



MIT ELECTION DATA
+ SCIENCE LAB

Elections Performance Index

Methodology Report

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2020 EPI Methodology

Contents

1	About the MIT Election and Data Science Lab (MEDSL)	3
2	Introduction	4
2.1	How the EPI was developed	5
2.2	Choice of indicators	6
2.3	Aggregation of indicators	10
3	Data overview	12
3.1	U.S. Census Bureau	12
3.2	Survey of the Performance of American Elections	12
3.3	Election Administration and Voting Survey	12
3.4	United States Elections Project	13
3.5	Being Online Is Not Enough and Being Online Is Still Not Enough	13
3.6	Data cleaning and modification of the EAVS	13
3.7	Indicator summaries and data sources	15
4	Indicators in detail	21
4.1	Data completeness	21
4.2	Disability- or illness-related voting problems (2008-2018)	25
4.3	Disability Access (2020)	32
4.4	ERIC Membership (2020-)	37
4.5	Mail ballots rejected	38
4.6	Mail ballots unreturned	43
4.7	Military and overseas ballots rejected	48
4.8	Military and overseas ballots unreturned	54
4.9	Online registration available	59
4.10	Postelection audit required	60
4.11	Provisional ballots cast	61
4.12	Provisional ballots rejected	67
4.13	Registration or absentee ballot problems	72
4.14	Registrations rejected	76
4.15	Residual vote rate	82
4.16	Risk-limiting audits (2020-)	88
4.17	Turnout	89
4.18	Voter registration rate	91

4.19 Voting information lookup tool availability	94
4.20 Voting wait time	95
5 Advisory Board	100
6 Endnotes	102

1 About the MIT Election and Data Science Lab (MEDSL)

By applying scientific principles to how elections are studied and administered, MEDSL aims to improve the democratic experience for all U.S. voters. MEDSL was founded at MIT in 2017 by Charles Stewart III. We are a dedicated group of social scientists and researchers who are committed to improving democracy in the United States by promoting the application of scientific principles to the understanding of election administration. The 2020 EPI was supported by the efforts of Charles Stewart III, Claire DeSoi, Abigale Belcrest, Joelle Gross, and Jack Williams at MEDSL. Previous versions were also supported by Stephen Pettigrew and Cameron Wimpy. MEDSL would like to thank the Pew Charitable Trusts for its initial support of the EPI, along with generous funding from the William and Flora Hewlett Foundation, Democracy Fund, and the provost of MIT.

2 Introduction

The Elections Performance Index (EPI) was originally released by the Pew Charitable Trusts in 2012 (covering data from the 2008 and 2010 elections) to be the first objective measure created to comprehensively assess how election administration functions in each state. The index was updated by Pew following the 2012 and 2014 elections. Pew transferred responsibility for subsequent updates of the index to the MIT Election Data and Science Lab (MEDSL) in 2017. The release of the index reflecting 2020 data is under the responsibility of MEDSL.

From 2008 to 2018, the EPI consisted of 17 indicators:

- Data completeness
- Disability- or illness-related voting problems
- Mail ballots rejected
- Mail ballots unreturned
- Military and overseas ballots rejected
- Military and overseas ballots unreturned
- Online registration available
- Post election audit required
- Provisional ballots cast
- Provisional ballots rejected
- Registration or absentee ballot problems
- Registrations rejected
- Residual vote rate
- Turnout
- Voter registration rate
- Voting information lookup tools
- Voting wait time

Two indicators were added to the EPI in 2020:

- Electronic Registration Information Center (ERIC) membership
- Risk-limiting audit required

Finally, the original disability- or illness-related voting problems indicator was retired in 2020, in favor of a new one. The new indicator measures a turnout differential between self-identified disabled and non-disabled voters, and the full description of this new measure is located in the indicator section entitled “Disability access (2020).”

By analyzing data on these indicators, the EPI makes it possible to compare election administration performance across states from one election cycle to the next and to begin to identify best practices and areas for improvement.

The 19 indicators can be used by policymakers, election officials, and others to shed light on issues related to such areas as voter registration, turnout, waiting times, absentee ballots, use of online technology, military and overseas voters, provisional ballots, access for people with disabilities, and the impact of voting machines or ballot design.

The online EPI interactive report presents these indicators in a format that allows a user to dig deeper and find the context behind each measurement. Using this tool, the user can see individual state pages that tell the stories about the state and individual indicator pages that explain what each indicator means and how to interpret differences.

Although we are transparent about the assumptions we make, we understand that people may disagree about what ought to be included in such an index. Our tool provides users with the functionality to adjust the indicators to create their own index.

The EPI presented here is based on data measuring the 2008, 2012, 2016, 2018, and 2020 general elections.

2.1 How the EPI was developed

The EPI was initially developed and constructed by The Pew Charitable Trusts, which published the first three iterations of the index in 2013, 2014, and 2016, covering elections from 2008, 2010, 2012, and 2014. In 2017, management and future development of the EPI was passed to the MIT Election Data and Science Lab, which is dedicated to the nonpartisan application of scientific principles to election research and administration.

In the early stages of the index, Pew worked with Charles Stewart III, the Kenan Sahin Distinguished Professor of Political Science at the Massachusetts Institute of Technology and the founding director of the MIT Election Data and Science Lab, to convene an advisory group (see Appendix for full list of members) of leading state and local election officials from 14 states, as well as academics from the country's top institutions, to help guide the initial development of an Elections Performance Index.

The EPI advisory group met five times between July 2010 and July 2012 during the development phase of the project, and once in August 2013, after the first edition of the EPI had been released, to review its progress. In developing the index, the group borrowed the best ideas from indexes in other public policy areas, identified and validated existing data sources, and determined the most useful ways to group these data.

To be useful, the right data must be married to an understanding of how elections function. Along with the advisory group, Pew surveyed a range of data sources to find approximately 40 potential indicators of election administration that could be used to understand performance or policy in this field. The challenge of identifying these data and compiling measurements resulted in Pew's February 2012 report "*Election Administration by the Numbers*," which provided an overview of elections data and how to use them.

Pew submitted these initial 40 measurements to strong validity and reliability tests and worked with the advisory committee from July 2010 to July 2012 to narrow them down. After the launch of the index, the indicators were reviewed for their performance and three more indicators were discussed for possible inclusion in the current edition of the Index. The 17 original indicators were the final measurements as decided in consultation with the advisory committee. We describe in more detail below how these indicators were

chosen, where these data came from, how they were prepared, and how they are used in the indicators.

In the summer of 2012, a team of academic researchers met at a two-day conference at MIT to subject all the proposed indicators to a thorough and rigorous scientific evaluation. The conference led to the removal of some indicators from the index, and led to a consideration of how other indicators are related to changes in policy and performance. Eventually, after the authors were given an opportunity to respond to comments and criticisms from conference participants, discussant feedback, and editor recommendations, the revised papers were collected together in a volume edited by Barry C. Burden and Charles Stewart III entitled *The Measure of American Elections*.¹

After the EPI was transferred to MEDSL, the lab's advisory board took up responsibility for giving advice about the addition of new indicators and the possible retirement of existing indicators. The two new indicators added for the 2020 edition of the EPI and the revised disability indicator were considered by the advisory board.

2.2 Choice of indicators

The Elections Performance Index is currently built on 19 indicators, with an overall score that represents the average of all normalized indicator scores for each state.

Deciding which indicators to include in the EPI was an iterative process, in which two broad considerations were kept in mind.

1. Any performance index, regardless of the subject, should reflect a comprehensive understanding of all salient features of the policy process being assessed.
2. Any indicator in the index must conform to a set of quality standards.

In developing the EPI, Pew, in consultation with Professor Stewart and the EPI advisory committee, pursued a systematic strategy to ensure that both of these considerations were given due weight.

Comprehensive understanding of election policy and administration

The initial conceptualization of election administration drew upon Heather Gerken's book *The Democracy Index*.² Building on this work, it became clear that a well-run election is one in which all eligible voters can straightforwardly cast ballots (convenience) and that only eligible voters cast ballots, which are counted accurately and fairly (integrity).

Elections can further be broken down into three major administrative phases: registration, voting, and counting.

Combining these two ideas, we conceptualized a rather simple yet powerful rubric to use in making sure all important features of election administration are accounted for in the construction of an index. This rubric can be summarized as shown in the table below.

CONVENIENCE	INTEGRITY
REGISTRATION	REGISTRATION
VOTING	VOTING
COUNTING	COUNTING

Each of the six cells in this table reflects a feature of election administration we sought to capture in the EPI. For instance, an EPI should strive to assess how easy it is for eligible voters to register (registration convenience) and how well registration lists are maintained, to ensure that ineligible voters are removed (registration integrity).

This rubric was used throughout the development process to help understand which aspects of elections were well-covered by the available indicators and to illuminate areas in which further work was needed to develop indicators.

Throughout the development process, it was apparent that indicators measuring the convenience of voting were much more abundant than indicators measuring security and integrity. This fact represents the current state of election data. Because of the intense policy interest in the security and integrity of elections, working with the elections community to develop a more robust set of integrity-related indicators is a priority of the EPI project moving forward.

It was also apparent that the row depicting “voting” is the phase in which there is the most objective information to help assess the performance of U.S. elections. The mechanics of voting produce copious statistics about how many people engage in different modes of voting (in person on Election Day, in-person early voting, and absentee/vote by mail), along with subsidiary statistics about those modes (for example, how many absentee ballots are requested, how many are returned, how many are rejected and for what reason, and the like). A close second is “registration,” which also produces many performance statistics as a byproduct of the administrative workflow

“Counting” is an area where high-quality measures of election performance remain in relatively short supply. The measures that do exist, such as whether a state required post election audits, tend to reflect inputs into election administration, rather than outputs of the process. By inputs, we mean that the measures reflect the presence of “best practices” set into law by the state, rather than outputs that assess the data produced by

the performance of a particular election practice. As with the issue of voting security and integrity, vote counting is one area in which effort must be expended in the future so that the EPI might cover the process of voting more comprehensively.

Quality standards

The first step of developing the EPI involved taking the conceptualization of election administration and policy reflected in previous table and brainstorming about the measures that could be associated with each of the six cells.³ That process, done in collaboration with the advisory committee, initially yielded more than 40 indicators. Some were well-established and easy to construct, such as a state's turnout rate. Others were less so, such as the correlation between canvassed vote counts and audited vote counts.

To move an indicator from the list of "candidate indicators" to those that appear in the index, we developed criteria for judging whether the indicator was valid and reliable enough to include. Most policy indicator projects think about this issue; with the advisory group, we surveyed the criteria behind many of today's leading policy indexes. These included projects such as the Environmental Performance Index⁴, County Health Rankings & Roadmaps⁵, World Justice Project Rule of Law Index⁶, and the Annie E. Casey Foundation's Kids Count Data Book.⁷

Drawing on these efforts, the EPI adopted the following criteria for helping to decide which candidate indicators to include in the current release of the Elections Performance Index.

1. **Any statistical indicator included in the EPI must be from a reliable source.** Preferably, the source should be governmental. If not, it should demonstrate the highest standards of scientific rigor. Consequently, the EPI relies heavily on sources such as the U.S. Election Assistance Commission, the U.S. Census Bureau, and state and local election departments.
2. **The statistical indicator should be available and consistent over time.** Availability over time serves two purposes. First, from a methodological perspective, it allows us to assess the stability of the measure, which is a standard technique for assessing reliability. Second, it allows the index to evolve to reflect developments with the passing of elections; states should be able to assess whether they are improving and should be able to calibrate their most recent performance against past performance, overall goals, and perceived potential. The issue of consistency is key because we want to make sure that an indicator measures the same thing over time, so that any changes in a measure reflect changes in policy or performance, not changes in definition.
3. **The statistical indicator should be available and consistent for all states.** Because the EPI seeks to provide comparable measurements, it is important that the measures included in the index be available for all 50 states, plus the District of Columbia. However, this is not always possible, given the variation in some state election practices. For instance, some states with Election Day registration do not require the use of provisional ballots; therefore, provisional balloting statistics may not be avail-

able for these states. With this in mind, some candidate indicators were excluded because data were available for too few states or because state practices varied so widely that it was impossible to form valid comparisons.

4. **The statistical indicator should reflect a salient outcome or measure of good elections.** In other words, the indicator should reflect a policy area or feature of elections that either affects many people or is prominently discussed in policy circles. An example of a policy area that is salient but affects relatively few voters concerns overseas and military voters, who comprise a small fraction of the electorate but about whom Congress has actively legislated in recent years.
5. **The statistical indicator should be easily understood by the public and have relatively unambiguous interpretations.** That an indicator should be easily understood is an obvious feature of a policy index. The desire to include indicators with unambiguous interpretations sometimes presented a challenge, for at least two reasons. First, values of some indicators were sometimes the consequence of policy and demographic features of the electorate. For instance, academic research demonstrates that registration rates are a result of both the registration laws enacted by states and factors such as education and political interest. In these cases, if it could be shown that changes in policy regularly produced changes in indicators, we included the indicators. Second, some features of election administration, such as the rejection rates of new voter registrations and absentee ballots, can be interpreted differently. A high rejection rate of new voter registrations could represent problems with the voter registration process or large numbers of voters who were attempting to register but were not eligible. Indicators that were deemed highly ambiguous were removed from consideration; indicators with less ambiguity were retained, but more discussion and research are warranted.
6. **The statistical indicator should be produced in the near future.** Because the EPI is envisioned as an ongoing project, it is important that any indicators continue in the future. In addition, because one function of the EPI is to document changes in policy outputs as states change their laws and administrative procedures, it is important to focus on indicators that can document the effects of policy change. There is no guarantee that any of the indicators in the EPI today will remain in the future. However, the indicators that were chosen were the ones most likely to continue, because they are produced by government agencies or as part of ongoing research projects.

2.3 Aggregation of indicators

The EPI is built on 19 indicators of electoral performance. Because election administration is so complex and involves so many activities, it is illuminating to explore each indicator separately, with an eye toward understanding how particular states perform, both in isolation and in comparison with one another. Another way to use the EPI is to combine information from various indicators to develop a summary measure of the performance of elections. It is useful to know how a state performs on most measures, relative to other states.

The overall state percentiles and “performance bars” used in the EPI interactive report are based on a method that essentially calculates the average of all indicator rankings for each state. This, by nature of averages, weighs the indicators equally.⁸

In addition, the summary measurement, which is calculated using the same basic averaging, is what drives the performance bar chart, whether a user selects all of the indicators in the interactive report or only a few. However, implementing this method required adjustment for two reasons: missing values and the issue of scaling.

Missing values

For many measures, especially those derived from the Election Administration and Voting Survey (EAVS) states were missing data due to the failure of the state or its counties to provide the information needed to calculate the indicator.⁹ The question arises as to how to rank states in these circumstances. For instance, nine states (Alabama, Arkansas, Connecticut, Minnesota, Mississippi, New Mexico, New York, Tennessee, and West Virginia) did not report enough data to calculate the percentage of mail ballots that were not returned in 2008. Therefore, we could compute the mail ballot nonreturn rate for only 42 states. (We included the District of Columbia as a state for this and similar comparisons.)

Scaling

Another issue that had to be addressed in constructing the EPI was how to scale the indicators before combining them into a summary measure. The general strategy was to construct a scale that ran from 0 to 1 for each indicator, with zero reserved for the state with the lowest performance measure in 2008, 2012, 2016, and 2020 (for presidential years) or 2010, 2014, and 2018 (for midterm years), and with 1 reserved for the state with the highest measure.

We “normalized” the rankings separately for presidential and midterm years. For presidential years, we set the top-ranked state for 2008, 2012, 2016, and 2020 combined to 1 (or 100 percent) and the bottom-ranked state to zero. For midterm years, we similarly set the top-ranked state for 2010, 2014, and 2018 combined to 1 and the bottom-ranked state to zero. Doing so allowed us to make comparisons across years, for presidential elections of the same time.¹⁰ As an example, Indiana in 2016, which had the best presidential year

absentee nonreturn rate (0.2 percent), would be set to one, while New Jersey in 2008, which had the worst rate (43 percent), would be set to zero. The remaining states (plus the District of Columbia) in those two years would then be set to values that reflected their relative distance between the high and low values.¹¹

Because many of the indicators are not naturally bound between zero and one, it is necessary to estimate what the natural interval is. Based on an indicator's high and low values for the relevant years combined, states would receive a score between zero and 1 that proportionately reflected their position between the high and low values. In the residual vote rate indicator, we use data from 2000, 2004, 2008, 2012, 2016, 2018, and 2020. As an example of this scaling, we know that the highest residual vote rate since 2000 was 3.85 percent in 2000 in Illinois, while the lowest was 0.17 percent in 2012 in the District of Columbia.

Therefore, the lowest residual vote rate found between 2000 and 2020 (0.17 percent) would be set to 1 (a lower residual vote rate indicates fewer voting accuracy problems) and the highest residual vote rate (3.85 percent) would be set to zero. All of the remaining states would receive a score between zero and 1 that reflected proportionately how far within this range each state's value was.

Exceptions to these normalization rules apply to the two new indicators added in 2020. The goal by adding these indicators was to highlight states that adopted two widely recognized best practices, risk-limiting audits and membership in the Electronic Research Information Center. Yet, the way the normalization typically works, simply adding these two indicators and normalizing them like the others would have resulted in significant drops in the scores of most states. Future editions of the EPI may adopt this practice, as more states adopt these practices. Until then, it is the intention of the EPI project to gradually phase in these new indicators, giving a boost to the overall Index score to a few states without harming the scores of the others.

A shortcoming of the overall approach is that it may make too much of small differences in performance, especially when most states perform at the high end of the range, with only a few at the low end. An example is data completeness, on which many states had rates at or near 100 percent. Thus it seems more valid to use the raw value of the indicator in the construction of a composite index score, rather than the normalized score.

3 Data overview

The Elections Performance Index relies on a variety of data sources, including census data, state-collected data, Pew reports, and public surveys. The data sources were selected based on significance at the state level, data collection practices, completeness, and subject matter. Although we present an introduction to these data sources, additional information on their strengths and limitations can be found in “Section 1: Datasets for Democracy” in the 2012 Pew report “Election Administration by the Numbers: An Analysis of Available Datasets and How to Use Them.”

3.1 U.S. Census Bureau

In November of every federal election year, the U.S. Census Bureau conducts a Voting and Registration Supplement (VRS) as part of its Current Population Survey (CPS). The VRS surveys individuals on their election-related activities. The EPI includes three indicators from this data source: disability- or illness-related voting problems, registration or absentee ballot problems, and the voter registration rate.

The CPS is a monthly survey, but the VRS is biennial, conducted every other November after a federal election. In 2018, the VRS interviewed approximately 123,000 eligible voters.¹² In 2020, the survey included approximately 134,000 eligible voters. While on occasion special questions are included in the VRS, the core set of questions is limited and ascertains whether the respondent voted in the most recent federal election and had been registered to vote in that election. Eligible voters who reported that they did not vote in the most recent federal election are asked why they did not vote.

3.2 Survey of the Performance of American Elections

The Survey of the Performance of American Elections (SPAЕ) is a public interest survey. The SPAЕ surveyed 10,000 registered voters (200 from each state) via internet in the week after the 2008 presidential election, and 10,200 voters after the 2012 and 2016 presidential elections and 2014 midterm election. The District of Columbia was added in 2012. In 2020, the SPAЕ surveyed a total of 18,200 voters, owing to an oversampling of 1,000 voters in 10 states, in addition to the standard 200 observations in the remaining states and DC. Data from this survey were used to create an indicator measuring waiting time to vote.

3.3 Election Administration and Voting Survey

The U.S. Election Assistance Commission administers EAVS, a survey that collects jurisdiction-level data from each state and the District of Columbia on a variety of topics related to election administration for each federal election. EAVS data make up the majority of the EPI’s indicators and are used for indicators related to turnout, registration, absentee ballots, military and overseas ballots, and provisional ballots.

3.4 United States Elections Project

The United States Elections Project provides data on the voting-eligible population and turnout for presidential and midterm elections. Michael McDonald, an associate professor of political science at the University of Florida, maintains the United States Election Project website.

3.5 Being Online Is Not Enough and Being Online Is Still Not Enough

Pew's reports *Being Online Is Not Enough* (2008), *Being Online is Still Not Enough* (2011), and *Online Voter Lookup Tools* (2013) reviewed the election websites of all 50 states and the District of Columbia. The reports examined whether these sites provide a series of lookup tools to assist voters. The 2008 report identified whether states had online tools for checking registration status and locating a polling place in time for the November 2008 election. The 2011 and 2013 reports identified whether states provided those two as well as three others, for finding absentee, provisional, and precinct-level ballot information, in time for the November 2010 and November 2012 elections. The tool scores for both years were used to evaluate states on their election websites.

3.6 Data cleaning and modification of the EAVS

The Election Assistance Commission's (EAC) EAVS data, historically, has had substantial missing or anomalous information. For 2020, the EAC took multiple steps to correct and confirm information prior to the publication of the EAVS data. To ensure that the EAVS data included in the EPI were as accurate and complete as possible, we conducted a multistep cleanup process.

Missing data

In some cases, states lacked responses for all of their jurisdictions; in others, data were missing for only a few jurisdictions. If a state lacked data for all jurisdictions, we attempted to gather the missing information by contacting the state or counties directly. If a state lacked data for just some jurisdictions, we decided whether to follow up based on the percentage of data missing and the distribution of that data throughout the state. If a state's data total was 85 percent or more complete, we did not follow up on the missing data unless it contained a high-population jurisdiction whose absence meant that a state-level indicator might not representatively reflect elections in that state. If a state's data were less than 85 percent complete, we always followed up on missing data.

We used several strategies to collect missing data. In all cases, we contacted the state to confirm that data from the EAVS were correct and to see if additional information was available. We contacted a state at least four times and reached out to at least two staff people before giving up. In specific cases, we contacted local election officials to obtain missing data.

In some cases, we succeeded in gathering missing data. For example, we found the number of voters from each jurisdiction who participated in the election on various state election websites, even if it had not been submitted to the Election Assistance Commission.

Finally, we imputed some of the missing data when the EAVS survey asked for the same information in different places throughout its questions. If the missing data could be found in another question, we would replace the missing value with this question's value.

When missing data were found, either from the state or through our own efforts, the data were added to the EAVS data set and used to calculate the indicators.

Anomalous data

Two primary strategies were used to identify anomalous data. First, each of the EAVS-based indicators used a pair of questions to develop the indicator value, such as the number of absentee ballots sent to voters and the number of absentee ballots returned. We looked at each question pair and identified instances where one value contradicted the other, for example, if the number of absentee ballots returned exceeded the number of absentee ballots sent out. In these cases, we marked both questions as missing.

The second strategy was to search for statistically improbable data, given responses to related questions and responses to previous releases of the EAVS. The potentially anomalous values were examined individually, and a decision about how to resolve the anomaly was made on a case-by-case basis. In most cases, the jurisdiction reporting the data was contacted for clarification or correction. This usually resulted in a correction of previously reported statistics. In a few cases, the originally reported data were revealed to be unreliable, in which case the data were set to missing. If we were able to gather any new data to replace the anomalous information, we included the new information in the data set and used it to develop the indicators.

