their scanning event rather than on an aggregate level such as in real elections. With the inclusion of more specific demographic variables, a participant's history of voting, in depth ballot design variables, and ballot length variables, a more comprehensive and descriptive model could be determined to generate and establish a predictive model. While this research assesses data generated from the 2018 RI Midterm

elections, the implications apply to elections in other states that use voting systems like those used in RI. There are many other states that utilize paper ballots and scanners (e.g., North Carolina, Arizona, Nebraska) that have increased voter populations with different demographic nuances, multiple urban areas per state and increased proportion of rural areas, and even structural differences in decision making in terms of state verses municipalities' thus providing ample opportunities for comparative studies and verification.

As demonstrated in ballot design and voting equipment literature, many voting systems have flaws. Due to concerns of both election officials and voters regarding newer and alternative voting systems, equipment use has begun to shift back to paper-based systems. Overlooking the impact ballot length on voting systems can lead to an entirely new set of concerns causing millions of voters to experience errors and delays throughout the voting process, providing voters with a false sense of system failure. Election systems are complex and, as technology changes, continue to grow in that complexity. Like any system, there are many critical components in the elections system that must be investigated prior to the accomplishment of a stable method for casting a vote. Rather than a continuous development of new voting methods, investigations and improvements on the voting methods that are currently in place across the U.S. are critical for voter trust, election security, and resources. This work provides an analysis of a mostly unexplored area of ballot research in the U.S. in assessing the effect of ballot length on voting error. This work implores and seeks to spark more in-depth assessments of election systems currently in place and the components that they are comprised of and how that impacts voter error within an election system at all levels of government.

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Appendix A

Processed DS200 Log File Data Using BOOTH Voting Package

Duration (mm:ss)	Scan Type	Ballot Cast Status
00:04	No Error	Successful
02:30	Ballot Jam. Please check the paper path.	Jam
00:03	No Error	Successful
00:03	No Error	Successful
00:03	No Error	Successful
00:03	No Error	Successful
00:02	No Error	Successful
00:05	Voter Accepted Blank Ballot	Successful
00:03	No Error	Successful
00:03	No Error	Successful
00:03	No Error	Successful
00:03	No Error	Successful
00:07	Voter Accepted Overvoted Ballot	Successful
00:04	No Error	Successful
00:02	No Error	Successful
00:02	No Error	Successful
00:02	No Error	Successful
00:02	No Error	Successful
00:03	No Error	Successful
00:03	No Error	Successful
00:02	No Error	Successful
00:03	No Error	Successful
00:03	No Error	Successful
00:03	No Error	Successful
00:03	No Error	Successful
00:03	No Error	Successful
00:02	No Error	Successful