3.7 Indicator summaries and data sources

Table 1: Online Capability Indicators

Indicator	Data source	Scaling anchors	Percent of missing data	Minimum and maximum observed values
Voting information lookup tools	“Being Online is Not Enough” (2008), “Being Online is Still Not Enough” (2011), “Online Voter Lookup Tools” (2013)	On-year	08: 0.00	08: [0,1]
		0: 0.000	10: 0.00	10: [0,1]
		1: 1.000	12: 0.00	12: [0,1]
		Off-year	14: 0.00	14: [0,1]
		0: 0.000	16: 0.00	16: [0,1]
		1: 1.000	18: 0.00	18: [0,1]
Online registration available	State election division information	On-year	08: 0.00	08: [0,1]
		0: 0.000	10: 0.00	10: [0,1]
		1: 1.000	12: 0.00	12: [0,1]
		Off-year	14: 0.00	14: [0,1]
		0: 0.000	16: 0.00	16: [0,1]
		1: 1.000	18: 0.00	18: [0,1]
			20: 0.00	20: [0,1]

Table 2: Registration

Indicator	Data source	Scaling anchors	Percent of missing data	Minimum and maximum observed values
Electronic Registration Information Center (ERIC) membership	ERIC website	On-year 0: NA 1: 1.000 Off-year 0: NA 1: 1.000	20: 0.00	2020: [NA,1]
Registration or absentee ballot problems	VRS	On-year 0: 0.139 1: 0.005 Off-year 0: 0.102 1: 0.007	08: 0.00 10: 0.00 12: 0.00 14: 0.00 16: 0.00 18: 0.00 20: 0.00	08: [0.008,0.134] 10: [0.007,0.102] 12: [0.012,0.138] 14: [0.009,0.097] 16: [0.010,0.139] 18: [0.009,0.076] 20: [0.005,0.117]
Registrations rejected	EAVS	On-year 0: 0.672 1: 0.000 Off-year 0: 0.638 1: 0.000	08: 29.00 10: 29.09 12: 17.97 14: 11.85 16: 9.50 18: 16.45 20: 12.48	08: [0.000,0.369] 10: [0.000,0.555] 12: [0.000,0.209] 14: [0.000,0.134] 16: [0.000,0.672] 18: [0.000,0.638] 20: [0.000,0.604]
Voter registration rate	VRS	On-year 0: 0.696 1: 0.959 Off-year 0: 0.640 1: 0.908	08: 0.00 10: 0.00 12: 0.00 14: 0.00 16: 0.00 18: 0.00 20: 0.00	08: [0.696,0.918] 10: [0.658,0.868] 12: [0.709,0.925] 14: [0.640,0.867] 16: [0.719,0.936] 18: [0.709,0.908] 20: [0.791,0.959]

Table 3: Voting

Indicator	Data source	Scaling anchors	Percent of missing data	Minimum and maximum observed values
Disability- or illness-related voting problems	VRS	On-year	08: 0.00	08: [0.064,0.260]
		0: 0.260	10: 0.00	10: [0.047,0.187]
		1: 0.034	12: 0.00	12: [0.035,0.248]
		Off-year	14: 0.00	14: [0.048,0.185]
		0: 0.187	16: 0.00	16: [0.034,0.223]
		1: 0.047	18: 0.00	18: [0.061,0.168]
Disability access	VRS	On-year	20: 0.00	20: [-0.165,0.000]
		0: -0.183		
		1: 0.000		
		Off-year		
		0: NA		
		1: NA		
Turnout	United States Elections Project	On-year	08: 0.00	08: [0.490,0.781]
		0: 0.422	10: 0.00	10: [0.296,0.560]
		1: 0.800	12: 0.00	12: [0.445,0.761]
		Off-year	14: 0.00	14: [0.283,0.585]
		0: 0.283	16: 0.00	16: [0.422,0.742]
		1: 0.642	18: 0.00	18: [0.393,0.642]
Voting technology accuracy (residual vote rate)	State election division records	On-year	08: 1.58	08: [0.002,0.032]
		0: 0.04	12: 1.14	12: [0.002,0.022]
		1: 0.00	16: 0.83	16: [0.002,0.031]
		Off-year	20: 3.55	20: [0.002,0.020]
		0: NA		
		1: NA		
Voting wait time	SPAЕ, CCES	On-year	08: 0.00	08: [0.490,0.781]
		0: 61.50	10: 0.00	10: [0.296,0.560]
		1: 0.11	12: 0.00	12: [0.445,0.761]
		Off-year	14: 0.00	14: [0.283,0.585]
		0: 15.40	16: 0.00	16: [0.422,0.742]
		1: 0.41	18: 0.00	18: [0.393,0.642]
		20: 0.00	20: [0.550,0.800]	

Table 4: Military and Overseas Voters

Indicator	Data source	Scaling anchors	Percent of missing data	Minimum and maximum observed values
Military and overseas ballots rejected	EAVS	On-year	08: 12.70	08: [0.007,0.129]
		0: 0.500	10: 1.72	10: [0.000,0.253]
		1: 0.000	12: 8.04	12: [0.002,0.206]
		Off-year	14: 6.71	14: [0.000,0.161]
		0: 0.253	16: 1.13	16: [0.000,0.500]
		1: 0.000	18: 7.10	18: [0.003,0.152]
			20: 2.68	20: [0.000,0.051]
Military and overseas ballots unreturned	EAVS	On-year	08: 8.39	08: [0.143,0.535]
		0: 0.565	10: 0.40	10: [0.013,0.880]
		1: 0.000	12: 5.39	12: [0.115,0.474]
		Off-year	14: 5.03	14: [0.103,0.848]
		0: 0.880	16: 0.73	16: [0.000,0.459]
		1: 0.013	18: 3.13	18: [0.104,0.774]
			20: 0.51	20: [0.000,0.565]

Table 5: Mail Ballots

Indicator	Data source	Scaling anchors	Percent of missing data	Minimum and maximum observed values
Mail ballots rejected	EAVS	On-year	08: 8.38	08: [0.000,0.010]
		0: 0.018	10: 6.92	10: [0.000,0.013]
		1: 0.000	12: 4.89	12: [0.000,0.009]
		Off-year	14: 2.22	14: [0.000,0.013]
		0: 0.013	16: 2.52	16: [0.000,0.009]
		1: 0.000	18: 1.90	18: [0.000,0.012]
			20: 2.34	20: [0.000,0.018]
Mail ballots nonreturned	EAVS	On-year	08: 6.97	08: [0.016,0.434]
		0: 0.434	10: 6.01	10: [0.000,0.516]
		1: 0.003	12: 7.17	12: [0.007,0.294]
		Off-year	14: 0.63	14: [0.009,0.495]
		0: 0.516	16: 0.34	16: [0.003,0.291]
		1: 0.000	18: 23.30	18: [0.005,0.328]
			20: 0.70	20: [0.016,0.273]

Table 6: Provisional Ballots

Indicator	Data source	Scaling anchors	Percent of missing data	Minimum and maximum observed values
Provisional ballots cast	EAVS	On-year	08: 6.29	08: [0.000,0.065]
		0: 0.131	10: 5.28	10: [0.000,0.052]
		1: 0.000	12: 4.36	12: [0.000,0.131]
		Off-year	14: 3.37	14: [0.000,0.113]
		0: 0.113	16: 3.36	16: [0.000,0.089]
		1: 0.000	18: 1.28	18: [0.000,0.078]
			20: 14.89	20: [0.000,0.068]
Provisional ballots rejected	EAVS	On-year	08: 9.07	08: [0.000,0.019]
		0: 0.019	10: 5.83	10: [0.000,0.008]
		1: 0.000	12: 4.80	12: [0.000,0.018]
		Off-year	14: 3.61	14: [0.000,0.007]
		0: 0.011	16: 3.74	16: [0.000,0.015]
		1: 0.000	18: 1.39	18: [0.000,0.011]
			20: 11.90	20: [0.000,0.009]

Table 7: Data Transparency

Indicator	Data source	Scaling anchors	Percent of missing data	Minimum and maximum observed values
Postelection audit required	EAVS Statutory Overview	On-year	08: 0.00	08: [0,1]
		0: 1.000	10: 0.00	10: [0,1]
		1: 0.000	12: 0.00	12: [0,1]
		Off-year	14: 0.00	14: [0,1]
		0: 1.000	16: 0.00	16: [0,1]
		1: 0.000	18: 0.00	18: [0,1]
			20: 0.00	20: [0,1]
Data completeness	EAVS	On-year	08: 0.00	08: [0.000,1.000]
		0: 0.000	10: 0.00	10: [0.594,1.000]
		1: 1.000	12: 0.00	12: [0.582,1.000]
		Off-year	14: 0.00	14: [0.625,1.000]
		0: 0.594	16: 0.00	16: [0.744,1.000]
		1: 1.000	18: 0.00	18: [0.765,1.000]
			20: 0.00	20: [0.863,1.000]
Risk-limiting audit required	National Conference of State Legislatures and state election offices	On-year	20: 0.00	20: [NA,1]
		0: NA		
		1: 1.000		
		Off-year		
		0: NA		
		1: NA		

4 Indicators in detail

4.1 Data completeness

4.1.1 *Data Source*

Election Administration and Voting Survey

The starting point for managing elections using metrics is gathering and reporting core data in a systematic fashion. The independent U.S. Election Assistance Commission (EAC) through its Election Administration and Voting Survey (EAVS) has established the nation's most comprehensive program of data-gathering in the election administration field. The greater the extent to which local jurisdictions gather and report core data contained in the EAVS, the more thoroughly election stakeholders will be able to understand key issues pertaining to the conduct of elections.

The nature of the items included in the EAVS makes it the logical choice of a source for assessing the degree to which election jurisdictions gather and make available basic data about the performance of election administration in states and local voting. The EAVS is a comprehensive survey consisting of six sections: voter registration, the Uniformed and Overseas Citizens Absentee Voting Act (UOCAVA) voting, domestic absentee voting, election administration, provisional ballots, and Election Day activities. The EAVS asks states and localities for basic data associated with each federal election: how many people voted, the modes they used to vote, and so forth. The survey is responsive to EAC mandates to issue regular reports, given in the National Voter Registration Act (NVRA) the UOCAVA, and the 2002 Help America Vote Act (HAVA). The EAVS survey instrument is 29 pages long, and the data set produced by the 2020 instrument included over 400 variables.

While states are required to provide some of the information requested in the EAVS, other items are not mandatory. Therefore, in using the EAVS to measure the degree to which states report basic data related to election administration, it is important to distinguish between what is basic among the data that are included in the EAVS and what may be considered either secondary or (more often) a more-detailed look at basic quantities. The data completeness measure is based on the reporting of basic measures.

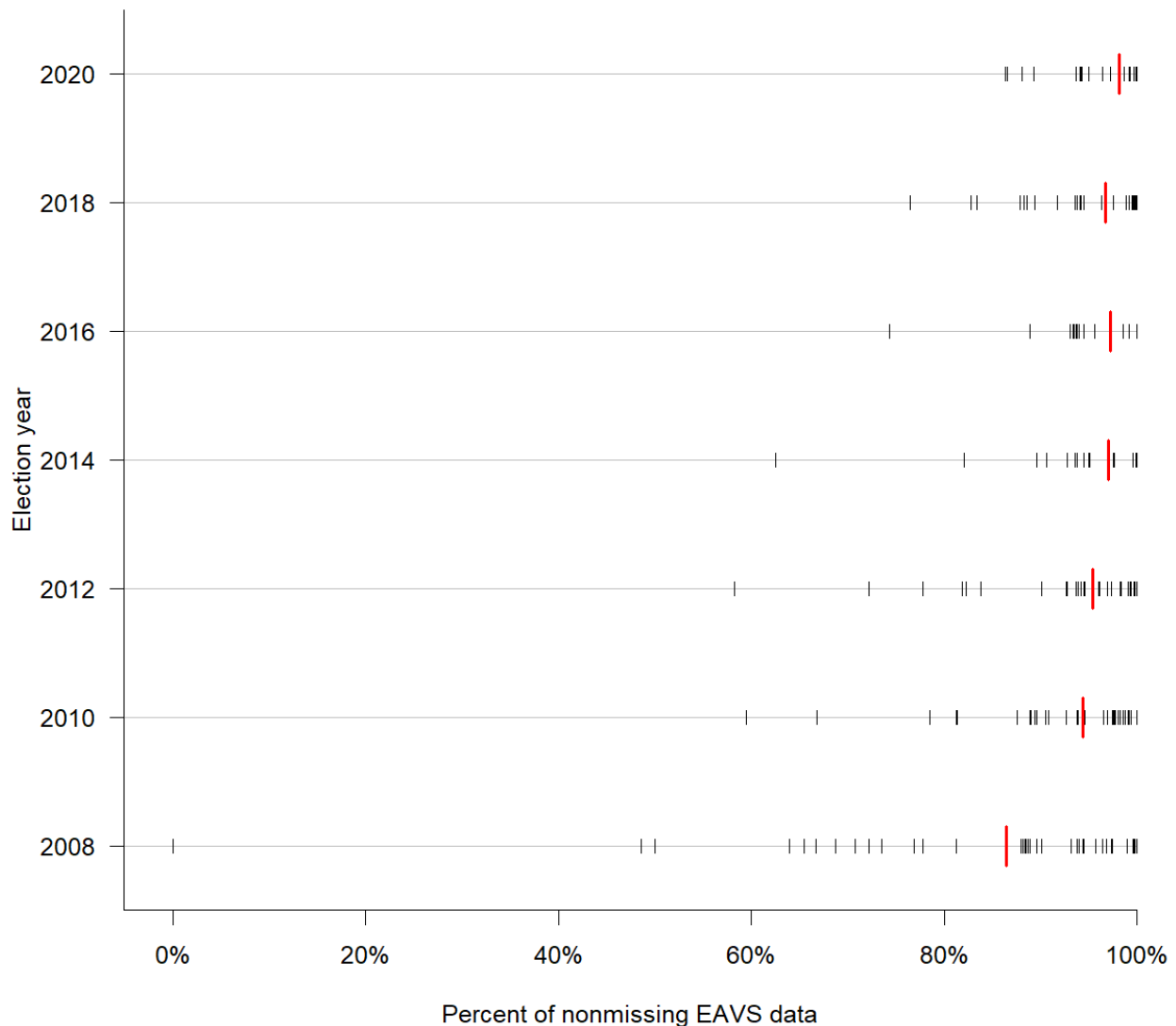
The central idea of this measure is to assess states according to how many counties report core statistics that describe the workload associated with conducting elections. The completeness measure starts with 15 survey items that were considered so basic that all jurisdictions should be expected to report them, for the purpose of communicating a comprehensive view of election administration in a community:

1. New registrations received.
2. New valid registrations received.
3. Total registered voters.
4. Provisional ballots submitted.
5. Provisional ballots rejected.
6. Total ballots cast in the election.
7. Ballots cast in person on Election Day.
8. Ballots cast in early voting centers.
9. Ballots cast absentee.
10. Civilian absentee ballots transmitted to voters.
11. Civilian absentee ballots returned for counting.
12. Civilian absentee ballots accepted for counting.
13. UOCAVA ballots transmitted to voters.
14. UOCAVA ballots returned for counting.
15. UOCAVA ballots counted.

Added to these 15 basic measures are three that help construct indicators used in the election index:

16. Invalid or rejected registration applications.
17. Absentee ballots rejected.
18. UOCAVA ballots rejected.

Figure 1: EAVS Data Completeness

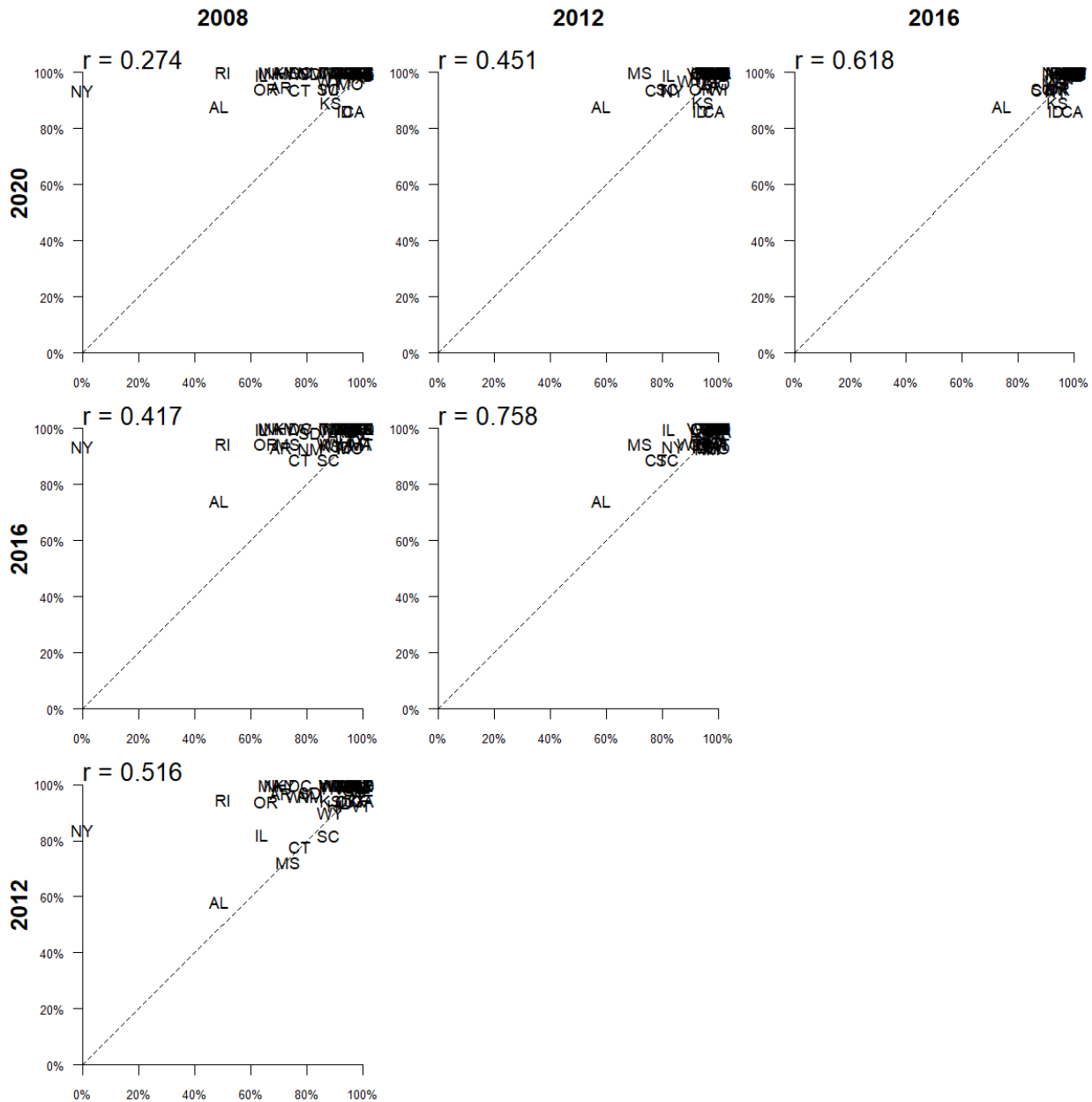


As illustrated by [Figure 1](#), which plots completeness rates for all the states from 2008 to 2020 the completeness rate of the 18 EAVS items has risen in almost all successive release of the index, from an average of 86 percent in 2008 to 96 percent in 2018. Between 2014-2018, there was actually a small decrease of around 1% for the first time in the history of the EPI, but completeness returned to the prior trend, increasing a small amount in 2020. The smaller vertical lines in [Figure 2](#) indicate the completeness rate of a particular state. (The larger, red lines indicate the average for the year.)

The biggest jump in average completeness occurred between 2008 and 2010, when New York went from reporting no data at the county level to reporting county-level statistics for about two-thirds of the items.

Figure 2 compares completeness rates across the five other election cycles covered by the EPI through the 2020 election. The dashed lines in the figure indicate where observations for the two years are equal.

Figure 2: Percent Completeness on Key EAVS Questions



As the graphs illustrate, overall completion levels of the key EAVS items improved considerably from 2008 to 2010, with nearly every state reporting more data in 2010 than in 2008. With many states reporting data at (or near) 100 percent, improvement slowed between 2010 and 2012. The graphs also indicate that only a handful of states are significantly below the 100 percent completeness rate.

4.2 Disability- or illness-related voting problems (2008-2018)

4.2.1 *Data source*

Voting and Registration Supplement to the Current Population Survey

Note: This indicator was discontinued for the 2020 election and replaced by “Disability access”, which is described in Section 4.3. Section 4.2 is reprinted from the 2018 methodology document.

Access to voting for the physically disabled has been a public policy concern for years. The federal Voting Accessibility for the Elderly and Handicapped Act, passed in 1984, generally requires election jurisdictions to ensure that their polling places are accessible to disabled voters. The Voting Rights Act of 1965, as amended, and HAVA also contain provisions that pertain to ensuring that disabled Americans have access to voting. HAVA, in particular, established minimum standards for the presence of voting systems in each precinct that allow people with disabilities the same access as those without disabilities.

Studies of the effectiveness of these laws and other attempts at accommodation have been limited. On the whole, they confirm that election turnout rates for people with disabilities are below those for people who are not disabled and that localities have a long way to go before they meet the requirements of laws such as the Voting Accessibility for the Elderly and Handicapped Act and HAVA.¹³ Investigations into the participation of the disabled and the accessibility of polling places have, at most, been conducted using limited representative samples of voters or localities. As far as can be ascertained, studies comparing jurisdictions have not been conducted.

4.2.2 *Coding convention*

This indicator is based on responses to the Voting and Registration Supplement of the Current Population Survey, which is conducted by the U.S. Census Bureau. Specifically, it is based on responses to item PES4, which asks of those who reported not voting: “What was the main reason you did not vote?” [Table 8](#) reports the proportion of voters who reported various reasons for not voting in 2014 and 2018.¹⁴

Table 8: Reason for Not Voting

Response category	2014	2018
Too busy, conflicting work or school schedule	29.1%	27.7%
Not interested, felt my vote wouldn't make a difference	16.9%	16.0%
Illness or disability (own or family's)	11.2%	13.2%
Other	9.4%	12.1%
Out of town or away from home	9.8%	9.5%
Forgot to vote (or send in absentee ballot)	8.5%	5.7%
Didn't like candidates or campaign issues	7.8%	5.5%
Inconvenient hours or polling place; lines too long	2.3%	3.4%
Registration problems	2.5%	3.2%
Transportation problems	2.2%	3.0%
Bad weather conditions	0.4%	0.6%

The *illness or disability (own or family's)* category forms the basis for this indicator. Note that it includes both individuals who say they were disabled and those who say they were ill. Furthermore, it includes disability or illnesses for a member of the family. A more precise measure of the degree to which disabled voters have access to voting would include information about which respondents were disabled.

Unfortunately, only in 2008 did the VRS begin asking respondents if they, themselves, were disabled. Therefore, before then, it was not possible to construct a measure that focused only on disabled respondents. However, it is possible to use information about the disability of respondents in 2010 and beyond to test the validity of the measure. The 2008 CPS began asking respondents if they had one of six disabilities. [Table 9](#) lists those disabilities, along with the percentage of nonvoters in 2014 and 2018 who reported having that disability and stated that the primary reason they did not vote was due to illness or disability. In addition, it reports the nonvoting rates due to illness or disability among respondents who reported no disabilities.

Table 9: Percent of Disabled People Did Not Vote Because of a Disability or Illness, by Disability Type

Disability	2014	2018
Difficulty dressing or bathing	57.4%	62.3%
Deaf or serious difficulty hearing	35.6%	38.9%
Blind or difficulty seeing even with glasses	40.9%	39.2%
Difficulty doing errands	52.2%	54.4%
Difficulty walking or climbing stairs	46.3%	49.0%
Difficulty remembering or making decisions	40.3%	42.8%
At least one of the above disabilities	38.6%	40.8%
No disabilities reported	6.7%	7.8%

Thus, a nonvoter with any one of the disabilities is several times more likely to give the “illness or disability” answer to the question of why he or she did not vote, compared with someone without any of these disabilities. Furthermore, the more disabilities a nonvoter lists, the more likely he or she is to give this response, as Table 10 below demonstrates.

Table 10: Percent of Disabled People Did Not Vote Because of a Disability or Illness, by Disability Type

	0	1	2	3	4 or more
2014	6.7%	27.8%	41.8%	48.8%	62.0%
2018	7.8%	29.0%	43.9%	50.1%	65.3%

We are using answers to this question as an indicator of how difficult it is for disabled voters to participate in elections. It would be ideal to measure this indicator by considering only the responses of disabled voters. Unfortunately, before 2008, the CPS did not ask respondents if they had a physical disability. Therefore, the indicator mixes the responses of disabled and nondisabled individuals. In 2008, the CPS began asking directly about disability status. This means that it will become possible to construct this indicator by relying solely on the answers of disabled respondents.

In the interim, it is important to know whether the relative ranking of states on this indicator is the same if we confined ourselves to disabled respondents, compared with constructing the indicator using the responses of all respondents. We are able to answer this question using the data after 2010, because we can construct the indicator both ways, using answers from all respondents and from only disabled respondents.

Figure 3: Disability Indicator with All Nonvoters Versus Only Disabled Nonvoters

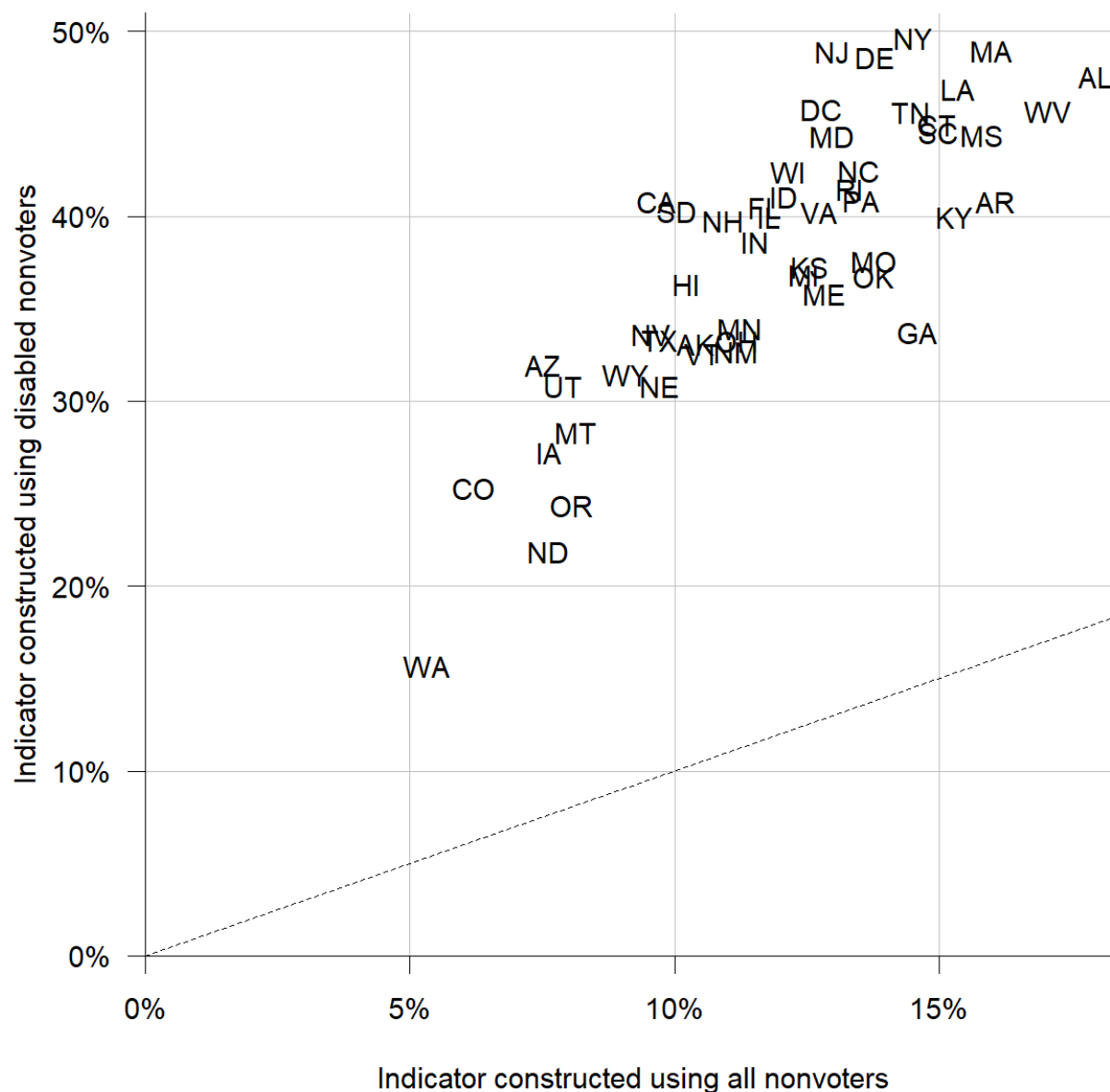


Figure 3 illustrates how this indicator changes as we narrow the respondents from the complete nonvoting population to the nonvoting population with disabilities, pooling together data from federal elections between 2010 and 2018. The x-axis represents the indicator as it is currently constructed for the EPI. The y-axis represents the indicator as it would be constructed if we used only the self-identified population with disabilities in the data set.

When we confine the calculation of this indicator to self-identified disabled nonvoters, values of this indicator are generally greater than if we calculate it using responses from all nonvoters.¹⁵ This is what we would expect if disabled respondents are more likely than nondisabled respondents to give this answer. In previous years, the two methods of con-

structuring this indicator were highly correlated, with a Pearson correlation coefficient of 0.8 or above.

4.2.3 Stability of rates across time

The rate at which registered voters report they failed to vote because of illness and disability will vary across time, for a variety of reasons. On the one hand, some of these reasons may be related to policy; for instance, a statewide shift to all vote-by-mail balloting (such as in Colorado, Oregon, Washington, Hawaii, and Utah) may cause a reduction in the percentage of nonvoters giving this reason for not voting. On the other hand, some of these reasons may be unrelated to election administration or policy, and therefore can be considered random variation.

One advantage of an indicator based on VRS data is that the survey goes back for many elections. The question about reasons for not voting has been asked in its present form since 2000. Therefore, it is possible to examine the intercorrelation of this measure at the state level across ten federal elections (2000, 2002, 2004, 2006, 2008, 2010, 2012, 2014, 2016, and 2018) to test its reliability.

Table 11: Between-year correlation of disability/illness indicator

	2000	2002	2004	2006	2008	2010	2012	2014	2016	2018
2000	1.000									
2002	0.589	1.000								
2004	0.318	0.499	1.000							
2006	0.451	0.593	0.565	1.000						
2008	0.485	0.486	0.404	0.551	1.000					
2010	0.536	0.645	0.523	0.561	0.547	1.000				
2012	0.313	0.336	0.504	0.441	0.502	0.540	1.000			
2014	0.335	0.535	0.384	0.632	0.628	0.455	0.515	1.000		
2016	0.518	0.605	0.372	0.531	0.593	0.616	0.348	0.533	1.000	
2018	0.642	0.492	0.427	0.508	0.490	0.525	0.433	0.529	0.577	1.000

Table 11 is the correlation matrix reporting the Pearson correlation coefficients for values of this indicator across these ten elections. The correlation coefficients between pairs of elections are moderately high. The fact that the coefficients do not decay across the 20 years' worth of data suggests that the underlying factor being measured by this indicator is stable within individual states; therefore, there is strong reliability to the measure. As a result, it may be prudent to consider combining data across years so that the reliability of the measure can be improved.

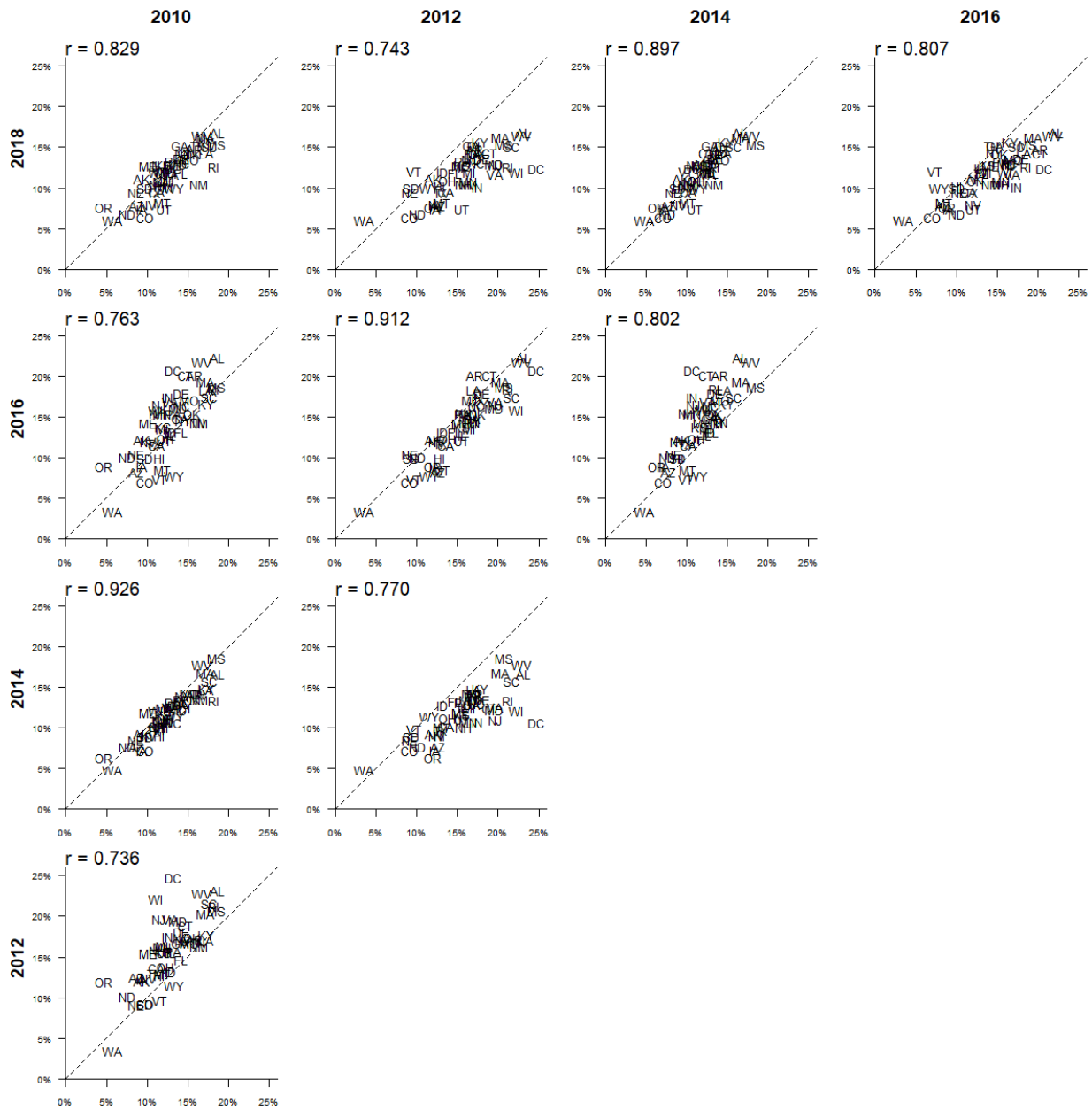
It is tempting to consider creating a single scale from this set of data (considering the observations from all of the elections, 2000 to 2018, together) because of the moderately high overall intercorrelations. However, comparing the averages for each year reveals that

more nonvoters give the “illness or disability” reason in presidential election years (14.8 percent national average) than in midterm election years (12.1 percent national average). Consequently, a more prudent strategy is to treat presidential and midterm election years separately.

We created two scales from the data set, one consisting of the average rates for the most recent three presidential election years, and the other consisting of the average rates for the three most recent midterm election years. In the original version of the EPI, we constructed the presidential election year measure using data from the 2000, 2004, and 2008 presidential elections and the midterm measure using data from the 2002, 2006, and 2010 midterm elections. In the 2012 version of the EPI, we updated the presidential election year measure by dropping the most distant presidential year previously used (2000), replacing it with in the most recent year (2012). Similarly, for the 2014 version of the EPI, we dropped the data from the most distant midterm election year, 2002, and substituted data for the most recent year, 2014.

Figure 4 compares the correlations across this measure for each year of the EPI to 2018. Rates for this indicator are made more stable by combining midterm and presidential election data across 3 of the most recent elections of the same type.

Figure 4: Percent of Nonvoters Due to Disability or Illness



4.3 Disability Access (2020)

4.3.1 *Data source*

Voting and Registration Supplement to the Current Population Survey

Access to voting for the physically disabled has been a public policy concern for years. The federal Voting Accessibility for the Elderly and Handicapped Act, passed in 1984, generally requires election jurisdictions to ensure that their polling places are accessible to disabled voters. The Voting Rights Act of 1965, as amended, and HAVA also contain provisions that pertain to ensuring that disabled Americans have access to voting. HAVA, in particular, established minimum standards for the presence of voting systems in each precinct that allow people with disabilities the same access as those without disabilities.

Studies of the effectiveness of these laws and other attempts at accommodation have been limited. On the whole, they confirm that election turnout rates for people with disabilities are below those for people who are not disabled and that localities have a long way to go before they meet the requirements of laws such as the Voting Accessibility for the Elderly and Handicapped Act and HAVA.¹⁶ Investigations into the participation of the disabled and the accessibility of polling places have, at most, been conducted using limited representative samples of voters or localities. As far as can be ascertained, studies comparing jurisdictions have not been conducted.

4.3.2 *Coding convention*

This indicator is based on responses to the Voting and Registration Supplement of the Current Population Survey, which is conducted by the U.S. Census Bureau. Specifically, it is based on the difference in turnout rates between people who reported having one of six disabilities and those who reported having none of these disabilities.

In 2008, the CPS began asking respondents if they had one of six disabilities. [Table 12](#) lists those disabilities, along with the percentage of nonvoters in 2018 and 2020 who reported having them. The table also lists the percentage of people with the indicated disabilities who reported voting. For comparison, it also lists the reported turnout rates of those who reported none of these disabilities.

Table 12: Percent of Disabled People Did Not Vote Because of a Disability or Illness, by Disability Type

Disability	2018		2020	
	% of eligible voters	Turnout Rate	% of eligible voters	Turnout Rate
Difficulty dressing or bathing	2.2%	47.5%	1.9%	60.7%
Deaf or serious difficulty hearing	3.9%	65.6%	4.0%	78.7%
Blind or difficulty seeing even with glasses	2.0%	56.5%	1.7%	70.6%
Difficulty doing errands	4.6%	45.4%	4.4%	62.8%
Difficulty walking or climbing stairs	7.6%	57.6%	7.1%	71.4%
Difficulty remembering or making decisions	4.0%	44.3%	4.0%	60.3%
At least one of the above disabilities	57.5%	57.5%	72.3%	72.3%
No disabilities reported	66.7%	66.7%	80.7%	80.7%

In prior years, the EPI measured disability related problems using another a different strategy. Previously, this indicator was based on answers to the question put to all non-voters, “What was the main reason you did not vote?” See Section 4.2 for a discussion of the previous indicator.

The link between the former and current measurement strategy can be shown by examining the percentage of non-voting respondents who identified as having a disability also chose illness or disability as the reason for not voting. A nonvoter with any one of the disabilities was several times more likely to give the illness or disability answer compared with someone without any of these disabilities. Furthermore, the more disabilities a non-voter listed, the more likely he or she was to give this response (Table 13).

Table 13: Percent of Disabled People Did Not Vote Because of a Disability or Illness, by Number of Disabilities

	0	1	2	3	4 or more
2018	7.8%	29.0%	43.9%	50.1%	65.3%
2020	8.3%	25.9%	37.9%	42.1%	54.2%

4.3.3 Stability of rates across time

The differential in turnout rates between people with and without disabilities will vary across time for a variety of reasons. On the one hand, some of these reasons may be related to policy; for instance, a statewide shift to all vote-by-mail balloting may lower the turnout gap, because the barriers to voting experienced by many people with disabilities have been lowered. On the other hand, some of these reasons may be unrelated to election administration or policy, and therefore can be considered random variation.

One advantage of an indicator based on VRS data is that the survey goes back for many elections. The question about disability status has been asked since 2008. Therefore, it is possible to examine the intercorrelation of this measure at the state level across seven federal elections (2008, 2010, 2012, 2014, 2016, 2018, and 2020) to test its reliability.

Table 14: Between-year correlation of disability/illness indicator

	2008	2010	2012	2014	2016	2018	2020
2008	1.000						
2010	0.413	1.000					
2012	0.390	0.320	1.000				
2014	0.101	0.363	0.223	1.000			
2016	0.417	0.460	0.264	0.277	1.000		
2018	0.497	0.389	0.363	0.240	0.430	1.000	
2020	0.186	0.019	-0.063	-0.192	0.179	0.251	1.000

Table 14 is the correlation matrix reporting the Pearson correlation coefficients for values of this indicator across these ten elections. Excluding 2020, the correlation coefficients between pairs of elections are moderately high. The fact that the coefficients do not decay across the 12 years' worth of data suggests that the underlying factor being measured by this indicator is stable within individual states; therefore, there is strong reliability to the measure. As a result, it may be prudent to consider combining data across years so that the reliability of the measure can be improved.

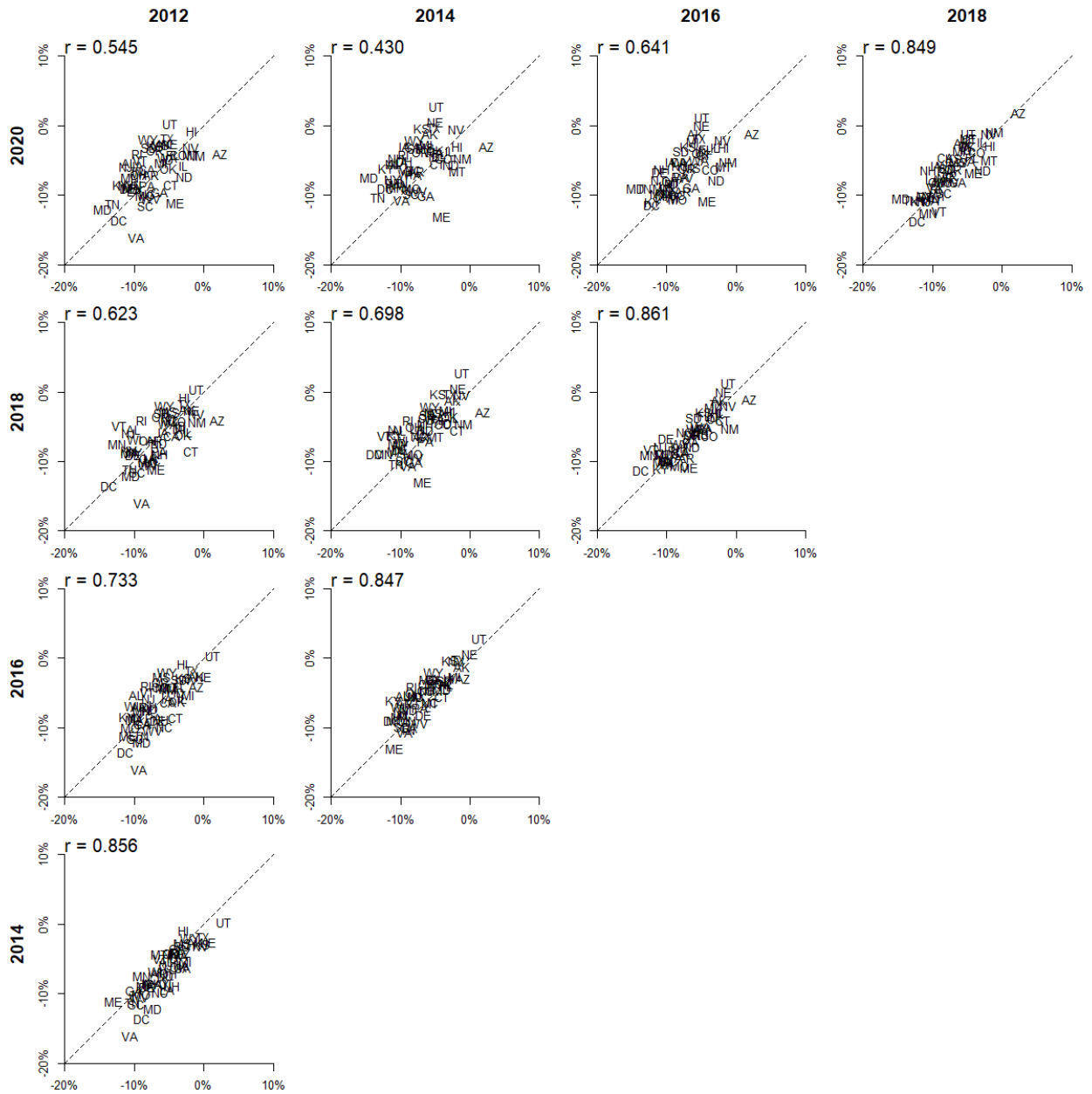
While the previous disability indicator did not combine presidential and midterm years due to the fact that more nonvoters give the “illness or disability” reason in presidential

election years than midterm years, the new indicator does not suffer from the discrepancies between elections. Consequently, a more prudent strategy is to treat federal elections together.

We created a scale from the data set, consisting of the statewide average difference in turnout for the three most recent election years. For the first observation of data in the dataset, we combined 2008, 2010, and 2012 to get the indicator value for 2012. In the next election, 2014, we drop 2008 and average over 2010-2014, and so on.

Figure 5 shows the correlations across these three measures for each observable year of this indicator.

Figure 5: Difference in Turnout Rates Comparing People with and without Disabilities



4.4 ERIC Membership (2020-)

4.4.1 Data source

Electronic Registration Information Center (ERIC)

Historically, keeping registration rolls up-to-date has been challenging for states. As a result, a number of registration records are not accurate. To minimize the amount of dead-wood (registrants who moved or died but remain on the registration list), seven states—Colorado, Delaware, Nevada, Utah, Virginia, and Washington—joined Pew Charitable Trusts in 2012 to form the Election Registration Information Center, or ERIC.

ERIC pulls data from the the Social Security Administration, the US Postal Service, and from its members' Department of Motor Vehicles and compares these lists to the official registration lists in its member states. It then notifies states of voters who likely moved or died. In addition, it encourages its members to reach out to voters who moved into their state to register in the new state.

As of the 2020 Election, 30 states and the District of Columbia are members of ERIC. The index measure is based simply on a binary coding of whether a state is a member of ERIC. If the state is not a member of ERIC, their EPI score is calculated without the indicator (not affecting non-participants EPI score). If a state is officially approved as an ERIC member before the election in question, the state gets coded appropriately. For the ten states which joined ERIC prior to 2017, the dates they joined were taken from the 2017 Final ERIC report. States which joined after 2017, were collected through the ERIC website. States were credited with being a member of ERIC if they were listed as a member on the website as of November 2020. Seven states were members in 2012. The number grew to 11 plus D.C. in 2014. It then increased to 19 states plus DC and 23 states plus DC in 2016 and 2018, respectively. [Table 15](#) displays each member of ERIC for each federal election since ERIC was founded

Table 15: ERIC membership by election year

Year	ERIC Member States
2012	CO, DE, MD, NV, UT, VA, WA
2014	CO, CT, DE, DC, LA, MD, MN, NV, OR, UT, VA, WA
2016	AL, AK, CO, CT, DE, DC, IL, LA, MD, MN, NV, NM, OH, OR, PA, RI, UT, VA, WA, WV, WI
2018	AL, AK, AZ, CO, CT, DE, DC, IL, IA, LA, MD, MN, MO, NV, NM, OH, OR, PA, RI, UT, VA, WA, WV, WI
2020	AL, AK, AZ, CO, CT, DE, DC, FL, GA, IL, IA, KY, LA, MD, MI, MN, MO, NV, NM, OH, OR, PA, RI, SC, TX, UT, VT, VA, WA, WV, WI

4.5 Mail ballots rejected

4.5.1 Data source

Election Administration and Voting Survey

The use of mail ballots has grown significantly over the past two decades as states have expanded the conditions under which absentee voting is allowed. However, not all mail ballots returned for counting are accepted for counting. Mail ballots may be rejected for a variety of reasons. The most common reasons for the rejection of absentee ballots in 2020 were related to signatures — either signatures on the return envelope not matching the signature on file (28%) or no signature at all (12%). Another 12% were rejected because the ballot was not received on time.¹⁷

4.5.2 Coding Convention

Expressed as an equation, the mail ballot rejection rate can be calculated as follows from the EAVS data sets:

$$\text{Mail ballot rejection rate} = \frac{\text{Domestic absentee ballots rejected}}{\text{Total participants}}$$

Table 16: EAVS variables used to calculate mail ballots rejected indicator

Descriptive name	2008 EAVS	2010- 2016 EAVS	2018- 2020 EAVS
Domestic absentee ballots rejected	c4b	qc4b	qc4a
Total participants	f1a	qf1a	qf1a

Because of missing data, it was not possible to compute domestic mail ballot rejection rates in two states in 2020 (Alabama and Kansas). [Table 17](#) reports states with missing values for this indicator from 2008 to 2020. Oregon is included in this indicator, using data provided by the state that describes its vote-by-mail system. Washington, Colorado, and Hawaii are similarly included using data from their vote-by-mail systems that started in 2010, 2016, and 2020 respectively.

With the onset of the COVID-19 pandemic, voting by mail became the most common way of voting during the 2020 election. Many states, including California, Nevada, and New Jersey (and non-states like the District of Columbia), automatically sent voters mail in ballots, and a handful of states, such as New Mexico and Nebraska, sent mail-in ballot application forms to all voters.

Table 17: States with too much missing data to calculate mail ballots rejected indicator

Year	State
2008	AL, AR, IL, IN, MS, NY, SD, WV
2010	AL, MA, MS, NM, NY
2012	AL, MS, NY, VT, WV
2014	AL, UT
2016	AL, NM, WI
2018	OR
2020	AL, KS

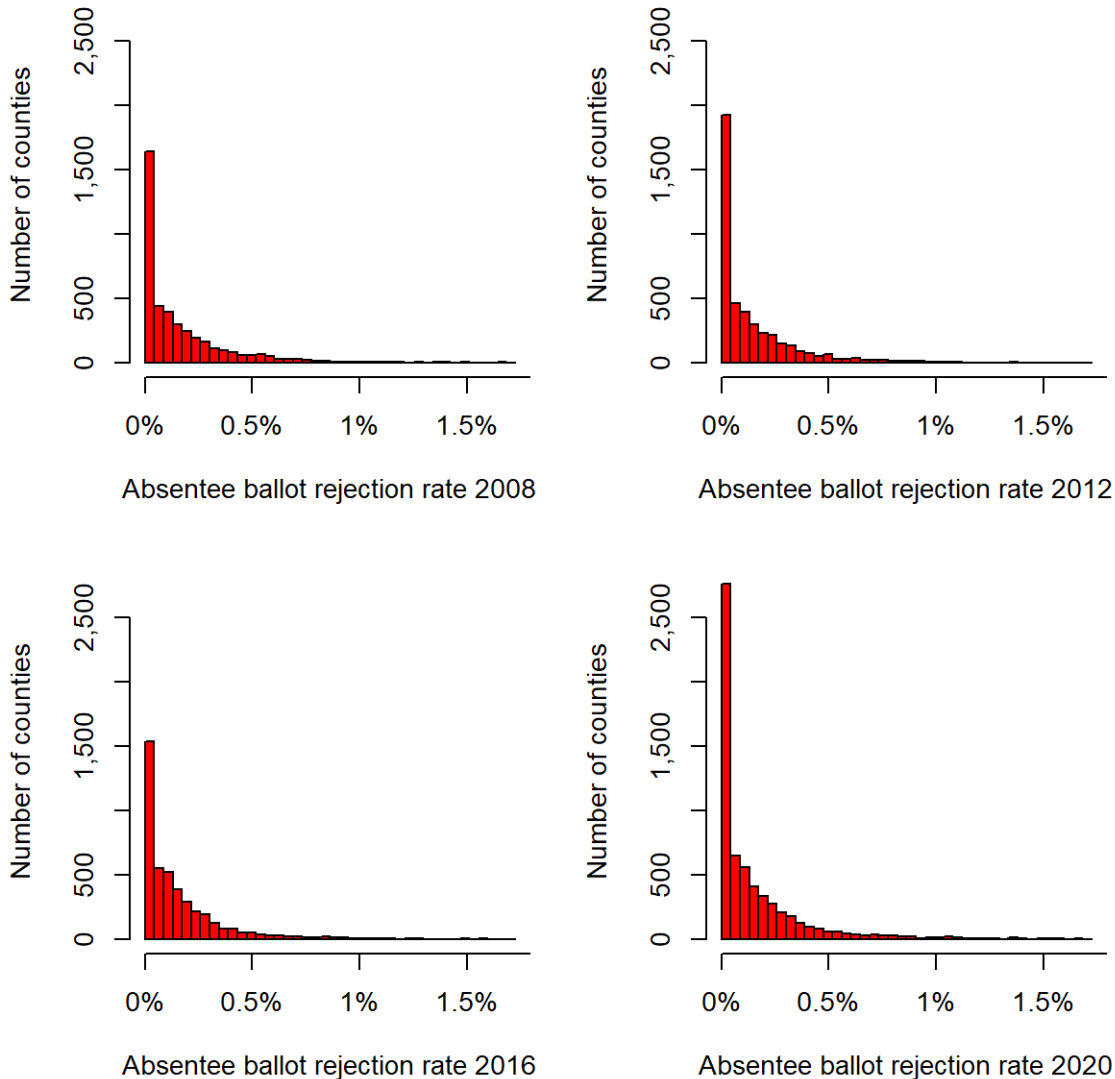
4.5.3 Comparisons over time

We begin by comparing domestic mail ballot rejection rates, measured at the county level, for 2008, 2012, 2016, and 2020. The raw data exhibit what is known as a pronounced “right skew”; that is, most counties have very low rejection rates, while a few have relatively high rates. This is illustrated in [Figure 6](#): histograms that show the distribution of rejection rates for each county for which we have the relevant data. Because of this pronounced right skew, any scatterplot that compares values across years will be misleading — the bulk of observations will be clumped around the origin, with our eye drawn toward the small number of outliers with extremely large values. To deal with this pronounced right skew, it is common to transform the measures by taking logarithms. One problem this creates is that a large fraction of counties had zero domestic mail ballots rejected, and the logarithm of zero is undefined. Therefore, in the scatterplot in [Figure 7](#), counties with zero rejected ballots have been set to 0.000001, which is slightly below the smallest nonzero usage rate that was actually observed. Finally, so that the influence of larger counties is visually greater than that of smaller counties, we weight the data tokens in proportion to the size of the county.

As [Figure 7](#) illustrates, for counties that reported the necessary data, the rejected rates were similar when they are compared across previous presidential years, with Pearson correlation coefficients ranging from .390 to .520.¹⁸ For 2020, the Pearson correlation coefficients, which measure the degree of similarity across these three presidential election cycles, are lower than the previous election years, ranging between .159 and .365.

The figure also illustrates how counties that report no rejected domestic mail ballots in one election cycle often report a considerably greater rejection rate in the next cycle. Sometimes this is because the county is very small. With domestic mail ballot rejection rates overall being relatively low (ranging from 0.2 to 0.4 percent of all ballots cast), a county with only a few hundred voters might experience an election cycle in which no domestic mail ballots were rejected. However, relatively large counties will sometimes report zero mail ballots in one election cycle and a relatively large number in the next. This sort of pattern calls for further investigation and research. Until then, this pattern alerts us to the need to be cautious when using data about the rejection of mail ballots.

Figure 6: Domestic Mail Ballot Rejection Rates by County



The EPI reports mail ballot rejection rates at the state level. The statewide rejection rates are similarly right-skewed; therefore, it is necessary to translate the rejection rates into logarithms before plotting the rejection rates across years. As with the measure calculated at the county level, the indicator calculated at the state level is stable across years, as seen in [Figure 8](#)

Particularly notable in 2020, absentee ballot rejection rates nationwide went down a very small amount from 2018, despite the dramatic increase in voting by mail due to the pandemic. However, many states saw substantial increases in their rejection rates. New Mexico, Arkansas, and New York had the highest rejection rates in 2020, where the states rejected 5.0, 4.1, and 3.6 percent of mail ballots respectively.