Appendix B

Sample Ballot from the 2018 Rhode Island Midterm elections

Mail Voter		Votante por Correo		Precinct 2842
State of Rhode Island Official Ballot General Election November 6, 2018 Providence		Papeleta Oficial del Estado de Rhode Island Elección General 6 de noviembre de 2018 Providence		Congressional District 2 Senate District 1 Representative District 5 Providence Ward 12
To mark your choice: Fill in the oval to the left of your choice. Do not make any marks outside of the oval. Marque su selección: Llene el óvalo a la izquierda de su selección. No haga ninguna marca fuera del óvalo.		To vote for a written candidate: To vote for a candidate whose name is not on the ballot, Fill in the oval to the left of "Write-in" and print the name clearly in the box. Votar por escrito: Para votar por un candidato cuyo nombre no aparece en la papeleta: Llene el óvalo a la izquierda de "voto por escrito" y escriba el nombre del candidato en el espacio.			
Senator in Congress Six Year Term Vote for 1 Senador en el Congreso Periodo de seis años Vote por 1 ☐ Sheldon Whitehouse DEMOCRAT ☐ Robert G. Flanders, Jr. REPUBLICAN ☐ Write-in Voto por escrito		Lieutenant Governor Four Year Term Vote for 1 Vicegobernador Periodo de cuatro años Vote por 1 ☐ Daniel J. McKee DEMOCRAT ☐ Joel J. Hellmann DEMOCRAT ☐ Paul E. Pence REPUBLICAN ☐ Jonathan J. Riccitelli Independent ☐ Ross K. McCurdy Independent ☐ Write-in Voto por escrito		Senator in General Assembly District 1 Two Year Term Vote for 1 Senador en la Asamblea General Districto 1 Periodo de dos años Vote por 1 ☐ Maryellen Goodwin DEMOCRAT ☐ Write-in Voto por escrito	
Representative in Congress District 2 Two Year Term Vote for 1 Representante en el Congreso Districto 2 Periodo de dos años Vote por 1 ☐ James R. Langevin DEMOCRAT ☐ Salvatore G. Calozzo REPUBLICAN ☐ Write-in Voto por escrito		Secretary of State Four Year Term Vote for 1 Secretaria de Estado Periodo de cuatro años Vote por 1 ☐ Marcia Rangelin-Vassell DEMOCRAT ☐ Write-in Voto por escrito		Representative in General Assembly District 5 Two Year Term Vote for 1 Representante en la Asamblea General Districto 5 Periodo de dos años Vote por 1 ☐ Marcia Rangelin-Vassell DEMOCRAT ☐ Write-in Voto por escrito	
Governor Four Year Term Vote for 1 Gobernador Periodo de cuatro años Vote por 1 ☐ Gina M. Raimondo DEMOCRAT ☐ William H. Gilbert MODERATE ☐ Allan W. Fung REPUBLICAN ☐ Anne Armstrong Compassion ☐ Luis Daniel Munoz Independent ☐ Joseph A. Trillo Independent ☐ Write-in Voto por escrito		Attorney General Four Year Term Vote for 1 Procurador General Periodo de cuatro años Vote por 1 ☐ Peter F. Neronha DEMOCRAT ☐ Alan Gordon DEMOCRAT ☐ Write-in Voto por escrito		Mayor Four Year Term Vote for 1 Alcalde Periodo de cuatro años Vote por 1 ☐ Jorge O. Elorza DEMOCRAT ☐ Jeffrey E. Lemire Independent ☐ Dianne S. Witman Independent ☐ Write-in Voto por escrito	
		General Treasurer Four Year Term Vote for 1 Tesorero General Periodo de cuatro años Vote por 1 ☐ Seth Magaziner DEMOCRAT ☐ Michael G. Riley REPUBLICAN ☐ Write-in Voto por escrito		Council Ward 12 Four Year Term Vote for 1 Concejal Districto 12 Periodo de cuatro años Vote por 1 ☐ Katherine A. Kerwin DEMOCRAT ☐ Write-in Voto por escrito	
State and Local Questions On Back Preguntas Estatales y Locales en la parte posterior					