Figure 7: Logged Domestic Mail Ballot Rejection Rates by County

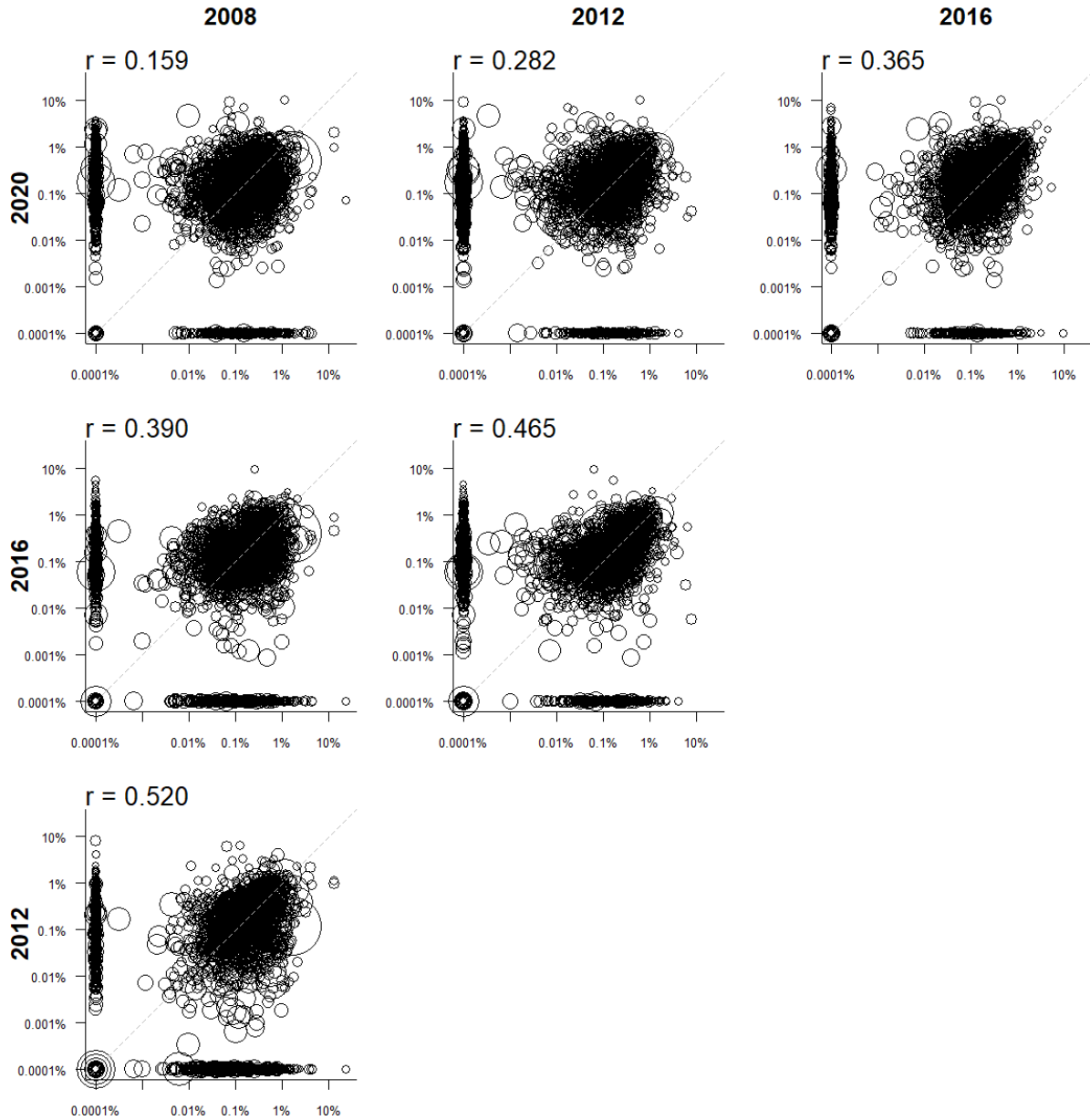
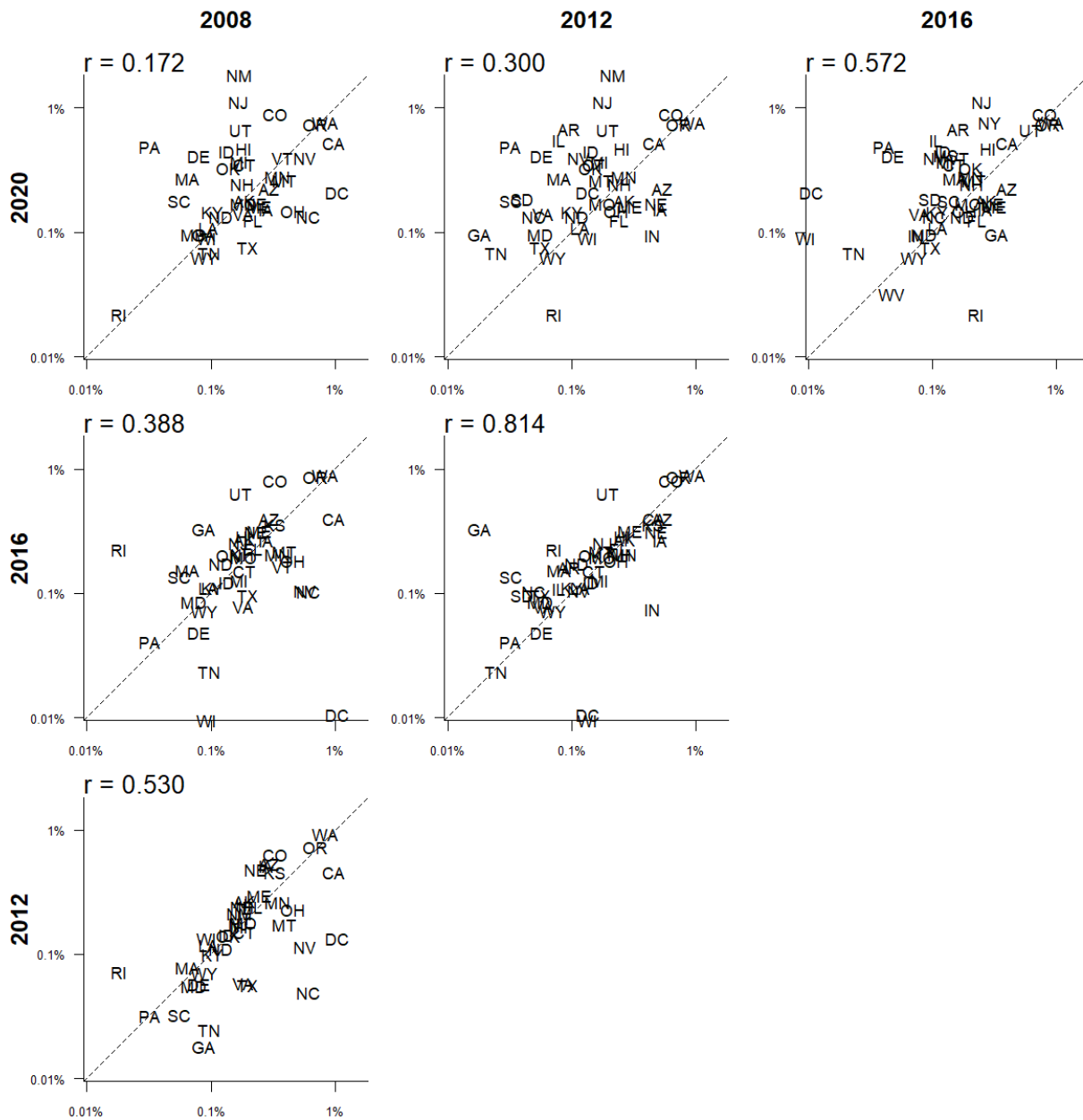


Figure 8: Logged Domestic Mail Ballot Rejection Rates by State



4.6 Mail ballots unreturned

4.6.1 Data Source

Election Administration and Voting Survey

Although use of mail ballots has grown as states have loosened the conditions under which votes may be cast by mail, not all mail ballots that are sent to voters are returned to be counted. In states that maintain permanent absentee lists, which allow voters to receive mail ballots automatically for all future elections, some of this is understandable in terms of voter indifference to particular elections. It is not hard to imagine that some voters who request a mail ballot decide either to vote in person¹⁹ or not at all. However, because generally no chain of custody is maintained for mail ballots from the point when they are mailed to voters until election officials receive them to be counted, it is possible that some ballots mailed back may be lost in transit.²⁰

4.6.2 Coding convention

Expressed as an equation, the domestic mail ballot nonreturn rate can be calculated as follows from the EAVS data sets:

$$\text{Mail ballot nonreturn rate} = 1 - \frac{\text{Total domestic absentee ballots returned}}{\text{Total domestic absentee ballots transmitted}}$$

Table 18: EAVS variables used to calculate mail ballots not returned indicator

Descriptive name	2008 EAVS	2010- 2016 EAVS	2018- 2020 EAVS
Returned domestic absentee ballots	c1b	qc1b	qc1b
Domestic absentee ballots transmitted	c1a	qc1a	qc1a

Data will be missing if a county has failed to provide any of the variables, detailed in [Table 18](#), included in the calculation. There were no states where it was impossible to compute domestic mail ballot nonreturn rates in 2016 and 2018 due to missing data. In 2020, two states did not report enough data to calculate the indicator (Alabama and Rhode Island). [Table 19](#) reports states with missing values for this indicator from 2008 to 2020. In 2018, states with over 50% vote-by-mail were excluded from this indicator. In 2020, this was updated to only exclude states that conduct an election using a vote-by-mail system.

4.6.3 Comparisons over time

We begin by comparing domestic mail ballot nonreturn rates, measured at the county level,

for 2008, 2012, 2016, and 2020. The raw data exhibit a pronounced “right skew”; that is, most counties have very low nonreturn rates, while a few have relatively high rates. This is illustrated in [Figure 9](#): histograms that show the distribution of nonreturn rates for 2008, 2012, 2016, and 2020 for each county for which we have the relevant data.

Table 19: States with too much missing data to calculate mail ballots not returned indicator

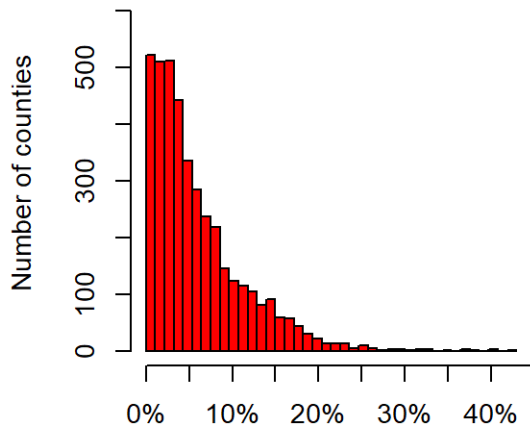
Year	State
2008	AL, AR, CT, MN, MS, NM, NY, TN, WV
2010	AL, IN, MS, NY, SD
2012	AL, KS, MS, NY, WV
2014	AL, UT
2016	No states with missing data
2018	No states with missing data
2020	AL, RI

Because of this right skew, any scatterplot that compares values across years will be misleading in that the bulk of observations will be clumped around the origin, with our eye drawn toward the small number of outliers with extremely large values. To deal with this right skew, it is common to transform the measures by taking logarithms. One problem this creates is that a large fraction of counties had zero domestic absentee ballots rejected, and the logarithm of zero is undefined. Therefore, in the scatterplot in [Figure 10](#), counties with zero rejected ballots have been set to 0.00001, which is slightly below the smallest nonzero rate that was actually observed.

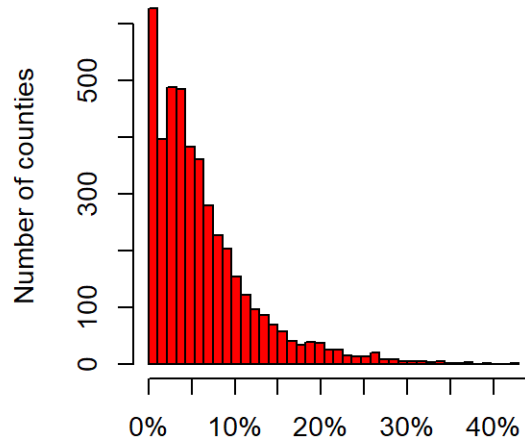
Finally, so that the influence of larger counties is visually greater than that of smaller counties, we weight the data tokens in proportion to the size of the county. As [Figure 10](#) illustrates, for counties that reported the necessary data, the nonreturn rates are similar when they are compared across years. The Pearson correlation coefficients, which measure the degree of similarity across these two election cycles, ranges between 0.296 and 0.536.

These graphs also illustrate how counties that report no unreturned domestic absentee ballots in one election cycle sometimes report a considerably greater nonreturn rate in the next cycle. Nonreturn rates are relatively high when we combine data nationwide: 10.2% in 2008, 22.7% in 2010, 10.4% in 2012, 35.1% in 2014, and 19.7% in 2016, 15.7% in 2018, and 22.2% in 2020. Therefore, it is unusual for a county to report precisely zero unreturned absentee ballots. Indeed, most counties reporting zero unreturned absentee ballots are very small, with very low numbers of absentee ballots sent out in the first place.²¹ As with the measure calculated at the county level, the indicator calculated at the state level is stable across years before 2020, as seen in [Figure 11](#).

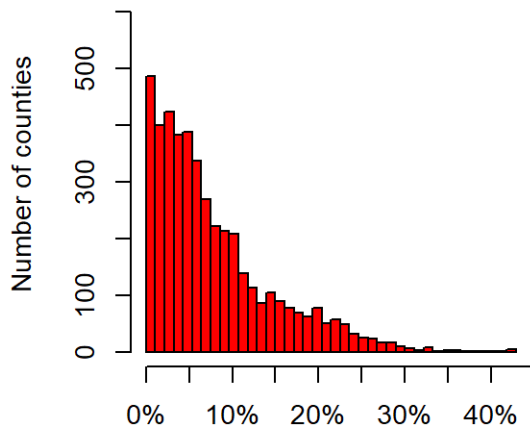
Figure 9: Domestic Mail Ballot Nonreturn Rates by County



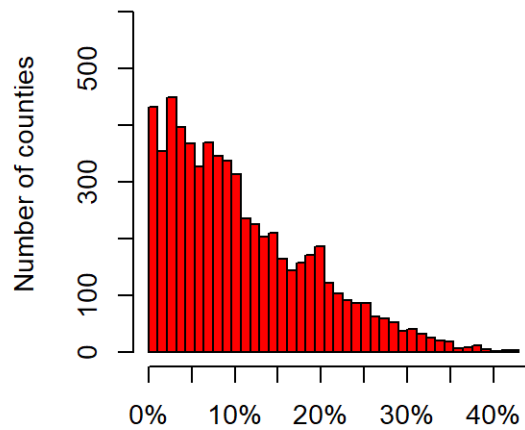
Absentee ballot nonreturn rate 2008



Absentee ballot nonreturn rate 2012



Absentee ballot nonreturn rate 2016



Absentee ballot nonreturn rate 2020

Figure 10: Logged Domestic Mail Ballot Nonreturn Rates by County

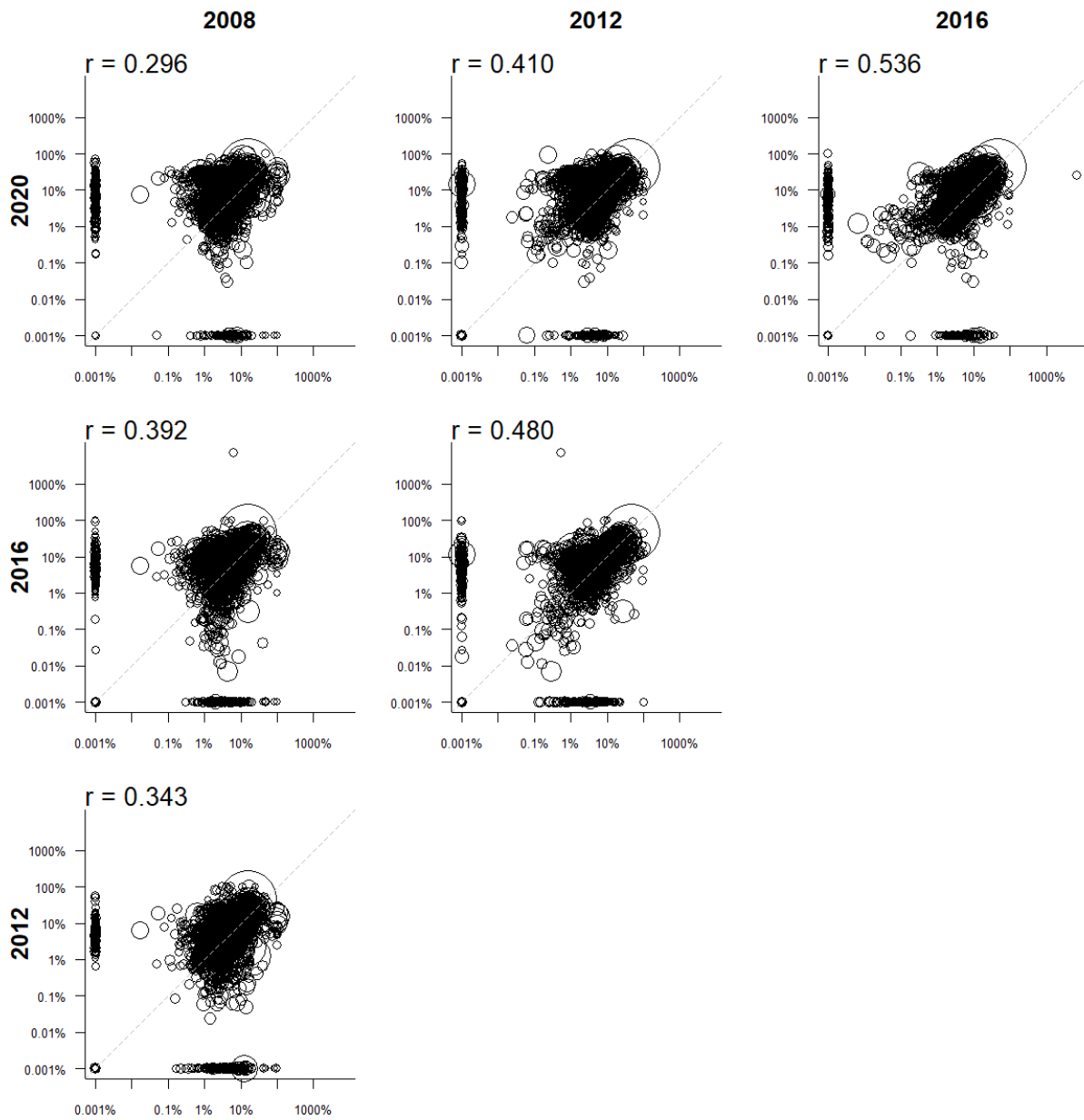
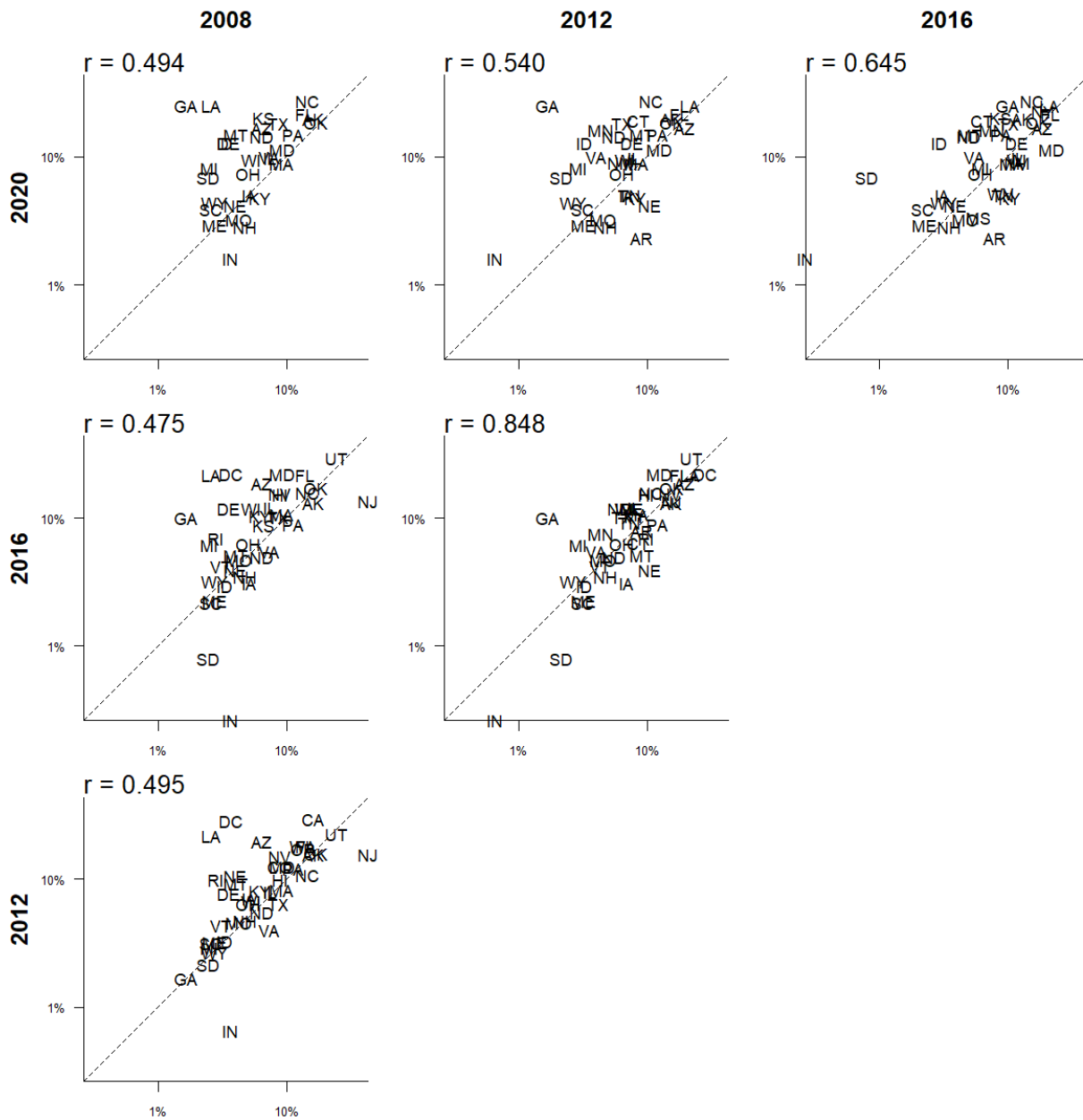


Figure 11: Logged Domestic Mail Ballot Nonreturn Rates by State



4.7 Military and overseas ballots rejected

4.7.1 Data source

Election Administration and Voting Survey

In recent years, increasing attention has been paid to the ability of overseas voters, especially those serving in the U.S. military, to vote in federal elections. Military and overseas voters face a number of obstacles to voting. A measure of these obstacles is the fraction of ballots returned by military and overseas voters that are then rejected.

By far, the principal reason ballots sent to UOCAVA voters are rejected is that the ballots are received by election officials after the deadline for counting. The share of these ballots rejected for this reason has varied since 2010, but has been in the range of 30 – 40 percent. Despite the passage of the MOVE Act, the percentage of UOCAVA ballots rejected because they missed the deadline has not obviously declined. Within the period covered by the EPI, the average percentage of ballots rejected for missing the deadline has been 43.7% (2008), 32.4% (2010), 40.4% (2012), 48.9% (2014), 44.4% (2016), 52.7% (2018), and 43.0% (2020).²²

However, reporting about why UOCAVA ballots are rejected is lacking. The percentage of rejected UOCAVA ballots that were accounted for by an undefined and undifferentiated other category was 31.2 percent in 2008, 49.0 percent in 2010, and 25.4 percent in 2012. The percentage of rejected ballots not categorized at all was 12.2 percent in 2008, 11.4 percent in 2010, and 18.4 percent in 2012. It is thus possible that the actual share of UOCAVA ballots rejected for lateness is even higher than indicated in the EAVS UOCAVA report.

4.7.2 Coding convention

Expressed as an equation, the UOCAVA absentee ballot rejection rate can be calculated as follows from the EAVS data sets:

$$\text{UOCAVA absentee ballot rejection rate} = \frac{\text{UOCAVA absentee ballots rejected}}{\text{UOCAVA ballots submitted for counting}}$$

Table 20: EAVS variables used to calculate UOCAVA ballots rejected indicator

Descriptive name	2008 EAVS	2010- 2016 EAVS	2018- 2020 EAVS
UOCAVA ballots rejected	b13	qb13a	qb18a
UOCAVA ballots returned	b2	qb2a	qb9a

Data will be missing if a county has failed to provide any of the variables, detailed in [Table 20](#), included in the calculation. Because of missing data, it was not possible to compute UOCAVA ballot rejection rates in three states in 2020, detailed in [Table 21](#)

Despite this, 2020 saw a marked decline in the number of UOCAVA ballots rejected compared to previous years. While values ranged from 4.4% to 6.6% over previous years, the 2020 election saw UOCAVA rejection rates drop to 1.6%. Whether this is related to increased voter participation by domestic mail ballots or a change in the number of UOCAVA voters abroad is presently unknown.

Table 21: States with too much missing data to calculate UOCAVA ballots rejected indicator

Year	State
2008	AL, AR, CT, DC, HI, IN, KY, MS, NY, OR, RI, SD, WV, WY
2010	MS, SD, VT, WV
2012	AL, HI, IL, MS, SC
2014	AL, AR, IL, UT
2016	AR, NM
2018	AR, IL, MS, RI
2020	AR, ID, NY

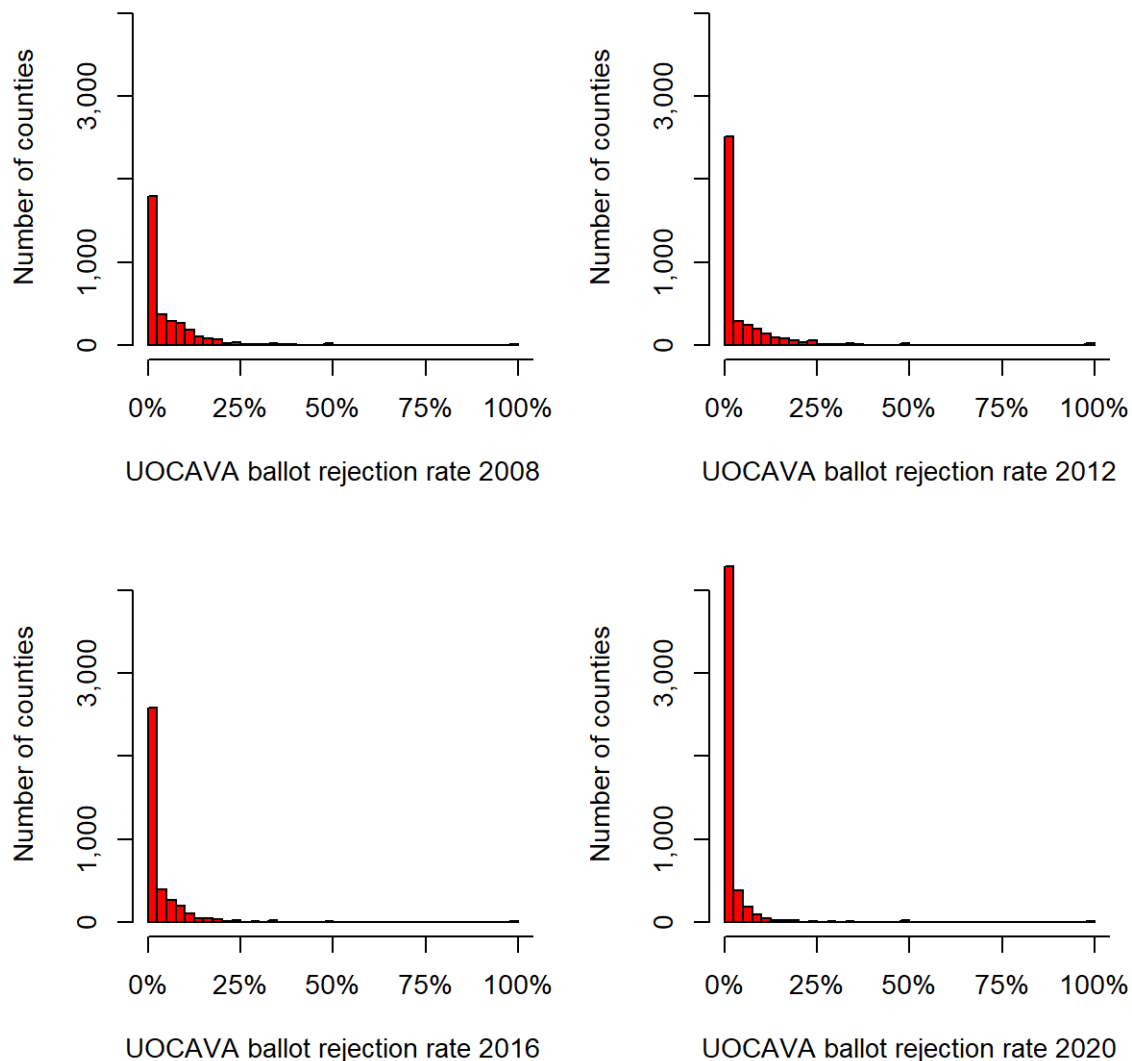
4.7.3 Comparisons over time

We begin by comparing domestic mail ballot rejection rates, measured at the county level, for 2008, 2012, 2016, and 2020. The raw data exhibit what is known as a pronounced “right skew”; that is, most counties have very low rejection rates, while a few have relatively high rates. This is illustrated in [Figure 12](#): histograms that show the distribution of rejection rates for each county for which we have the relevant data.

Because of this pronounced right skew, any scatterplot that compares values across years will be misleading in that the bulk of observations will be clumped around the origin, with our eye drawn toward the small number of outliers with extremely large values. To deal with this pronounced right skew, it is common to transform the measures by taking logarithms. One problem this creates is that a large fraction of counties had zero domestic mail ballots rejected, and the logarithm of zero is undefined. Therefore, in the scatterplot in [Figure 13](#), counties with zero rejected ballots have been set to 0.0001, which is slightly below the smallest nonzero rejection rate that was actually observed. Finally, so that the influence of larger counties is visually greater than that of smaller counties, we weight the data tokens in proportion to the size of the county.

As [Figure 13](#) illustrates, for counties that reported the data necessary to calculate rejection rates, rates are weakly correlated across years. The Pearson correlation coefficient, which measures the degree of similarity across these two election cycles, ranges between 0.020 and 0.340.²⁴

Figure 12: UOCAVA Ballot Rejection Rates by County



The relatively small correlation in this measure across years is likely explained by several factors. A major issue is the evolving nature of laws related to UOCAVA ballots. The Military and Overseas Voter Empowerment (MOVE) Act of 2009, which requires election officials to transmit requested UOCAVA ballots at least 45 days before a federal election, was implemented in time for the 2010 general election, but several states were given waivers for that election. Further, difficulties in meeting the demands of the act were reported in many states that had not been given waivers. By 2012, the MOVE Act was fully implemented, and the county-level correlations in rejection rates from 2010 to 2014 were still relatively low. While this may be because of the unsettled nature of the law’s implementation, we cannot rule out the possibility that these low correlations reflect inadequate record-keeping of UOCAVA statistics at the local level. This is clearly a matter that demands further research.

The EPI reports UOCAVA ballot rejection rates at the state level. The statewide rejection rates are slightly right-skewed; therefore, it is necessary to translate the rejection rates into logarithms before plotting the rejection rates across years. As with the measure calculated at the county level, the indicator calculated at the state level is stable across years.

The UOCAVA rejection rate measure exhibits a relatively low interyear correlation at the state level, much as it does at the local level. While the Pearson correlation coefficient describing the relationship between 2008 and 2010 was a moderate 0.66 (not pictured here), but the other interyear correlations are much lower. As noted above, we suspect that these low to moderate interyear correlations are due to a combination of unsettled law and unsettled record keeping.

Figure 13: Logged UOCAVA Ballot Rejection Rates by County

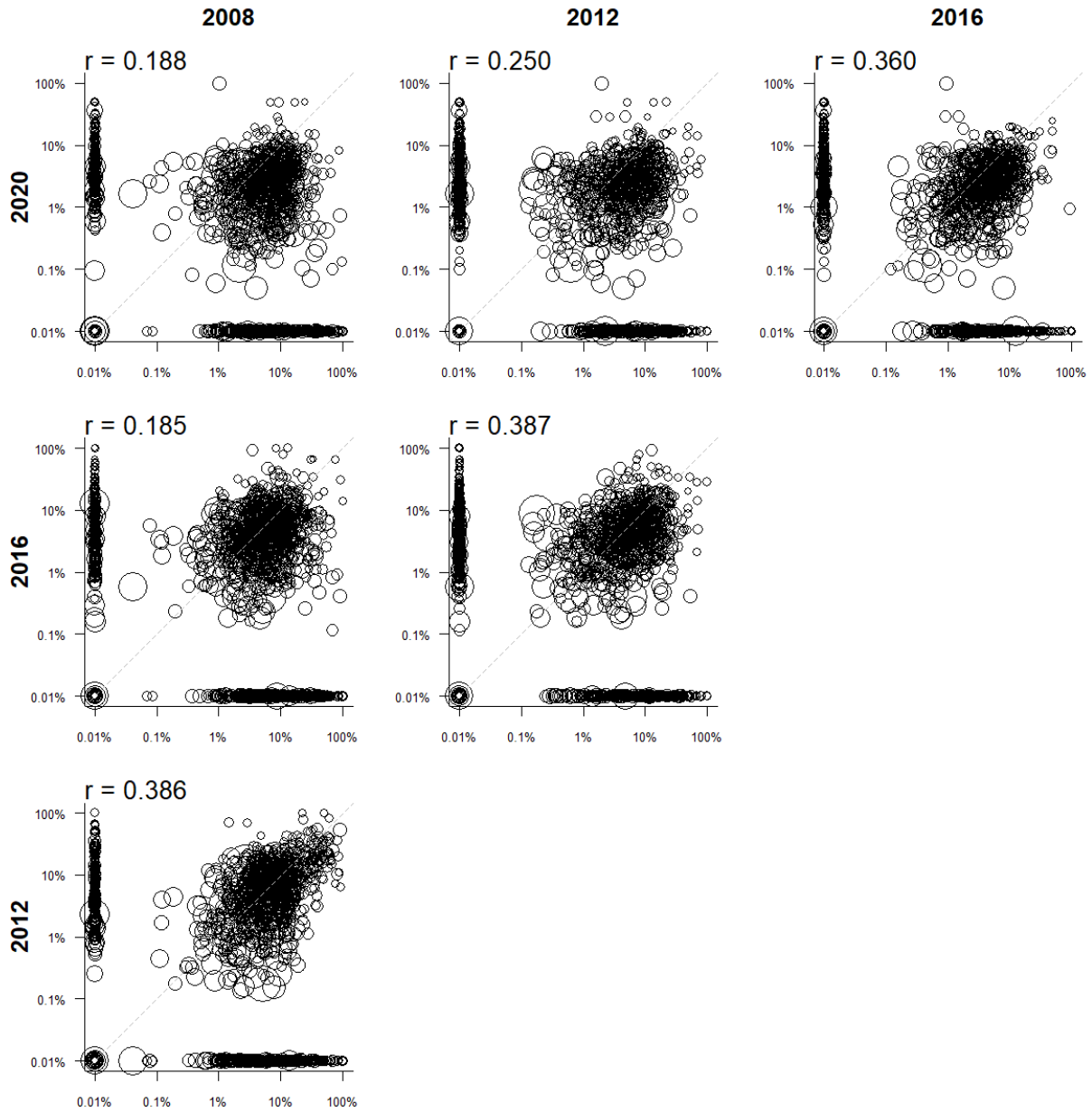
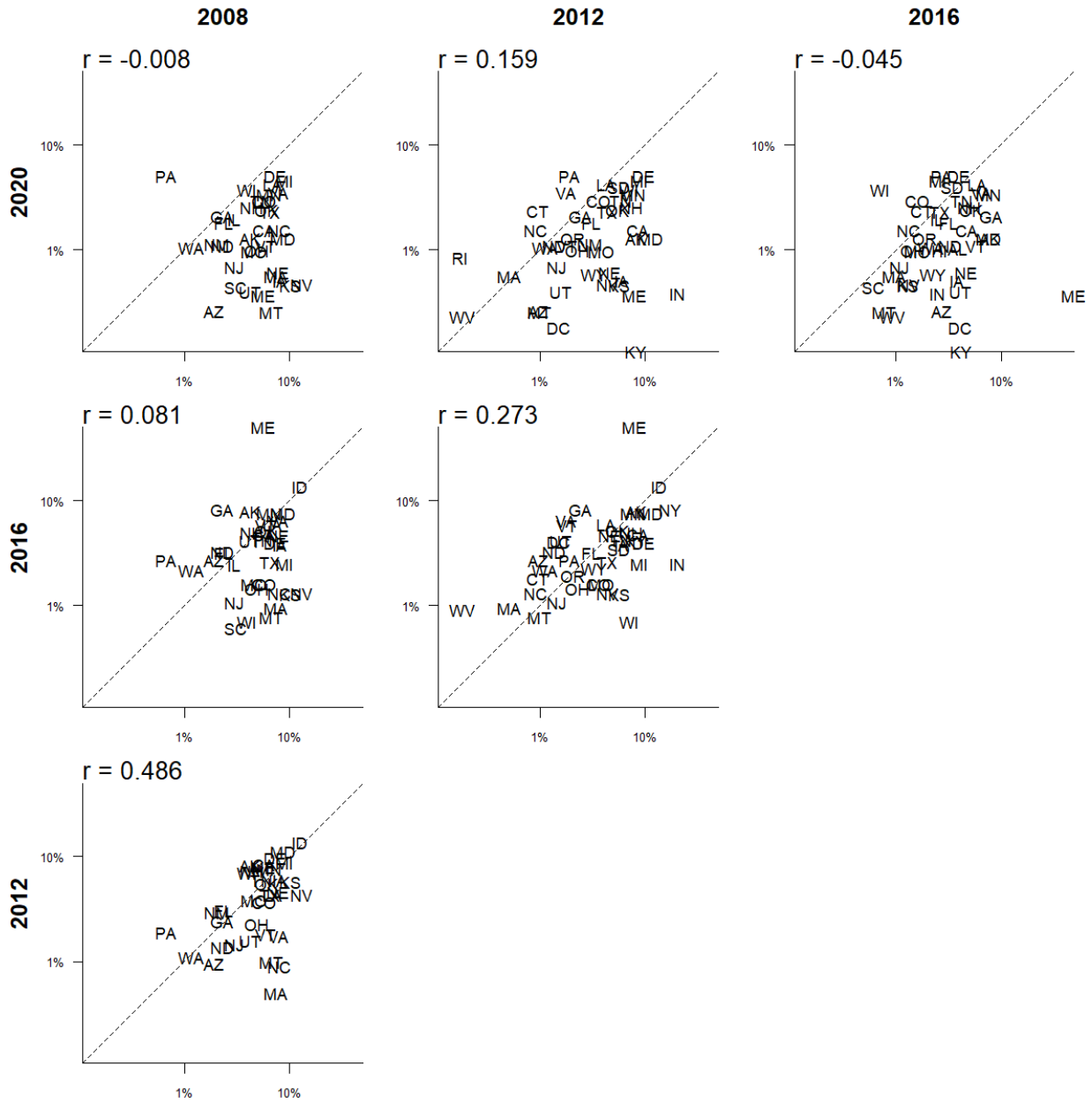


Figure 14: Logged UOCAVA Ballot Rejection Rates by State



4.8 Military and overseas ballots unreturned

4.8.1 Data source

Election Administration and Voting Survey

Despite the challenges of transmitting UOCAVA ballots to voters overseas, the return rate of UOCAVA ballots has been increasing over the years, as the return rate of civilian absentee ballots has been falling. In 2008, for instance, if we examine the set of counties that reported all the necessary data to calculate return rates for both UOCAVA and domestic absentee ballots, the UOCAVA non-return rate was 28.0%, compared with 10.2% for domestic civilian absentee ballots. Similar analysis for 2016 reveals that the non-return rate for UOCAVA ballots had fallen to 19.9%, while the non-return rate for domestic civilian absentee ballots had risen to 19.7%. Whatever the source for this turnaround, overseas voters now have at least as great a chance that their ballots will get back to the election office as civilians.

In earlier years, the very high nonreturn rate for UOCAVA ballots was probably related for the period for which a ballot request was in force. Under the original UOCAVA provisions, an application to become a UOCAVA voter could be valid for two federal election cycles. The MOVE Act changed this, allowing states to narrow to a single calendar year the period to which a ballot request applied. The original UOCAVA provision may have resulted in a large number of ballots being mailed that were not needed (or wanted), at a cost to election offices. The decline in the non-return rate suggests that this provision of the MOVE Act may have had its intended effect.

4.8.2 Coding convention

Expressed as an equation, the UOCAVA ballot nonreturn rate can be calculated as follows from the EAVS data sets:

$$\text{UOCAVA nonreturn rate} = 1 - \frac{\text{Total UOCAVA ballots returned}}{\text{Total UOCAVA ballots transmitted}}$$

Table 22: EAVS variables used to calculate UOCAVA not returned indicator

Descriptive name	2008 EAVS	2010- 2016 EAVS	2018- 2020 EAVS
UOCAVA ballots returned	b2	qb2a	qb9a
UOCAVA ballots transmitted	b1a	qb1a	qb5a

Data will be missing if a county has failed to provide any of the variables, detailed in [Table 22](#), included in the calculation. Because of missing data, it was not possible to compute UOCAVA ballot non-return rates in three states in 2020.

Table 23: States with too much missing data to calculate UOCAVA not returned indicator

Year	State
2008	CT, HI, MS, NY, OR, WV
2010	No states with missing data
2012	AL, IL, MS
2014	IL, UT, VT
2016	NY
2018	AR, CT, HI, IL, MS, ND, RI
2020	AR, ID, NY

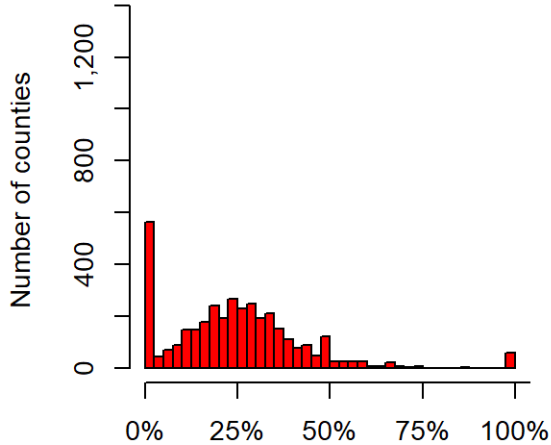
4.8.3 Comparisons over time

We begin by comparing UOCAVA ballot nonreturn rates, measured at the county level, for 2008, 2012, 2016, and 2020. Although there are outliers for all years, on the whole the data series does not exhibit the pronounced skew that is evident with many indicators based on EAVS data. This is illustrated in the histograms in [Figure 15](#), which show the distribution of nonreturn rates for 2008, 2012, 2016, and 2020 for each county for which we have the relevant data.

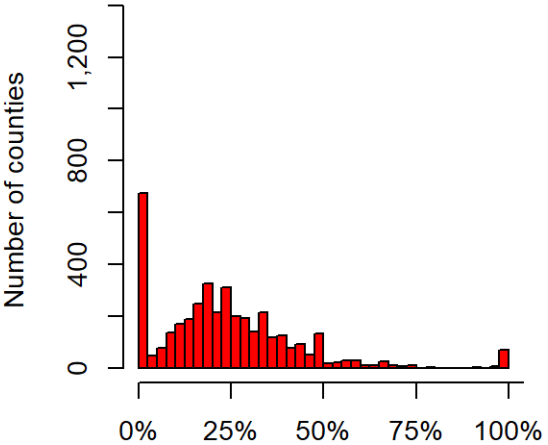
The scatterplots in [Figure 16](#) show the nonreturn rates measured at the county level from 2008 to 2020 and plotted against each other. Because the data do not exhibit a pronounced skew, we use the raw (rather than logged) rates. So that the influence of larger counties is visually greater than that of smaller counties, we weight the data tokens in proportion to the number of registered voters in each county. As [Figure 16](#) illustrates, for counties that reported the data necessary to calculate nonreturn rates, there is a weak relationship between nonreturn rates when we compare any two years. In addition, nonreturn rates are generally higher in midterm years than in the presidential years. The Pearson correlation coefficients, which measure the degree of similarity across these presidential election cycles, range between 0.012 and 0.293.

The EPI reports UOCAVA ballot nonreturn rates at the state level. [Figure 17](#) compares nonreturn rates at the state level in 2008, 2012, 2016, 2020. As with the measures calculated at the county level, the indicator calculated at the state level is not very stable when we compare across years.

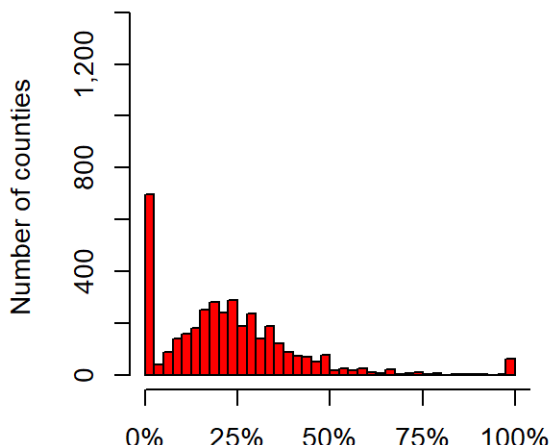
Figure 15: UOCAVA Ballot Nonreturn Rates by County



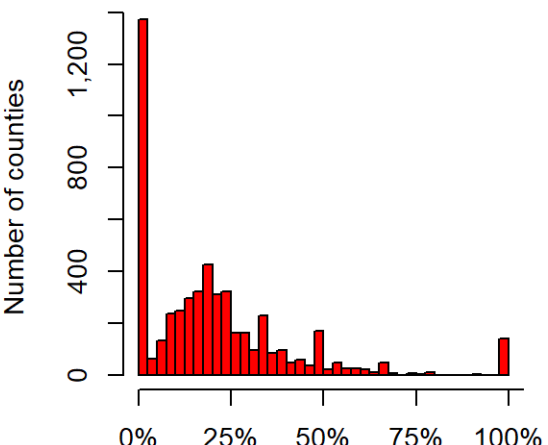
UOCAVA ballot non-return rate 2008



UOCAVA ballot non-return rate 2012



UOCAVA ballot non-return rate 2016



UOCAVA ballot non-return rate 2020

Figure 16: UOCAVA Ballot Nonreturn Rates by County

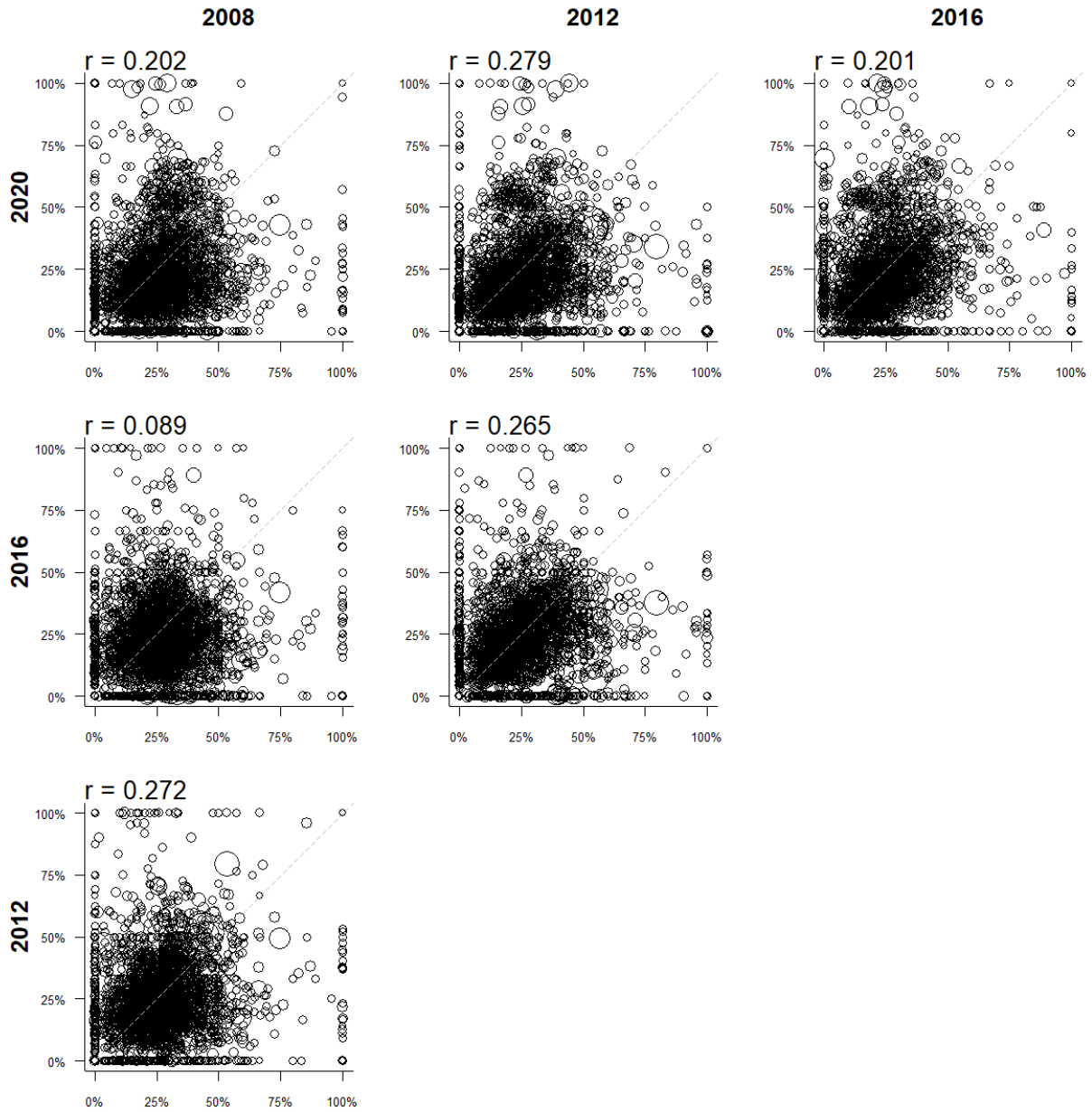
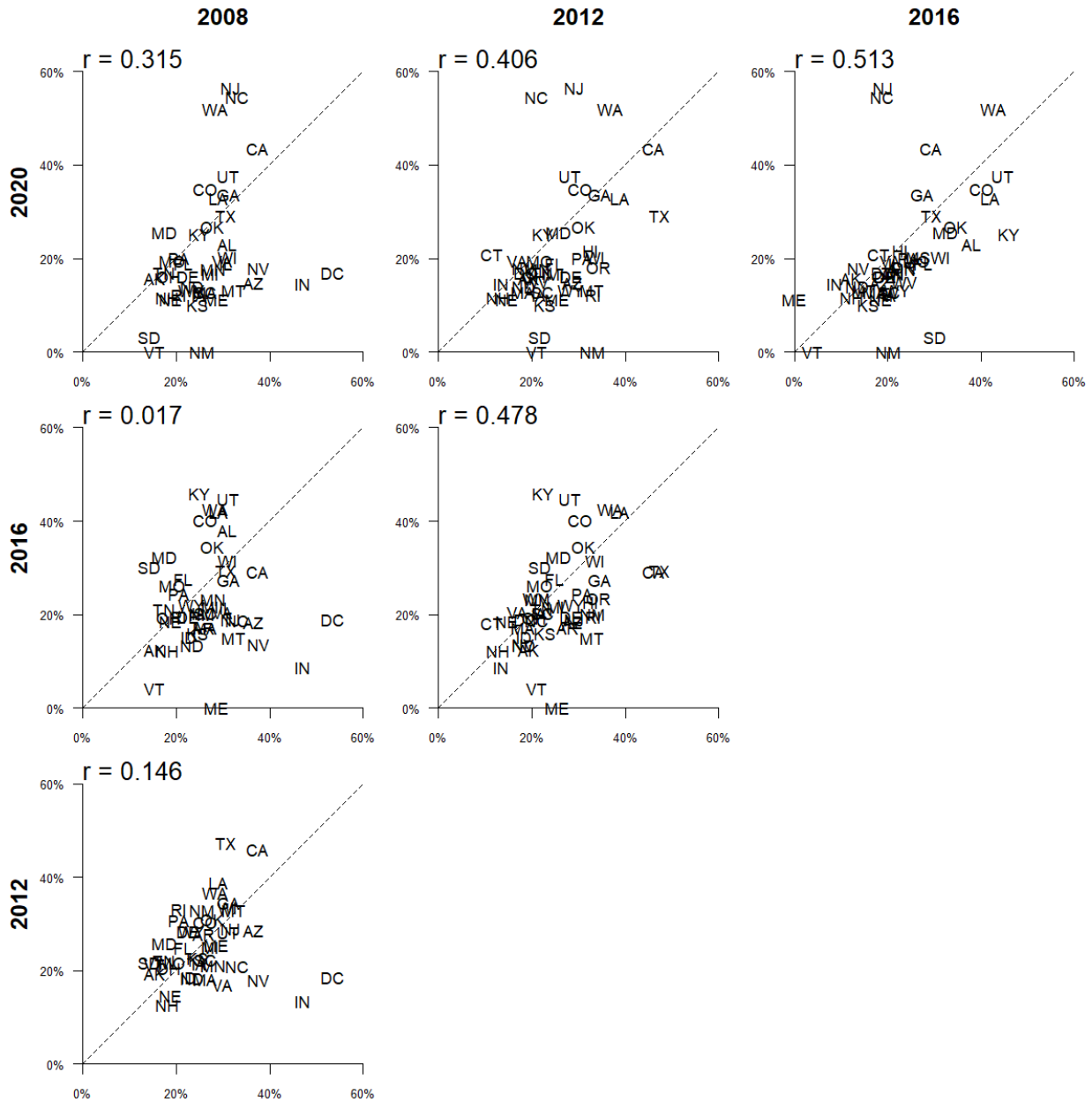


Figure 17: UOCAVA Ballot Nonreturn Rates by State



4.9 Online registration available

4.9.1 *Data source*

National Conference of State Legislatures and state election offices

Increasingly, business transactions have migrated online, which has resulted in savings for businesses and greater convenience for consumers. Voter registration, in a sense, is a similar type of transaction; one which can benefit both election offices and voters by moving online. Compared with traditional paper processes, online registration has been shown to save money, increase the accuracy of voter lists, and streamline the registration process. In addition to reducing state expenditures, online tools can also be more convenient for voters.

We consider a state as having online voter registration if it offers the option of an entirely paperless registration process that is instituted in time for eligible voters to register online for the corresponding election. If the state has a tool that helps a voter fill out the form online but he or she still has to print it (and possibly physically sign it) before returning it to a local election office, this does not constitute online voter registration. States that have an e-signature program that electronically populates the voter registration record from information on file with a different state agency (for example, Department of Motor Vehicles) also are not included.

Beginning with the 2014 release of the index, we give states that allow voter registrations to be updated online “half credit” for having online registration. North Dakota, the only state without voter registration, is not given a score for this indicator.