State Questions	State Questions	Local Question
Preguntas Estatales	Preguntas Estatales	Pregunta Local
QUESTIONS 1 - 3 (Chapter 047 - Public Laws 2018) Shall the action of the General Assembly, by an act passed at the January 2018 session, authorizing the issuance of bonds, refunding bonds, and/or temporary notes of the State of Rhode Island for the capital projects and in the amount with respect to each such project listed below (Questions 1-3) be approved, and the issuance of bonds, refunding bonds, and/or temporary notes authorized in accordance with the provisions of said act? PREGUNTAS 1 - 3 (Capítulo 047 - Leyes Públicas 2018) ¿Deberá la acción de la Asamblea General, aprobada por una ley en la sesión de enero de 2018, autorizando la emisión de bonos, bonos de reembolso y/o papeles temporales del Estado de Rhode Island para los proyectos de capital y en la cantidad con respecto a cada uno de esos proyectos enumerados a continuación (Preguntas 1-3) ser aprobada, y por lo tanto, debe ser autorizada la emisión de bonos, bonos de reembolso y/o papeles temporales según las disposiciones de dicha ley? 1. RHODE ISLAND SCHOOL BUILDINGS - \$250,000,000 To provide state assistance to cities and towns for the construction of new public schools and renovation of existing public schools. 1. EDIFICIOS ESCOLARES DE RHODE ISLAND - \$250,000,000 Para proporcionar asistencia estatal a las ciudades y pueblos para la construcción de nuevas escuelas públicas y la renovación de las escuelas públicas existentes. ☐ Approve ☐ Reject ☐ Rechar	3. GREEN ECONOMY AND CLEAN WATER - \$47,300,000 For environmental and recreational purposes, to be allocated as follows: (a) Coastal Resiliency and Public Access Projects - \$5,000,000 (b) Capital for Clean Water and Drinking Water - \$7,800,000 (c) Wastewater Treatment Facility Resiliency Improvements - \$5,000,000 (d) Dam Safety - \$4,400,000 (e) Dredging - Downtown Providence Rivers - \$7,000,000 (f) State Bikeway Development Program - \$5,000,000 (g) Brownfield Remediation and Economic Development - \$4,000,000 (h) Local Recreation Projects - \$5,000,000 (i) Access to Farmland - \$2,000,000 (j) Local Open Space - \$2,000,000 3. ECONOMÍA AMBIENTALISTA Y AGUA POTABLE - \$47,300,000 Para fines medioambientales y recreativos, distribuidos de la siguiente manera: (a) \$5,000,000 para la Resiliencia Costera y Proyectos de Acceso Público (b) \$7,800,000 para el Capital para Agua Potable y Limpia (c) \$5,000,000 para Mejoras en la Resiliencia de las Instalaciones de Tratamiento de Aguas Residuales (d) \$4,400,000 para la Seguridad de los Embalses (e) \$7,000,000 Dragado: Ríos de la Ciudad de Providence. (f) \$5,000,000 para el Programa Estatal del Desarrollo de Ciclovías (g) \$4,000,000 para el Programa de Remediación Brownfield y el Desarrollo Económico (h) \$5,000,000 para los Proyectos Recreativos Locales (i) \$2,000,000 para el Acceso a Tierras de Cultivo (j) \$2,000,000 para los Espacios Públicos. ☐ Approve ☐ Rechar	4. SCHOOL CAPITAL IMPROVEMENTS \$160,000,000 BONDS (Article VIII of Providence Home Rule Charter and City Council Ordinance 2015-49) Shall an Ordinance of the City Council effective on August 2, 2018 authorizing the issuance of up to \$160,000,000 general obligation bonds of the City pursuant to Rhode Island General Laws §45-12-2 and § 807 of the City's Home Rule Charter in order to fund the school capital improvements plan for the fiscal years 2019-2024, subject to approval of state school housing aid at a reimbursement rate or state share ratio of not less than 75% for those expenditures eligible for state aid, be approved? 4. MEJORAS DE CAPITAL ESCOLARES \$160,000,000 BONOS (Artículo VIII de la Carta de Autonomía de la Ciudad de Providence y la Ordenanza del Consejo Municipal 2015-45) ¿Deberá ser aprobada la ordenanza del Consejo Municipal efectiva el 2 de agosto del 2018, autorizando la emisión de hasta \$160,000,000 en bonos de obligación general de la ciudad, conforme con las Leyes Generales de Rhode Island §45-12-2 y §807 de la Carta de Autonomía de la Ciudad con el fin de financiar el plan de mejoras de capital escolar para los años fiscales 2019-2024, sujeto a la aprobación de la ayuda estatal de vivienda escolar a una tasa de reembolso o proporción de contribución estatal de no menos del 75% para aquellos gastos que sean elegibles para la ayuda estatal? ☐ Approve ☐ Rechar

Appendix C

Ballot Length Metrics Data

Precinct (Coded)	Pages	Sheets	Candidate Questions	State Questions	Local Questions	Bilingual	Total Questions	Candidate Select	Total Select	Total Words
1	2	1	12	3	3	0	18	15	21	729
2	2	1	12	3	3	0	18	15	21	729
3	2	1	12	3	3	0	18	15	21	729
4	2	1	12	3	3	0	18	15	21	729
5	2	1	12	3	3	0	18	15	21	729
6	2	1	13	3	0	0	16	19	22	627
7	2	1	13	3	0	0	16	19	22	627
8	2	1	13	3	0	0	16	19	22	627
9	2	1	13	3	0	0	16	19	22	627
10	2	1	13	3	0	0	16	19	22	627
11	2	1	13	3	0	0	16	19	22	627
12	2	1	13	3	0	0	16	19	22	627
13	2	1	13	3	0	0	16	19	22	627
14	2	1	13	3	0	0	16	19	22	627
15	2	1	11	3	0	0	14	18	21	614
16	2	1	11	3	0	0	14	18	21	614
17	2	1	11	3	0	0	14	18	21	614
18	2	1	11	3	0	0	14	18	21	614
19	2	1	11	3	0	0	14	18	21	614
20	2	1	11	3	1	1	15	11	15	110
21	2	1	11	3	1	1	15	11	15	110
22	2	1	11	3	1	1	15	11	15	110
23	2	1	11	3	1	1	15	11	15	110
24	2	1	11	3	1	1	15	11	15	110
25	2	1	11	3	1	1	15	11	15	110
26	2	1	11	3	1	1	15	11	15	110
27	2	1	11	3	1	1	15	11	15	110
28	2	1	11	3	1	1	15	11	15	110
29	2	1	11	3	1	1	15	11	15	110
30	2	1	11	3	1	1	15	11	15	110
31	2	1	11	3	1	1	15	11	15	110
32	2	1	11	3	1	1	15	11	15	110