4.10 Postelection audit required

4.10.1 *Data source*

Statutory Overview of the Election Administration and Voting Survey

One of the lessons learned from careful scrutiny of the 2000 election results is that many states did not have a systematic program of auditing the performance of voting equipment after an election. Such an audit of voting equipment requires different procedures and approaches than do counting and recounting ballots, and it has different goals. States that have postelection audit requirements should be able to spot emerging problems with voting equipment before they cause crises, allowing election administrators to improve the voting equipment.

Generally speaking, a postelection audit involves the close scrutiny of election returns from a sample of precincts or voting machines, or both. The audit might involve simply recounting all of the ballots cast among the sample and comparing the recount with the original total. An audit might also involve scrutiny of other records associated with the election, such as logbooks. Sampling techniques can follow different protocols, ranging from simple random samples of a fixed percentage of voting machines to “risk-limiting” audits that select the sample depending on the likelihood that recounting more ballots would overturn the election result.²⁵ Although postelection audits are recognized as a best practice to ensure that voting equipment is functioning properly, that proper procedures are being followed, and that the overall election system is reliable, the practice of auditing is still in its relative infancy. Therefore, a consensus has not arisen about what constitutes the necessary elements of an auditing program.

As a consequence, this measure is based simply on the binary coding of whether the state requires a postelection audit of vote totals. The requirement may come from statute, administrative rule, or administrative directive. The primary data source is the Statutory Overview portion of the EAC’s Election Administration and Voting Survey, supplemented by direct communication with state election offices. It is not based on a further coding of the specific provisions in state law, nor is it based on the findings of the audits themselves. (For instance, it is not based on measures of how close audited election results come to the original, certified results.)

4.11 Provisional ballots cast

4.11.1 Data source

Election Administration and Voting Survey

The provisional ballot mechanism allows voters whose registration status is in dispute to cast ballots, while leaving the registration status question to be resolved after Election Day. Provisional ballots have other uses, too. Some states have begun using them essentially as change-of-address forms for voters who have moved. Some jurisdictions allow provisional ballots cast in the wrong precinct to be counted.

Unless provisional ballots are being given to voters for other administrative reasons, a large number may indicate problems with voter registration records. The meaning of a small number of provisional ballots, from an election administration standpoint, is more open to question. On the one hand, it may indicate that registration records are up to date; on the other hand, it may be the result of poll workers not offering voters with registration problems the provisional ballot option when appropriate.

4.11.2 Coding convention

Expressed as an equation, the provisional ballot participation rate can be calculated as follows from the EAVS data sets:

$$\text{Provisional ballot participation rate} = \frac{\text{Total provisional ballots cast}}{\text{Total participants in the election}}$$

Table 24: EAVS variables used to calculate provisional ballot participation indicator

Descriptive name	2008 EAVS	2010- 2016 EAVS	2018- 2020 EAVS
Provisional ballots cast	e1	qe1a	qe1a
Total participants	f1a	qf1a	qf1a

Table 25: States with too much missing data to calculate provisional ballot participation indicator

Year	State
2008	AL, IL, IN, ME, MS, NY, WV, WY
2010	IL, MS, NY, SC, WV, WY
2012	MS, SC, WV, WY
2014	IN, UT, WY
2016	AL, WI
2018	AR, VA
2020	No states with missing data

For the first time in the history of the EPI, all states reported enough data in 2020 to calculate the provisional participation indicator for 2020. Table 25 reports states with missing values for this indicator from 2008 to 2016. We also did not include these rates for states that do not use provisional ballots (Idaho, Minnesota, and New Hampshire) because they have Election Day registration or for North Dakota, which does not require voters to register.

4.11.3 Comparisons over time

We begin by comparing provisional ballot usage rates, measured at the county level. The data are right-skewed; most counties have very low usage rates, while a few have relatively high rates. This is illustrated in Figure 18, which shows the distribution of usage rates for each county for which we have the relevant data.

Because of this pronounced right skew, any scatterplot that compares two years will be misleading because the bulk of observations will be clumped around the origin, with our eye drawn toward the small number of outliers with extremely large values.

To deal with this problem, we transform the measures by taking logarithms. One problem that emerges is that a large fraction of counties had no provisional ballots in particular years, and the logarithm of zero is undefined. Therefore, in the scatterplot in Figure 19, counties with zero provisional ballots have been set to 0.0000001, which is slightly below the largest nonzero usage rate that was observed. Finally, so that the influence of larger counties is visually greater than that of smaller counties, we weight the data tokens in proportion to the size of the counties. As these graphs illustrate, for counties that reported the necessary data, usage rates are similar across any pair of compared years. The Pearson correlation coefficient, which measures the degree of similarity across these four election cycles, ranges between 0.519 and 0.711. Again, provisional participation rates in 2020 have a weaker correlation with previous presidential years.

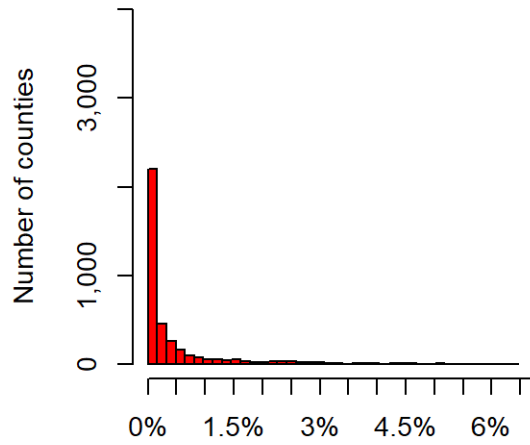
These graphs also illustrate how counties that report no provisional ballots in one election cycle often report a considerably greater usage rate in the next cycle. Sometimes this

is because the county is very small. With provisional ballot usage rates overall being relatively low, between 1 and 2 percent on average between 2008 and 2016. In 2020, provisional participation rates dropped even further, averaging .01% of ballots cast at the state level.

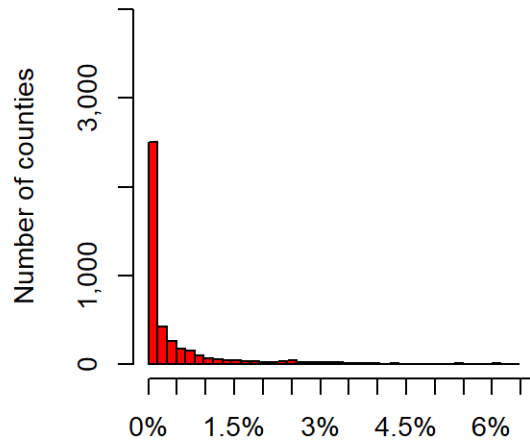
There are fluctuations in the participation rate, where a county with only a few hundred registered voters might very well experience an election cycle in which no provisional ballots were used. However, relatively large counties will sometimes report zero provisional ballots in one election cycle and a relatively large number in the other cycle. This sort of behavior calls for further investigation. Until such research is conducted, this pattern alerts us to the need to be cautious when using data on the use of provisional ballots.

The EPI reports provisional ballot use at the state level. The statewide usage rates are similarly right-skewed; therefore, it is necessary to translate the rates into logarithms before plotting the usage against each other. As with the measures calculated at the county level, the indicator calculated at the state level is very stable when we compare across years.

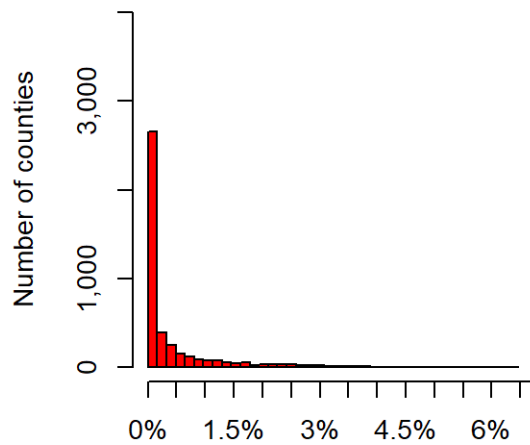
Figure 18: Provisional Ballot Participation Rates by County



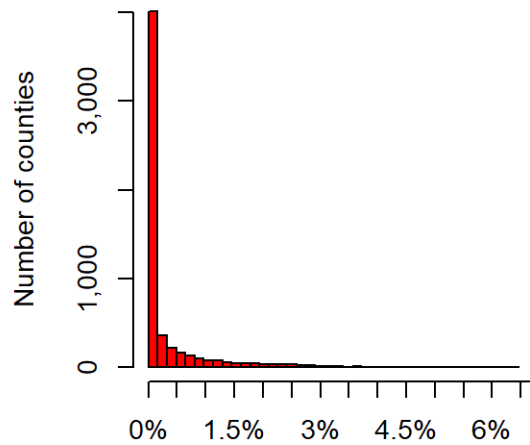
Provisional ballot participation rate 2008



Provisional ballot participation rate 2012



Provisional ballot participation rate 2016



Provisional ballot participation rate 2020

Figure 19: Logged Provisional Ballot Participation Rates by County

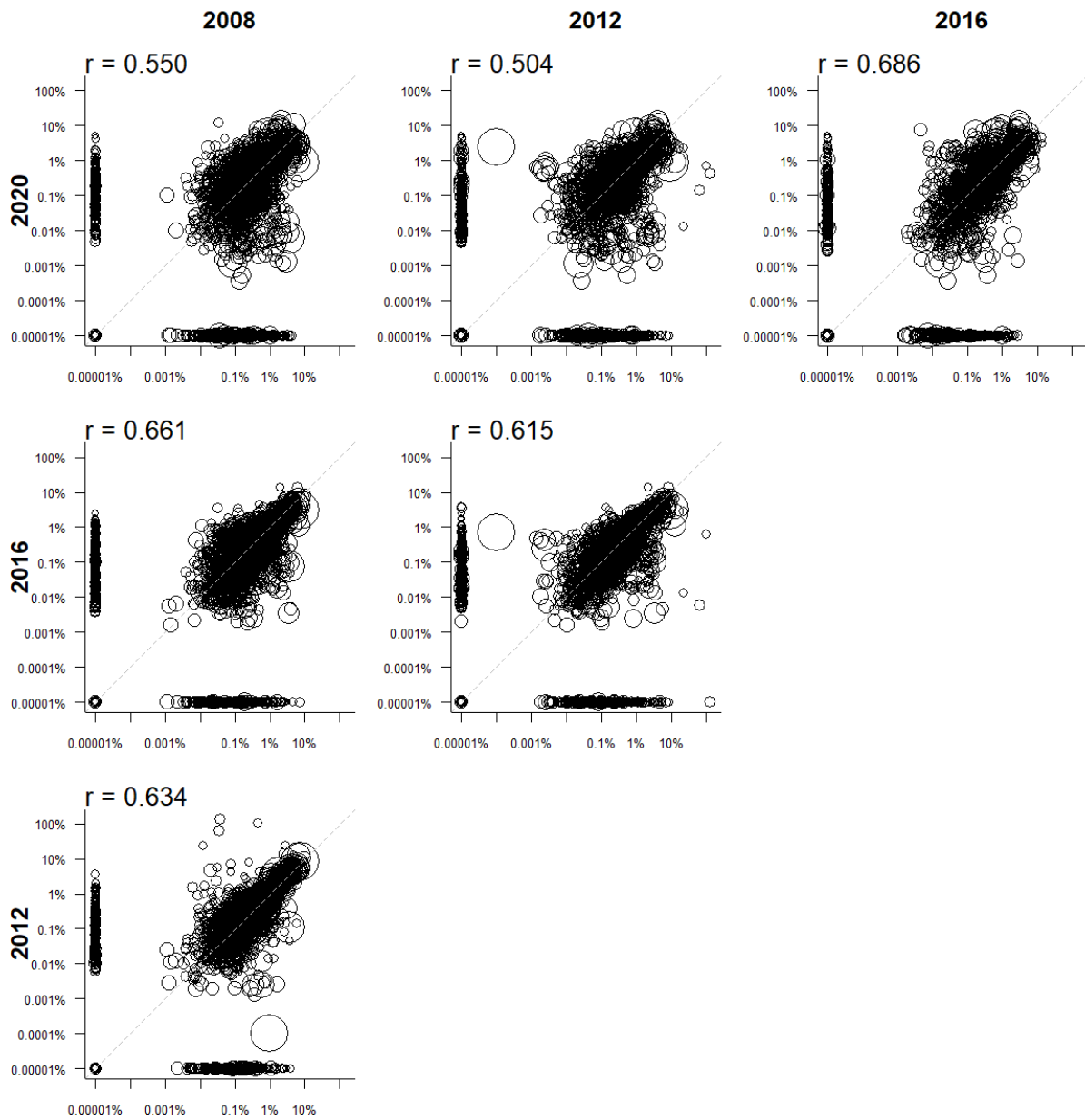
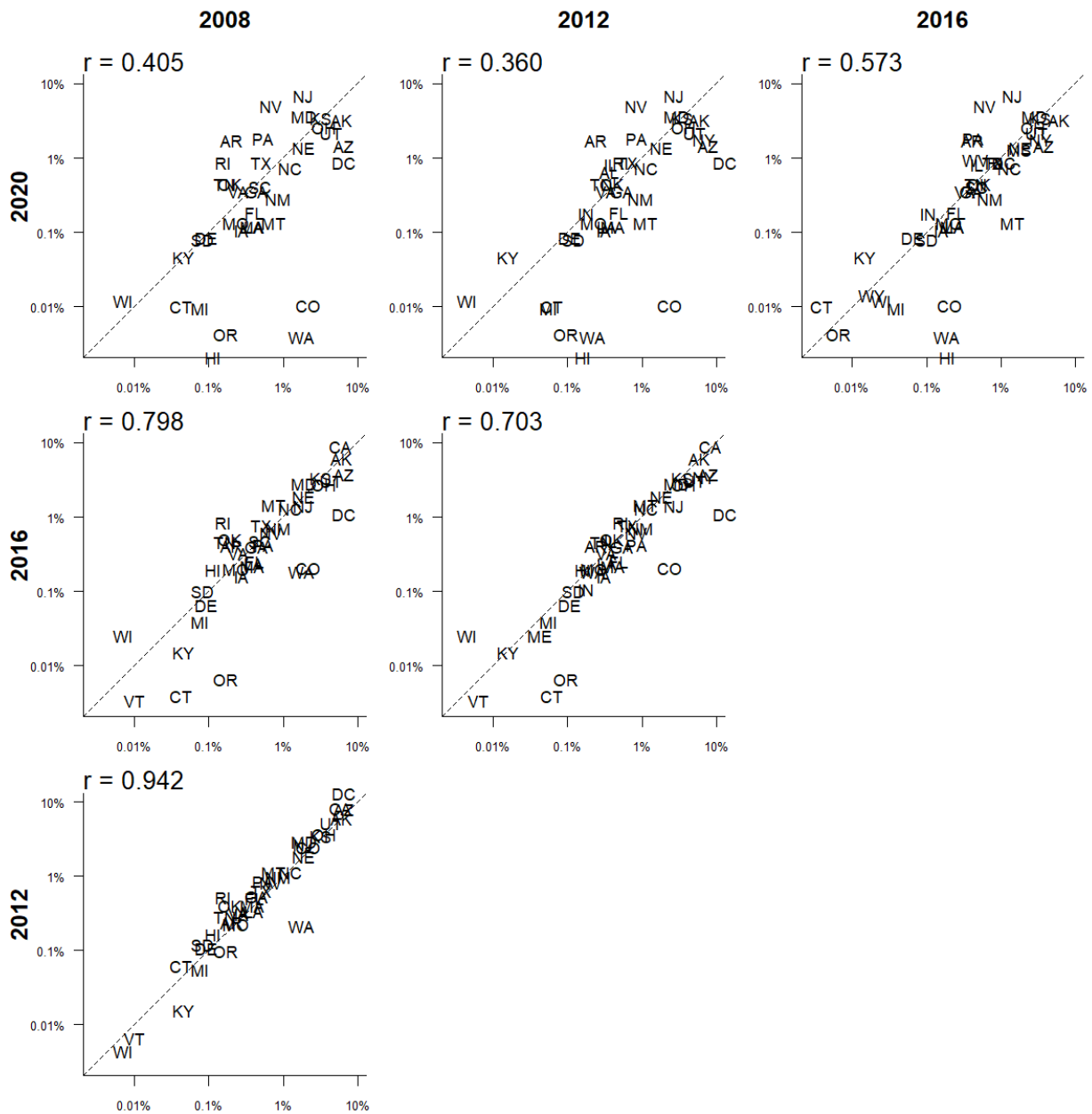


Figure 20: Logged Provisional Ballot Participation Rates by State



4.12 Provisional ballots rejected

4.12.1 Data source

Election Administration and Voting Survey

Provisional ballots are cast for a variety of reasons. Whether a provisional ballot is eventually counted depends on why the voter was issued such a ballot and the rules for counting provisional ballots in the voter's state.

States vary in the criteria they use to determine if a provisional ballot should be issued and, later, counted. The most significant difference among states is that some reject provisional ballots cast in the wrong precinct, while others count part of those ballots.

4.12.2 Coding convention

Expressed as an equation, the provisional ballot rejection rate can be calculated as follows from the EAVS data sets:

$$\text{Provisional ballot rejection rate} = \frac{\text{Rejected provisional ballots}}{\text{Total participants in the election}}$$

Table 26: EAVS variables used to calculate provisional ballots rejected indicator

Descriptive name	2008 EAVS	2010- 2016 EAVS	2018- 2020 EAVS
Provisional ballots rejected	e2c	qe1d	qe1d
Total participants	f1a	qf1a	qf1a

Table 27: States with too much missing data to calculate provisional ballots rejected indicator

Year	State
2008	AL, AR, IL, IN, ME, MS, NM, NY, OR, SD, WV, WY
2010	MS, NY, SC, WY
2012	MS, SC, VT, WV, WY
2014	IN, UT, WY
2016	AL, SD, WI
2018	AR, VA
2020	No states with missing data

For the first time in the history of the EPI, all states reported enough data in 2020 to calculate the provisional ballots rejected indicator for 2020.

The decision was made to use total participants in the general election as the denominator, rather than number of provisional ballots issued, for two reasons. First, states that issue large numbers of these ballots, measured as a percentage of all votes cast in an election, tend to also accept a large number of those ballots, measured as a percentage of provisional ballots cast. Thus, the percentage of provisional ballots rejected as a percentage of provisional ballots cast measures only the legal context under which provisional ballots are used and does little beyond that to illustrate the health of elections in a state. Second, the number of provisional ballots rejected represents voters who tried to vote and were turned away. Large numbers of such voters relative to the number of total participants in the election represent not only lost opportunities by voters to cast ballots, but also greater opportunities for disputes about an election's results. In other words, a large number of provisional ballots left uncounted for whatever reason, as a share of total participants, indicates a mix of administrative problems and the potential for litigation, neither of which can be considered positive.

4.12.3 *Comparisons over time*

We begin by comparing provisional ballot usage rates, measured at the county level. The raw data exhibit a pronounced right skew. That is, most counties have very low rejection rates, while a few have relatively high rates. This is illustrated in [Figure 21](#), which shows the distribution of rejection rates for 2008, 2012, 2016, and 2020 for each U.S. county for which we have the relevant data. Because of this pronounced right skew, any scatterplot that compares values across two years will be misleading in that the bulk of observations will be clumped around the origin, with our eye drawn toward the small number of outliers with extremely large values. To deal with this pronounced right skew, it is common to transform the measures by taking logarithms. One problem this creates is that a large fraction of counties had zero provisional ballots rejected in these three years, and the logarithm of zero is undefined. Therefore, in the scatterplot in [Figure 22](#), counties with zero provisional ballots have been set to 0.0000001, which is slightly below the smallest nonzero rejection rate that was observed. Finally, so that the influence of larger counties is visually greater than that of smaller counties, we weight the data tokens in proportion to the size of the county.

As these graphs illustrate, for counties that reported the necessary data in 2008, 2012, 2016, and 2020, rejection rates are somewhat similar across these years. The Pearson correlation coefficient, which measures the degree of similarity across these election cycles, ranges between 0.516 and 0.654.

These graphs also illustrate how counties that report no rejected provisional ballots in one election cycle often report a considerably greater rejection rate in the next cycle. Sometimes this is because the county is very small. With provisional ballot rejection rates overall being relatively low, averaging no more than half a percentage point during this period, a county with only a few hundred registered voters might experience an election cycle in

which no provisional ballots were rejected. However, relatively large counties will sometimes report zero provisional ballots rejected in one election cycle and a relatively large number in the other cycle. This sort of behavior calls for further investigation. Until such research is conducted, this pattern alerts us to the need to be cautious when using data on the rejection of provisional ballots.

The EPI reports the rates of provisional ballot rejection at the state level. The statewide rejection rates are similarly right-skewed; therefore, it is necessary to translate the rejection rates into logarithms before plotting the rejection rates across time. As with the measure calculated at the county level, the indicator calculated at the state level is very stable when we compare across years.

Figure 21: Provisional Ballot Rejection Rates by County

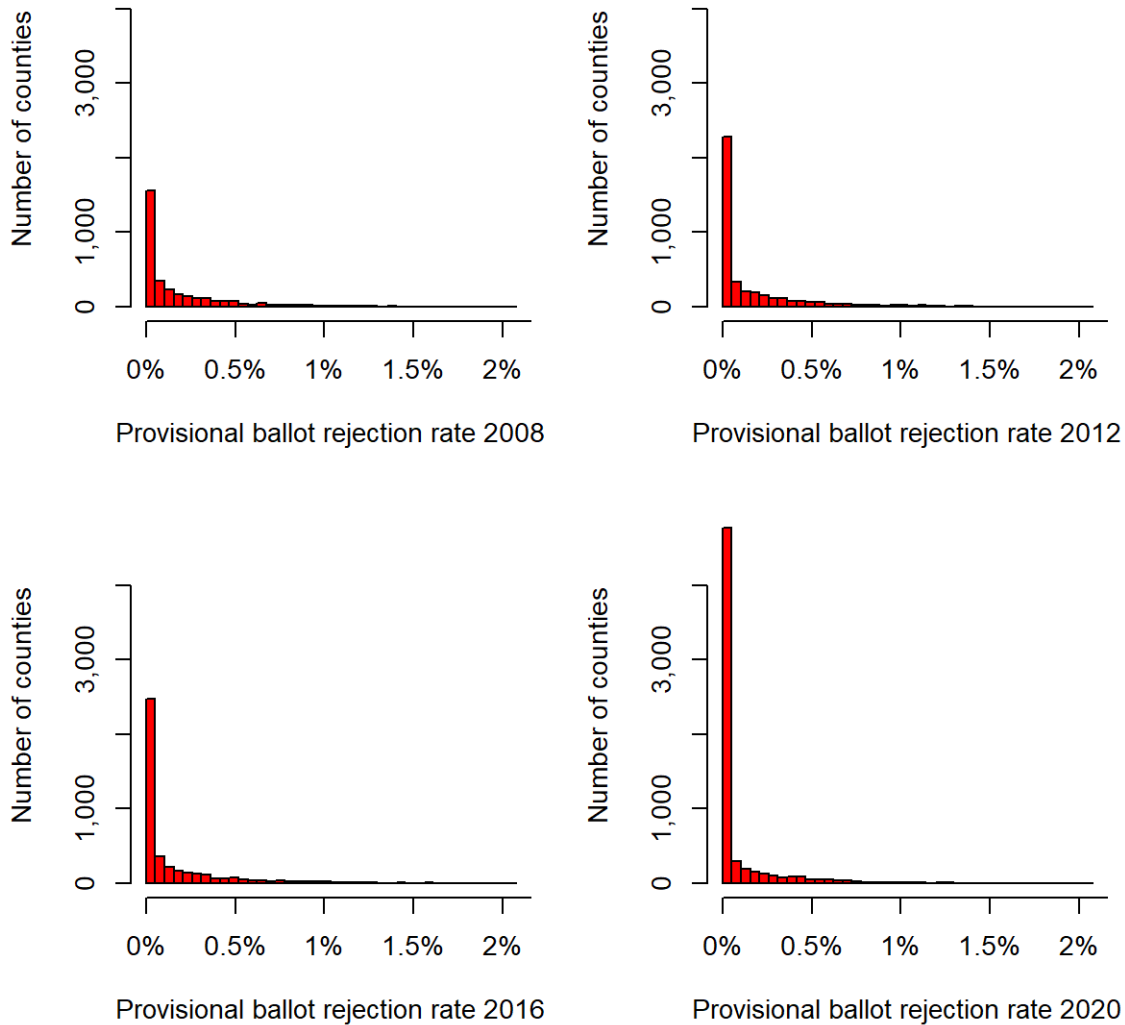
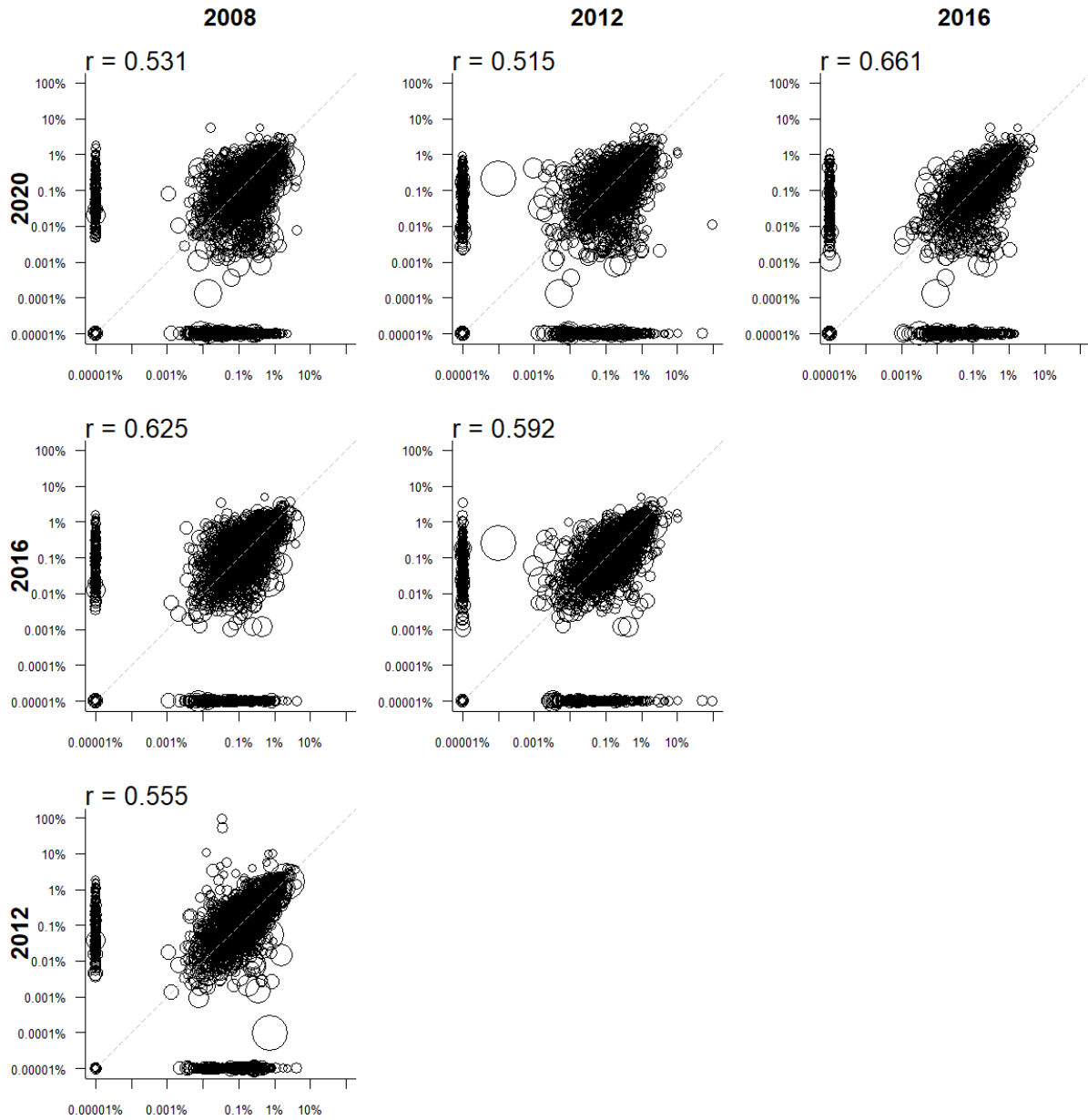


Figure 22: Logged Provisional Ballot Rejection Rates by County



4.13 Registration or absentee ballot problems

4.13.1 Data source

Voting and Registration Supplement to the Current Population Survey

Previous research has indicated that problems with voter registration present the greatest frustrations for voters trying to cast a ballot in an election.²⁶ Voters often believe they are registered when they are not, registered voters sometimes are not listed in the pollbooks, and voters are sometimes registered in a precinct other than where they show up to vote on Election Day. Reducing the number of people who fail to vote due to registration problems was a major goal of the Help America Vote Act.

4.13.2 Coding convention

This indicator is based on responses to the Voting and Registration Supplement of the CPS. Specifically, it is based on responses to item PES4, which asks of those who reported not voting: “What was the main reason you did not vote?” Response categories comprise the following in [Table 28](#).²⁷

Table 28: Reasons for Not Voting

Response category	2016	2020
Not interested, felt my vote wouldn't make a difference	15.8%	18.2%
Didn't like candidates or campaign issues	25.4%	15.0%
Other	11.4%	15.0%
Too busy, conflicting work or school schedule	14.7%	13.6%
Illness or disability (own or family's)	12.0%	13.4%
Out of town or away from home	8.1%	6.3%
Registration problems	4.5%	5.1%
Concerns about the coronavirus (COVID-19) pandemic		4.5%
Forgot to vote (or send in absentee ballot)	3.1%	3.8%
Inconvenient hours or polling place; lines too long	2.2%	2.7%
Transportation problems	2.7%	2.4%
Bad weather conditions	0.0%	0.1%

The ‘Registration problems’ response category forms the basis for this indicator.

4.13.3 Stability of rates across time

The rate at which registrants report they did not vote because of registration problems or failure to receive an absentee ballot will vary across time, for a variety of reasons. Some of these reasons may be related to policy—for instance, a shift to a permanent absentee ballot list may cause an increase in the percentage of nonvoters giving this reason for not voting. Some of these reasons may be unrelated to election administration or policy, and

therefore can be considered random variation.

One advantage of VRS data is that they go back many elections. The question about reasons for not voting has been asked in its present form since 2000. Therefore, it is possible to examine the intercorrelation of this measure at the state level across ten federal elections, from 2000 to 2020.

Table 29: Between-year correlation of registration problems indicator

	2000	2002	2004	2006	2008	2010	2012	2014	2016	2018	2020
2000	1.000										
2002	0.452	1.000									
2004	0.370	0.634	1.000								
2006	0.287	0.533	0.319	1.000							
2008	0.431	0.268	0.330	0.441	1.000						
2010	0.204	0.462	0.526	0.473	0.205	1.000					
2012	0.432	0.454	0.457	0.528	0.183	0.381	1.000				
2014	0.314	0.628	0.353	0.536	0.116	0.347	0.383	1.000			
2016	0.532	0.472	0.334	0.350	0.438	0.075	0.494	0.253	1.000		
2018	0.243	0.410	0.421	0.291	0.105	0.317	0.388	0.434	0.283	1.000	
2020	0.271	0.234	0.179	0.398	0.115	0.048	0.298	0.212	0.094	0.386	1.000

Table 29 is the correlation matrix reporting the Pearson correlation coefficients for values of this indicator across these ten elections.

The correlation coefficients between pairs of elections are moderately high, which suggests the underlying factor that is being measured by this indicator is stable within individual states; therefore, there is strong reliability to the measure. As a result, it may be prudent to consider combining data across years so that the reliability of the measure might be improved.

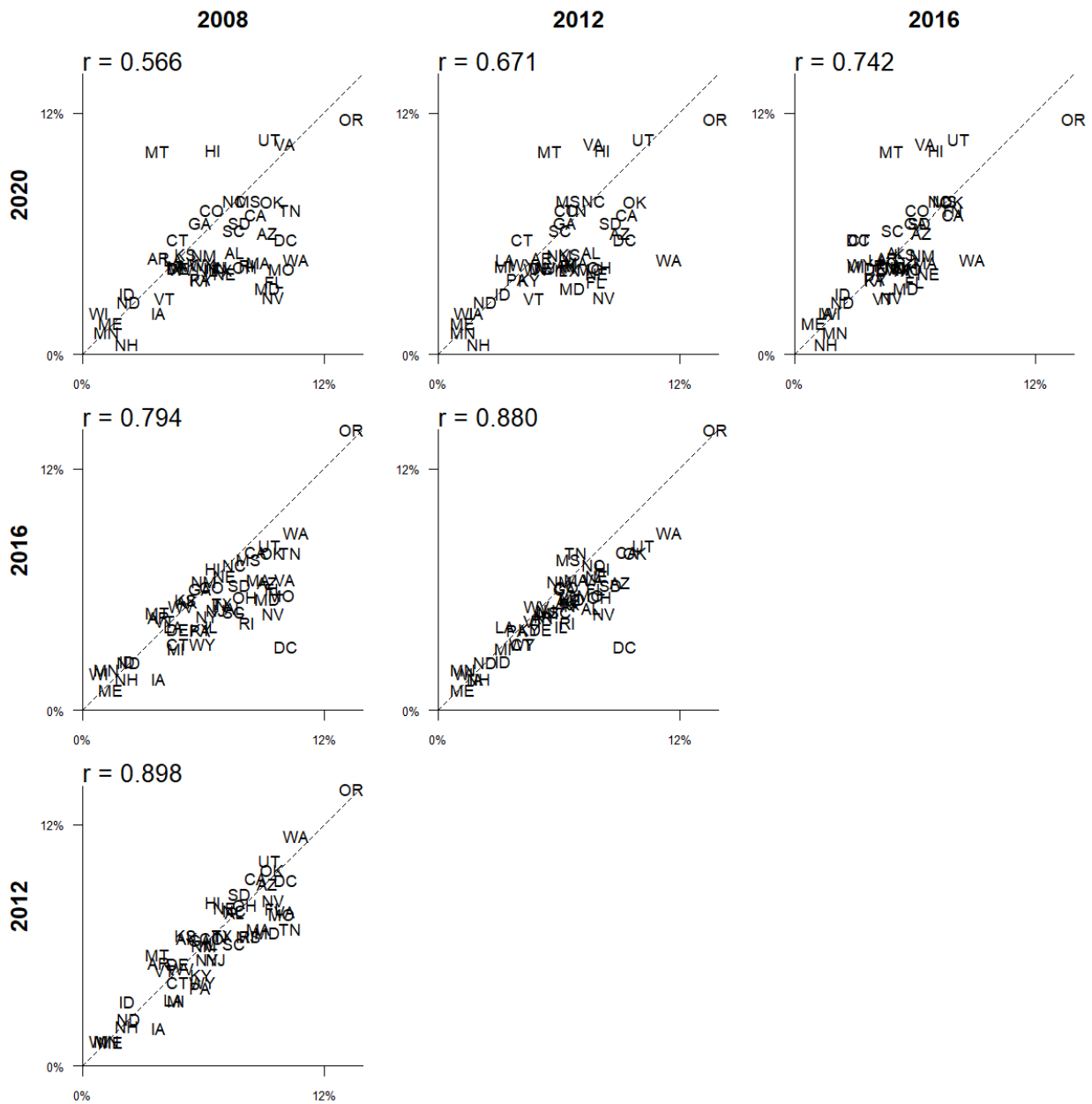
It is tempting to consider creating a single scale from this set of data because of the moderately high overall intercorrelations. However, comparing the averages for each year reveals that more nonvoters give the “registration problem” reason in presidential election years (6.7 percent national average) than in midterm election years (4.0 percent national average). Consequently, a more prudent strategy is to treat presidential and midterm election years separately.

We created two scales from the data set, one consisting of the average rates for the most recent three presidential election years, and the other consisting of the average rates for the three most recent midterm election years. In the original version of the EPI, we constructed the presidential election year measure using data from the 2000, 2004, and 2008 presidential elections and the midterm measure using data from the 2002, 2006, and 2010 midterm elections. In the 2010 version of the EPI, we updated the presidential election year measure by dropping the most distant presidential year previously used (2000), substi-

tuting in the most recent year (2012). In a similar fashion, for the 2014 version of the EPI, we dropped the data from the most distant midterm election year, 2002, and substituted data for the most recent year, 2014. For the 2016 score, we dropped data from 2004 and added data from 2016. Finally, for the 2020 score, we dropped data from 2008 and added data from 2020. Thus the midterm and presidential year version of the indicator will evolve over time.

Figure 24 shows the correlations across these measures as they have evolved. The Pearson correlation coefficients quantifying these relationships range are significantly higher than any of the coefficients in the correlation matrix in [Table 29](#), which rely on data from only one year.

Figure 24: Percent of Nonvoters Due to Registration Problems



4.14 Registrations rejected

4.14.1 Data source

Election Administration and Voting Survey

Although in most states it is necessary to register ahead of time in order to vote, research into voter registration is in its infancy. As a consequence, it is not known how many rejected registration forms are the result of ineligible voters attempting to register and how many are eligible voters who are turned away because of errors made in filling out or processing their registration forms.

Regardless of why registrations are rejected, a state or county that rejects a large share of registrations must devote a greater portion of its limited resources to activities that do not lead to votes being counted. This can be particularly challenging as an election approaches, since most registrations are received and processed in the weeks leading up to an election, when election offices also must deal with many other tasks. If a locality has a high rate of rejected registrations because of administrative problems, the situation can lead to other problems such as people who mistakenly think they have registered. This, in turn, could lead to more provisional ballots being cast, longer lines at the polls, and greater confusion on Election Day.

4.14.2 Coding convention

Expressed as an equation, the registration rejection rate can be calculated as follows from the EAVS data sets:

$$\text{Registration rejection rate} = \frac{\text{Invalid/rejected registrations}}{(\text{Invalid/rejected}) + (\text{valid}) \text{ registrations}}$$

Table 30: EAVS variables used to calculate registrations rejected indicator

Descriptive name	2008 EAVS	2010-2016 EAVS	2018-2020 EAVS
Invalid/rejected (other than duplicates) registration forms	a5e	qa5e	qa3e
New valid registration forms	a5b	qa5b	qa3b

Data will be missing if a county has failed to provide any of the variables, detailed in [Table 30](#), included in the calculation. The data reported for an election year includes applications received from the close of registration for the November of the previous federal election until the close of registration for the election being analyzed. For instance, for the 2020 EAVS, the registration numbers include applications received from after the close of reg-

istration for the November 2018 election until the close of registration for the November 2020 election. Each year since the beginning of the EPI, more states have provided enough information to calculate the registration rejection indicator. Because of missing data, it was not possible to compute registration rejection rates in eight states in 2020.

Table 31: States with too much missing data to calculate registrations rejected indicator

Year	State
2008	AR, AZ, CA, CO, DC, HI, ID, KY, MA, MD, MO, MS, NH, NM, NY, OH, OK, OR, RI, SC, SD, TN, UT, WA, WI, WV, WY
2010	AZ, CA, CT, FL, HI, ID, MO, MS, NE, NH, NM, NY, OK, OR, RI, SC, TN, VT, WA, WI, WY
2012	AL, AR, AZ, CA, CT, GA, HI, ID, KS, MS, NM, NY, OK, OR, RI, SC, SD, TN, VT, WV, WY
2014	CT, HI, ID, IL, KS, KY, MS, NM, OR, RI, SC, UT, WY
2016	AZ, CT, HI, ID, KS, NM, OR, RI, SC, WA, WI, WY
2018	AR, CT, HI, ID, IL, KS, MO, OR, RI, SC, WY
2020	CT, HI, ID, KS, MO, OR, SC, WY

Table 31 reports states with missing values for this indicator from 2008 to 2020. Rejected voter registrations is the EPI indicator that is the most beset with missing-value problems from the states. North Dakota has no voter registration and therefore was not included in this measure.

4.14.3 Comparisons over time

We begin by comparing registration rejection rates, measured at the county level. The histograms in Figure 25 show the distribution of rejection rates for 2008, 2012, 2016, and 2020 for each county in the United States for which we have the relevant data. The data exhibit what is known as a pronounced “right skew.” That is, most counties have very low rejection rates (with a peak on the left of both histograms representing the large portion of counties with rejection rates at or near zero), while a few have relatively high rates (the small smattering of observations in the right-hand “tail” of each histogram).

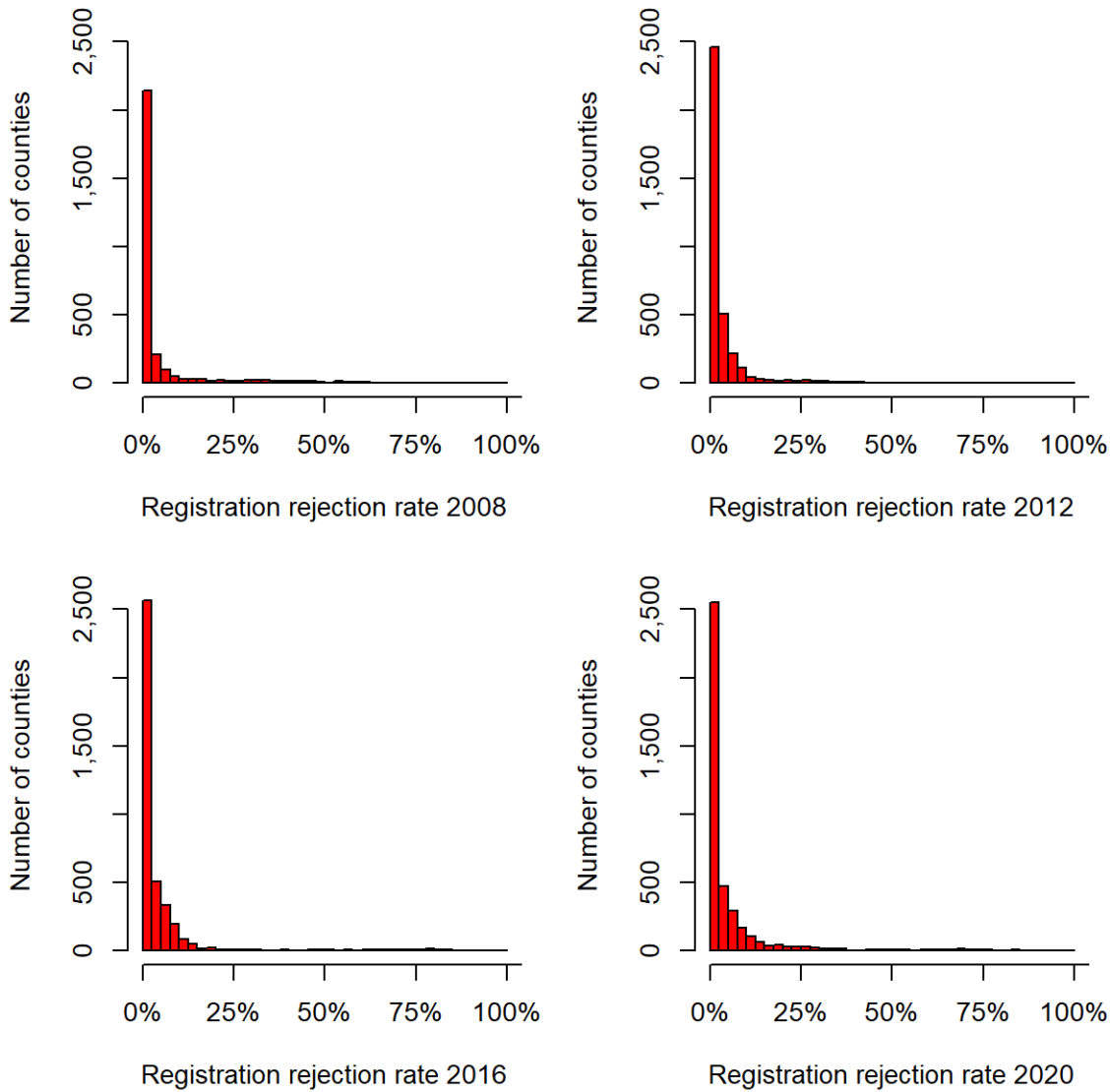
Because of this pronounced right skew, any scatterplot that compares values across years will be misleading in that the bulk of observations will be clumped around the origin, but the viewer’s eye will be drawn to the small number of outliers with extremely large values. To deal with this pronounced right skew, we rely on the common practice of transforming the measures by taking logarithms. However, one problem this creates is that a large fraction of counties had zero rejected registration forms in each year, and the logarithm of zero is undefined. Therefore, in the scatterplot in Figure 26, counties with zero rejected registration forms have their rejection rate set to 0.000001, which is slightly below the

lowest nonzero rejection rate that was actually observed. Finally, so that the influence of larger counties is visually greater than that of smaller counties, we weight the data tokens in proportion to the size of the county's registration activity.

As these graphs illustrate, for counties that reported the data necessary to calculate rejection rates for 2008, 2012, 2016, and 2020, rejection rates are moderately similar across years. The Pearson correlation coefficient, which measures the degree of similarity across two election cycles, ranges between 0.419 and 0.600.

These graphs also illustrate how counties that report zero rejections in one election cycle often report a considerably greater rejection rate in the next cycle. With rejection rates overall being relatively low, in many cases, the jump in rejection rate between years is simply because a county is very small. For example, a county that receives only 20 new registration applications per election cycle may easily reject none in 2008 but reject two, or 10 percent, in 2010. However, relatively large counties will sometimes report zero rejections in one election cycle and a relatively large number in the other cycle. This sort of pattern calls for further investigation and research. Until such research is conducted, this pattern alerts us to the need to be cautious when using data about the rejection rates of voter registration forms.

Figure 25: Registration Rejection Rates by County



As Figure 27 illustrates, for states that reported the data necessary to calculate rejection rates for all EPI years rejection rates are very similar from 2016 to 2020. When we aggregate rejection rates to the state level, as seen in Figure 27, the two recent presidential election (2016 to 2020) are similar with Pearson scores for all observed presidential elections ranging from 0.089 and 0.907.

Figure 26: Logged Registration Rejection Rates by County

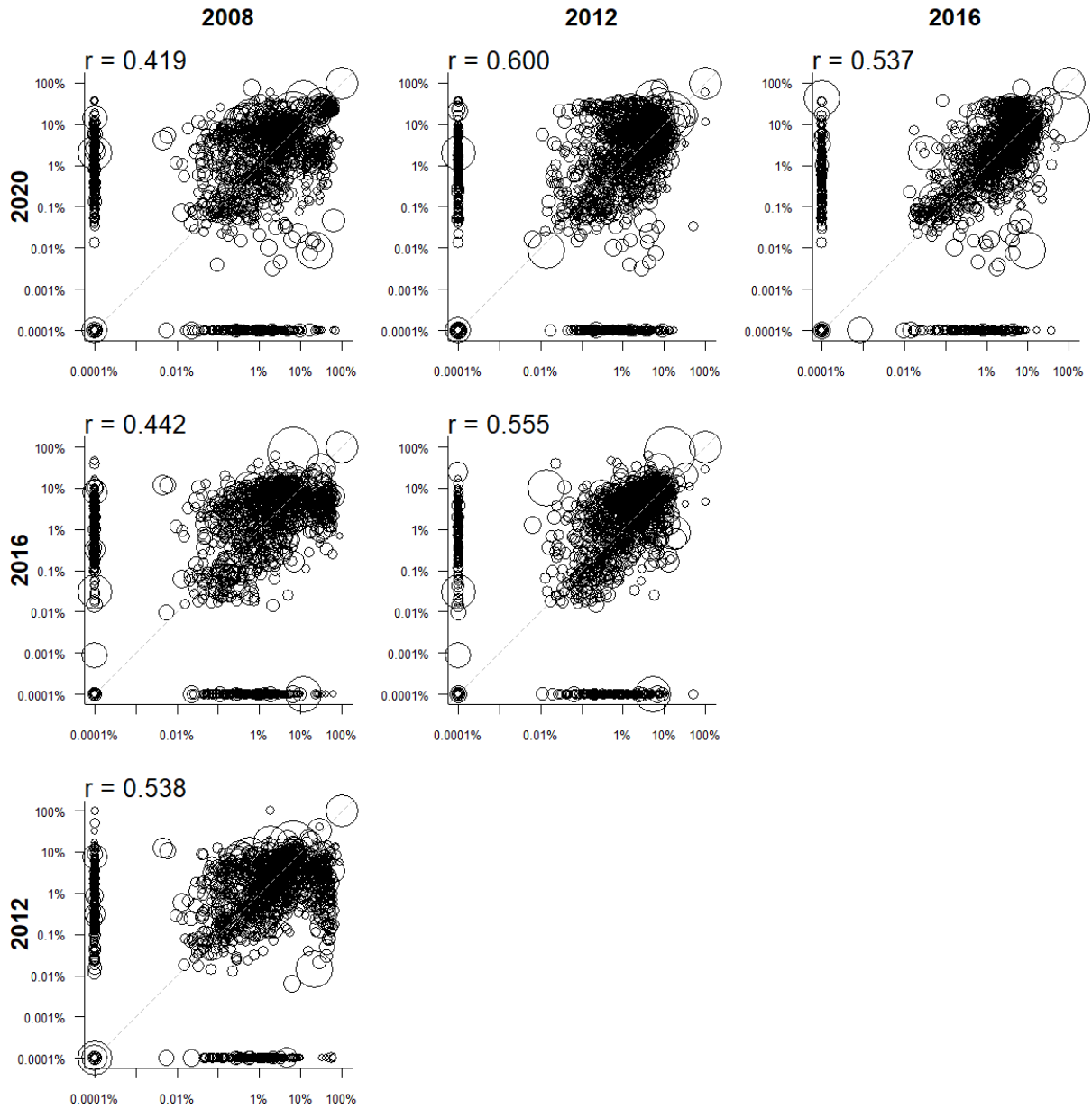
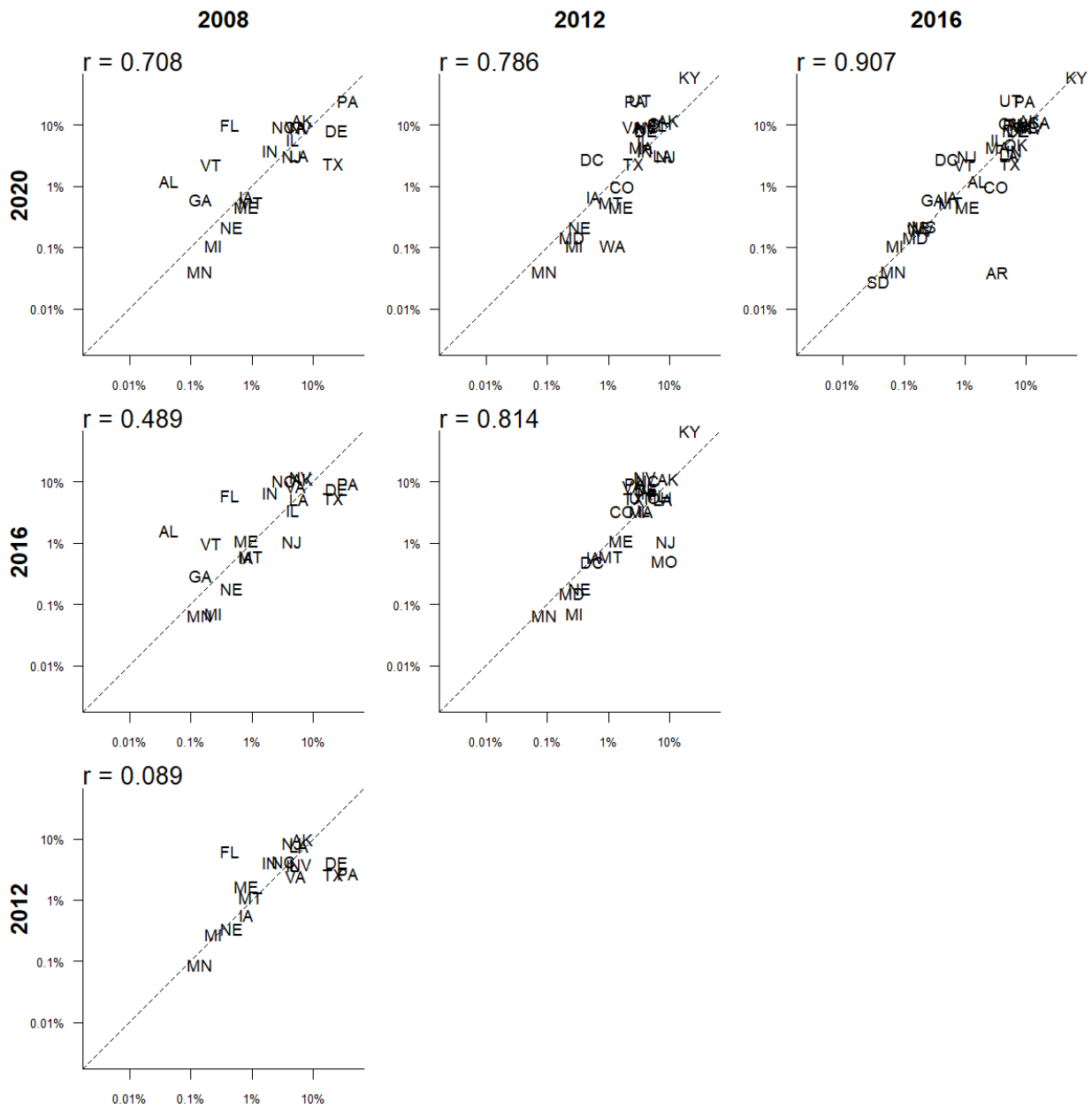


Figure 27: Registration Rejection Rates by State



4.15 Residual vote rate

4.15.1 Data source

States boards of elections

The controversies surrounding “hanging chads” and “butterfly ballots” after the 2000 presidential election demonstrated to Americans how efforts to vote might be undermined by malfunctioning voting equipment or confusion induced by poor ballot design. The leading way to assess the accuracy of voting technology is using the residual vote rate, which measures votes that are “lost” at the point when ballots are cast for president. Efforts to improve the technology of voting should be evident by the reduction of the residual vote rate, the measurement in the Voting Technology Accuracy indicator.