Appendix D

Sample Set of Final Data Formatted

Event Description	Precinct (Coded)	Pages	Sheets	Candidate Questions	State Questions	Local Questions	Bilingual	Total Questions	Candidate Select	Total Select	Total Words	Differentiated Error	Binary Error
Multiple ballots were detected. Please remove ballots and insert them one ballot at a time. Ensure your ballot is not folded or damaged.	1	2	1	12	3	3	0	18	15	21	729	HMI	1
Ballot was removed during scanning. Please re-insert the ballot completely.	2	2	1	12	3	3	0	18	15	21	729	HMI	1
Multiple ballots were detected. Please remove ballots and insert them one ballot at a time. Ensure your ballot is not folded or damaged.	4	2	1	12	3	3	0	18	15	21	729	HMI	1
System Error - Contact Election Official.	4	2	1	12	3	3	0	18	15	21	729	Machine	1
Ballot Jam. Please remove ballot and re-insert.	2	2	1	12	3	3	0	18	15	21	729	Machine	1
Ballot Could Not Be Read. Please remove your ballot and re-insert the opposite end first.	5	2	1	12	3	3	0	18	15	21	729	Machine	1
Ballot Could Not Be Read. Please remove your ballot and re-insert the opposite end first.	5	2	1	12	3	3	0	18	15	21	729	Machine	1
Voter Accepted Overvoted Ballot	2	2	1	12	3	3	0	18	15	21	729	Marking	1
Voter Rejected Overvoted Ballot	3	2	1	12	3	3	0	18	15	21	729	Marking	1
Voter Accepted Overvoted Ballot	4	2	1	12	3	3	0	18	15	21	729	Marking	1
No Error	3	2	1	12	3	3	0	18	15	21	729	No	0
No Error	3	2	1	12	3	3	0	18	15	21	729	No	0
No Error	3	2	1	12	3	3	0	18	15	21	729	No	0
No Error	4	2	1	12	3	3	0	18	15	21	729	No	0
No Error	5	2	1	12	3	3	0	18	15	21	729	No	0

Appendix E

Ballot Scanner Codes, Categorization, and Observation Counts

		Scanner Event Codes	Count
Event Type	No Error	No Error	387233
	Machine Error	Ballot Jam. Please check the paper path.	269
		System Error - Contact Election Official.	8
		Ballot Jam. Please remove ballot and re-insert.	71
		Ballot Could Not Be Read. Please remove your ballot and re-insert the opposite end first.	4229
		Error scanning ballot. Please remove your ballot and re-insert the opposite end first. Ensure all stubs are removed from the ballot.	1677
		Shutdown initiated	5
		Ballot too short Please remove ballot.	19
		Voting Machine Not Programmed For Your Ballot	236
	Marking Error	Voter Rejected Overvoted Ballot	2159
		Voter Accepted Overvoted Ballot	3147
		Voter Rejected Blank Ballot	637
		Voter Accepted Blank Ballot	1906
		Automatically rejected Ballot with Unreadable mark	10014
	HMI Error	Ballot was not inserted far enough. Please remove your ballot and re-insert it completely.	675
		Ballot was removed during scanning. Please re-insert the ballot completely.	1678
		Multiple ballots were detected. Please remove ballots and insert them one ballot at a time. Ensure your ballot is not folded or damaged.	2694