The residual vote rate can be defined as the sum of over- and undervotes in a particular election, divided by the total number of voters who turned out. Pioneered by the Caltech/MIT Voting Technology Project, this measure has become a standard benchmark in assessing the overall accuracy of machines and documenting the improvement as old machines were replaced by new ones.²⁸ Although other measures of voting machine quality exist, no other widely used metric today can be applied uniformly throughout the country.

4.15.2 Coding convention

Expressed as an equation, the residual vote rate can be calculated as follows:

$$\text{Residual vote rate} = \frac{\text{Reported total turnout} - \text{Total votes counted}}{\text{Reported total turnout}}$$

The residual vote rate must be calculated with respect to a particular election. The only election that is comparable across the entire country is the race for president, so this indicator is based on the residual vote rate for the president. Therefore, it is calculated only for presidential election years. In midterm elections, there is too much variability in terms of which races are atop the ticket in each state and in terms of the competitiveness of statewide races, which make the residual vote rate a weak interstate measure of voting machine accuracy.

The data were gathered for this measure from the official returns of state election offices. Two special considerations must be kept in mind in calculating this measure. First, the residual vote rate can be calculated only if a state requires local jurisdictions to report turnout (the number of voters taking ballots in a particular election). In 2020 seven states were excluded for this reason: Mississippi, Missouri, Oklahoma, Pennsylvania, Texas, Kansas, and Kentucky.

Second, the residual vote rate can be influenced by whether states publish tabulations of write-in votes. States that allow but do not publish write-in votes for president can have a higher residual vote calculated for them than is warranted. Therefore, special care was

taken to ensure that write-in votes were included in the residual vote calculations reported here.

The most serious criticism of the residual vote rate is that it conflates undervotes caused by conscious abstention and inadvertent mistakes. Based on research utilizing various data sources, it appears that 0.5 to 0.75 percent of voters abstain from voting for the office of president each presidential election cycle.²⁹ The statewide residual vote rate has rarely dipped below 0.5 percent; only two states had residual vote rates below this benchmark in both 2012 and 2016, for instance.³⁰

Despite the fact that one state, Nevada, had an especially low residual vote rate in 2016, the nationwide average residual vote rate in 2016 rose significantly compared to recent years. Among states that report the necessary information to calculate it, the residual vote rate rose to 1.4% in 2016, compared to 1.05% over the three presidential elections from 2004 to 2012.³¹ Given the way the residual vote rate indicator is constructed, by normalizing the score between the historical high and low values, a state that experienced an “average” increase of the residual vote rate in 2016 of 0.35 points over 2012 will see a decline in this indicator of 9.1 points. Furthermore, given how the overall EPI index is constructed, a state that otherwise keeps up with the other states in terms of performance, but sees an average increase in the residual vote rate because of increased abstentions, will see a decline in the index score.

It can be argued that to penalize a state when more of its voters abstain in an election is unfair. At the same time, the fact that Nevada had a historically low residual vote rate in 2016, despite an increase in abstentions, is evidence that states can choose policies that will make it less likely that the residual vote rate will be contaminated by a surge in abstentions. In particular, since the 1970s Nevada has given voters the option to choose “none of these candidates” in presidential elections. In 2016, the percentage of Nevadans choosing this opinion increased to 2.56%, compared to 0.57% in 2012. Its residual vote rate ended up declining from 0.17% to 0.004%.

Finally, in calculating the residual vote rate for a state, counties that reported more votes for president than total turnout were excluded.

4.15.3 *Stability of rates across time*

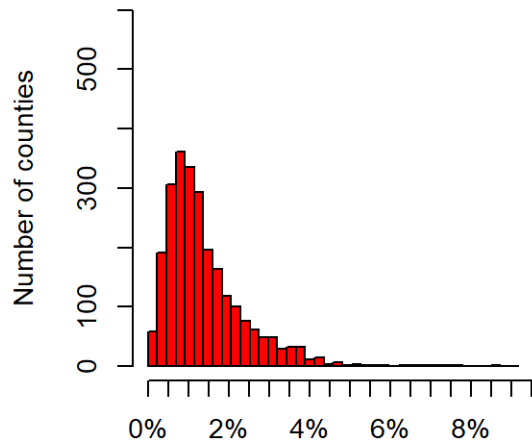
We begin by comparing residual vote rates, measured at the county level, for 2008, 2012, 2016, and 2020. The raw data exhibit a pronounced right skew. That is, most counties have very low residual vote rates, while a few have relatively high rates. This is illustrated in the histograms in [Figure 28](#), which show the distribution of residual vote rates in 2008, 2012, 2016, and 2020 for each county for which we have the relevant data.

Because of this pronounced right skew, any scatterplot that compares values from one year to another will be misleading in that the bulk of observations will be clumped around the origin, with our eye drawn toward the small number of outliers with extremely large values. To deal with this pronounced right skew, it is common to transform the measures by taking logarithms. One problem this creates is that some counties (especially small ones) had zero residual votes in particular years, and the logarithm of zero is undefined. Therefore, in the scatterplot in [Figure 29](#), counties with zero residual votes have been set to 0.00001, which is slightly below the lowest nonzero residual vote rate that was actually observed. Finally, so that the influence of larger counties is visually greater than that of smaller counties, we weight the data tokens in proportion to the size of the county.

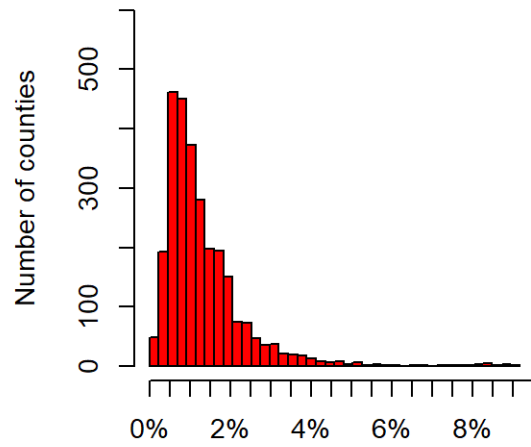
As [Figure 29](#) illustrates, for counties that reported the data necessary to calculate residual vote from 2008 to 2020, residual vote rates are related to a moderate degree from one election to the next. The correlation in rates between 2012 and 2008, 2016 and 2012, and between 2016 and 2020 are much greater than in the previous election pairs, which likely reflects the fact that localities have settled into a stable set of voting machines, following the rapid upgrading of machines immediately after the 2000 presidential election.

The EPI reports residual vote rates at the state level. The statewide residual vote rates are not especially right-skewed; therefore, [Figure 30](#) represents the comparison of residual vote rates using raw percentages rather than logged ones. As with the measures calculated at the county level, the indicator calculated at the state level is fairly stable when we compare 2012 with 2008.

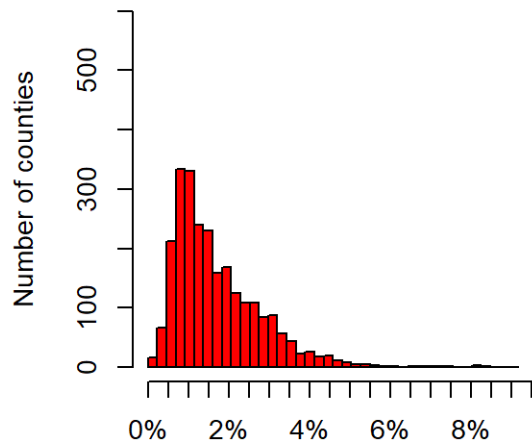
Figure 28: Residual Vote Rate by County



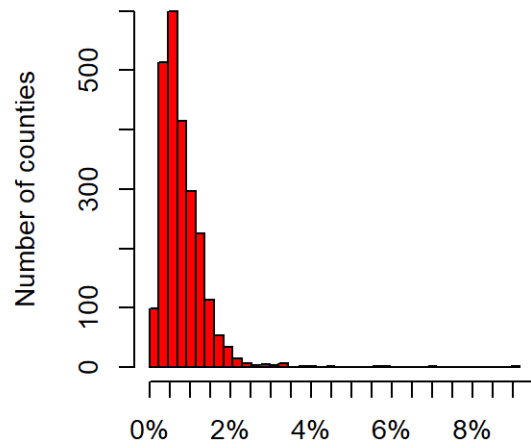
Residual vote rate 2008



Residual vote rate 2012



Residual vote rate 2016



Residual vote rate 2020

Figure 29: Logged Residual Vote Rate by County

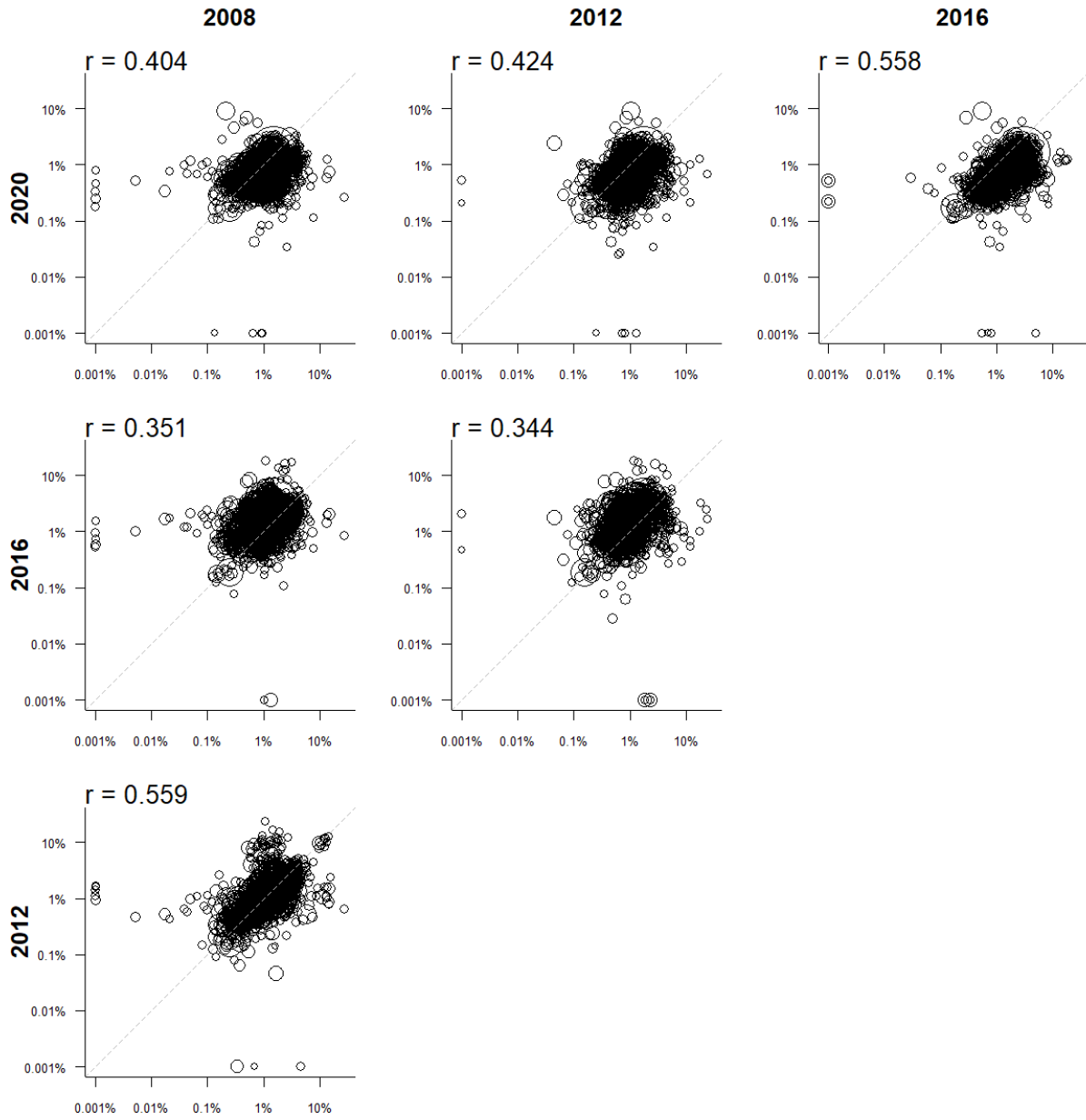
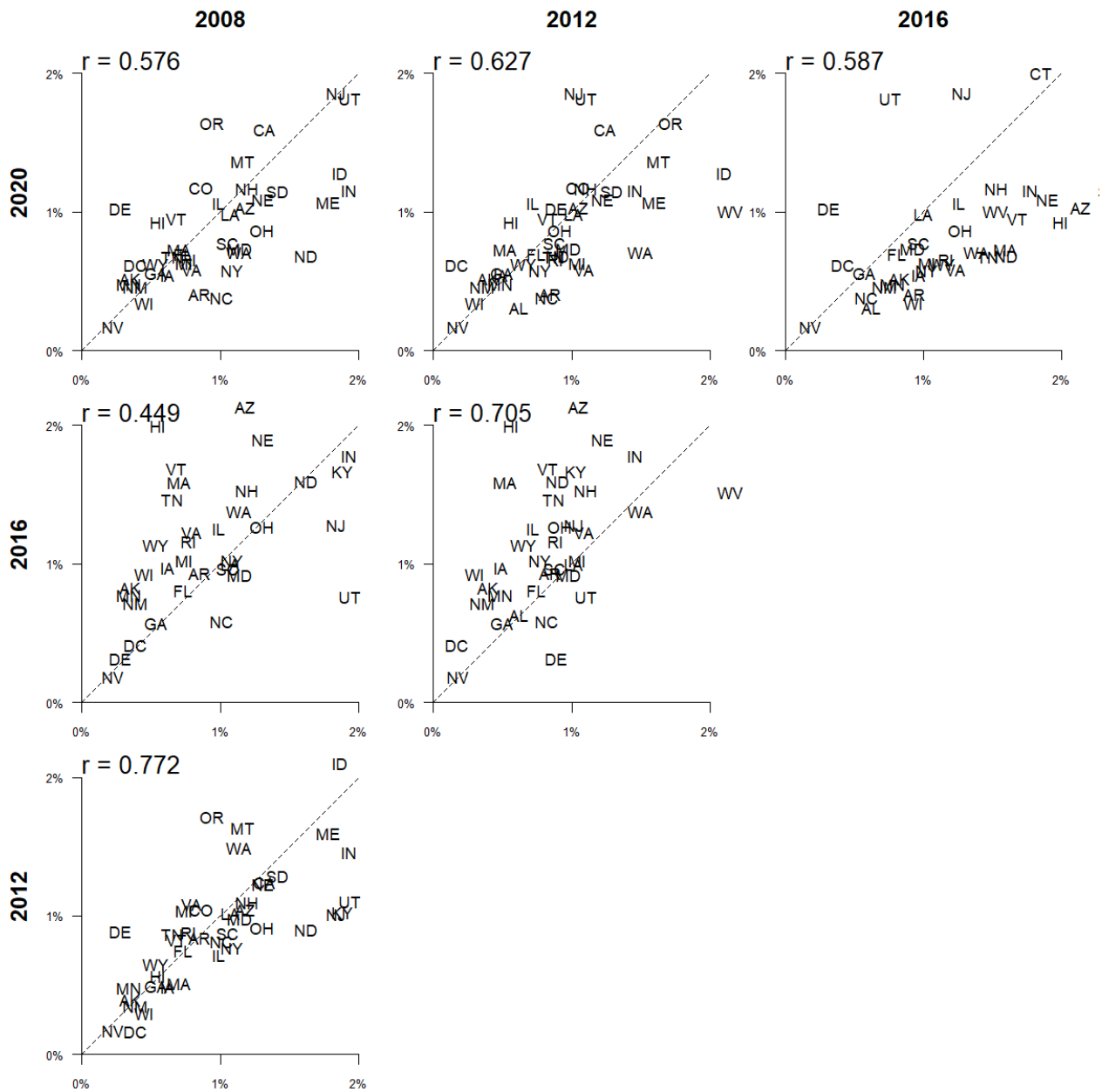


Figure 30: Residual Vote Rate by State



4.16 Risk-limiting audits (2020-)

4.16.1 *Data source*

National Conference of State Legislatures and state election offices

In recent years, increased scrutiny has been given to the quality of postelection audits, including, among other things, their methodology for ballot selection and sample size. Risk-limiting audits are a ballot-level audit that tests the outcome at a given precinct based on a sample of ballots and includes methods for escalation of the sample up to a full manual recount.³² The escalation test is determined by the likelihood that a selection of more ballots would overturn the election results. Ever since risk-limiting audits were introduced, numerous states have piloted risk-limiting audits, allowed counties to conduct them as an alternative to traditional audits, and a few have mandated them statewide. For this indicator, states that mandate risk-limiting audits statewide in statutes are coded at the highest value, while states that do not conduct risk-limiting audits are coded as missing. The effect of this coding is to reward states in score and rank for having risk-limiting audits, but not penalize states for not adopting the auditing method.

4.17 Turnout

4.17.1 *Data source*

United States Elections Project³³

Perhaps the most highly visible measure of the health of elections is the turnout rate—that is, the percentage of eligible voters who vote. A very large body of academic literature exists on the factors that cause turnout rates to rise and fall, the classic study being *Who Votes?* by Raymond E. Wolfinger and Steven J. Rosenstone.³⁴

The most powerful predictors of who will turn out are demographic, most notably education and income. However, the presence of certain registration laws has been shown to affect turnout, as demonstrated by Wolfinger and Rosenstone and those who have followed in their footsteps.

4.17.2 *Coding convention*

This indicator is based on data collected by the University of Florida’s Michael McDonald and reported on the United States Elections Project website. The measure of the numerator, turnout, is based on one of two factors. First, for states that report actual turnout, this figure is used. For states that do not report actual turnout, turnout is estimated by taking the number of votes cast for the statewide office receiving the most votes in an election. In presidential election years, this is almost always the presidential election. In midterm election years, this is most often the gubernatorial or U.S. Senate election.

The denominator is voting-eligible population (VEP) as calculated by McDonald. VEP is an improvement on the voting-age population (VAP), which has long been reported by the Census Bureau. While VAP has the virtue of being easily calculated from Census Bureau reports, it is flawed because it includes individuals of voting age who are ineligible to vote, notably convicted felons (in most states) and noncitizens (in all states). Failure to account for ineligible voters among the voting-age population causes the turnout rate to be depressed, because the denominator is too large.

4.17.3 *Stability of rates across time*

The graphs in [Figure 31](#) show the turnout rate for all states in the 2008, 2012, 2016, and 2020 elections plotted against each other.

4.18 Voter registration rate

4.18.1 Data source

Voting and Registration Supplement of the Current Population Survey

In nearly every state, the most basic requirement for voting, once age and citizenship requirements have been met, is registering to vote. Voter registration started becoming common in the late 19th century but often applied only to larger cities and counties in a state. By the 1960s, however, universal registration requirements had become the norm across the United States. Today, only North Dakota does not require voters to register, although it maintains a list of voters, to help with the administration of elections.

If being registered to vote is a prerequisite to voting, then the percentage of eligible voters on the rolls is an important measure of the accessibility of voting. Registration rates vary across the states due to a combination of factors, related to the demographic characteristics of voters and to state registration laws. Although registration is necessary for most Americans to vote, little academic research has been done to explain why individuals register to vote; most studies focus on why registered voters turn out. An important exception is research by Glenn Mitchell and Christopher Wlezien.³⁵ Their study confirms that the factors influencing turnout are very similar to those influencing registration. Another study finds that the act of registration itself may stimulate turnout;³⁶ therefore, it is not surprising that the same factors will be found to influence both.

One factor hindering the direct study of voter registration rates, as opposed to using turnout as a proxy, is the inflated nature of voter registration lists. Official lists tend to overreport the number of registered voters because of the lag between the time when registered voters die or move out of state and when those events are reflected in the voter rolls. States differ in their method and frequency of removing dead registrants from the rolls, and many states do not have effective methods for definitively identifying voters who move out of state.³⁷

The failure to immediately remove registered voters who have moved or died means that not only will registration rolls generally contain more names than there are actual registrants in a state, but the degree to which the rolls contain “deadwood” will depend on the frequency and diligence of registration roll maintenance across states.

The number of people on voter registration rolls will sometimes exceed the number of eligible voters in a state. In the 2020 Election Administration and Voting Survey 2020 Comprehensive Report issued by the EAC, for instance, Alaska, Illinois, Maine, and New Hampshire reported more active registrants than the estimated eligible population (Appendix A: Descriptive Tables, Voter Registration Table 1: Registration History). The active percent of active registration of the Citizen Voting Age Population of these states are 111.7% in Alaska, 100.2% in Illinois, 105.2% in Maine, 101.6% in New Hampshire.

Because of the high variability in the manner in which voter registration lists are maintained, an alternative technique was used to estimate voter registration rates, relying on responses to the Voting and Registration Supplement of the Current Population Survey.

As shown below, registration rates calculated using the VRS are more stable over time than those calculated using official state statistics. This does not overcome the problem of overestimating registration rates due to inaccurate responses. However, under an assumption that respondents in one state are no more likely to misreport their registration status than residents of any other state, the registration rates calculated using the VRS are more likely to accurately reflect the relative registration rates across states than are the rates calculated using official reports.³⁸

4.18.2 *Coding convention*

This indicator is based on responses to the VRS of the Census Bureau's CPS. It is based on a combination of three variables:

- **PES1:** In any election, some people are not able to vote because they are sick or busy or have some other reason, and others do not want to vote. Did (you/name) vote in the election held on Tuesday, [date]?
- **PES2:** [Asked of respondents who answered no to PES1] (Were you/Was name) registered to vote in the (date) election?
- **PES3:** [Asked of respondents who answered no to PES2] Which of the following was the MAIN reason (you/name) (were/was) not registered to vote?

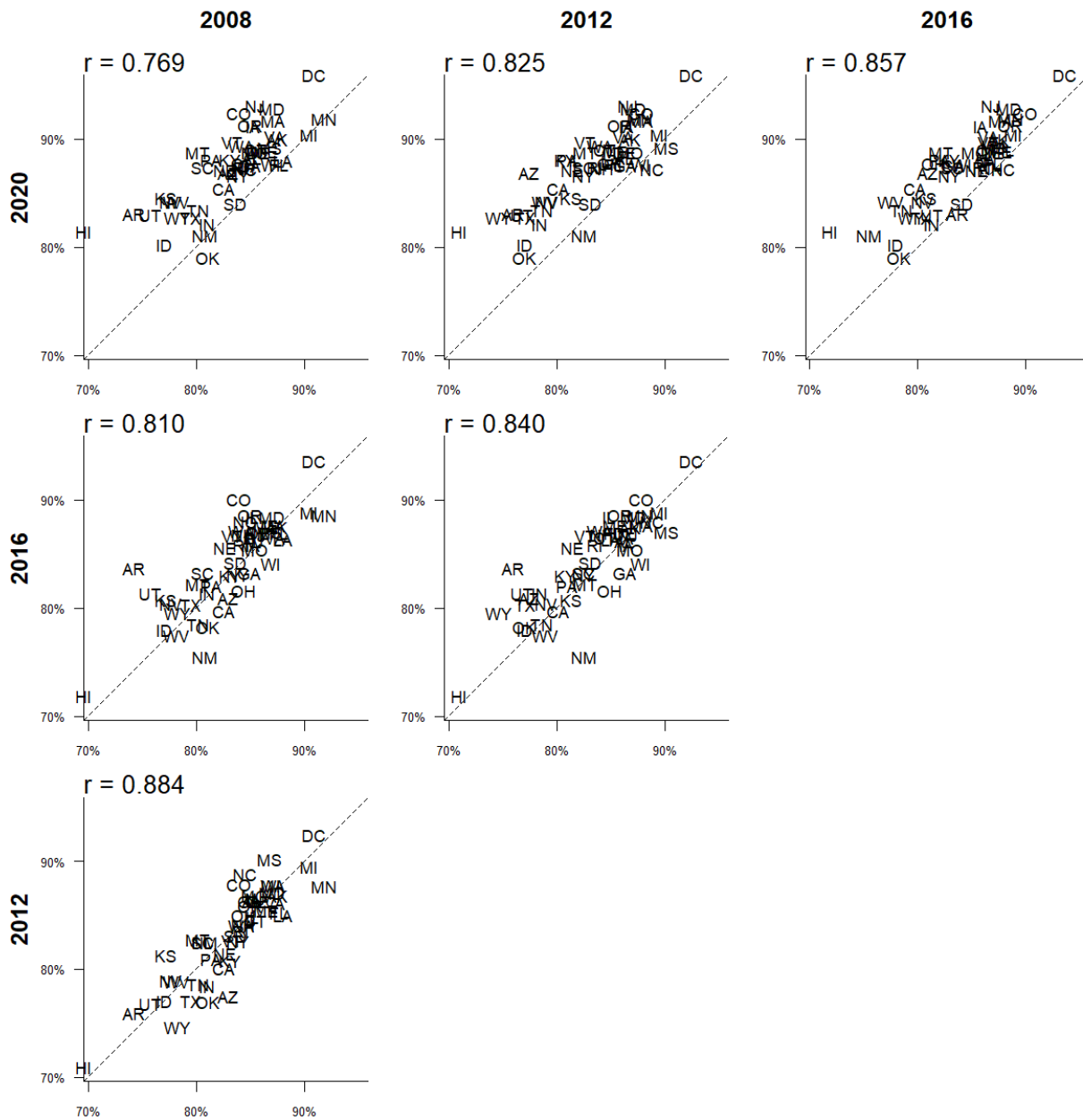
Registered voters are those who answered yes to PES1 or PES2 (the latter if the respondent answered no to PES1). In addition, respondents were removed from the analysis if they answered "not eligible to vote" to PES3 as they reason they were not registered.³⁹

Using the combined answers to these three questions allows one to estimate the percentage of eligible voters in each state who are registered. North Dakota has been removed from this measurement because its citizens are not required to register in order to vote.

4.18.3 *Stability of rates across time*

Figure 32 shows the estimated registration rate (using the VRS data) for all states across all election cycles from 2008, 2012, 2016, 2020. The high interyear correlations show that this method produces estimates of voter registration rates that are reliable across time.

Figure 32: Registration Rate by State



4.19 Voting information lookup tool availability

4.19.1 Data source

Pew's *Being Online is Not Enough* (2008), *Being Online is Still Not Enough* (2011), and *Online Lookup Tools for Voters* (2013)

Americans have incorporated the internet into their daily lives; elections are no exception. These indicators measure whether citizens can find the official election information they need online. Websites that quickly and easily deliver the information citizens seek about an upcoming election can improve the voting experience and ease the burden placed on election officials' limited resources.

For 2008, this indicator combines two measures: whether state election sites have voter registration verification and whether they have polling place locators. Both indicators are binary in nature and can be summed to create a score ranging from a minimum of 0 to a maximum of 2. For a state to receive credit for having any website tool, the resource must be a statewide tool available through an official state website such as the secretary of state's, and it must have been available before the 2008 election.

In 2010, the examination of online tools for the EPI expanded to five measures, including the two from 2008 (voter registration verification and polling place locators). The new measures were whether state election sites let voters see their precinct-level sample ballots, whether absentee voters can check their ballot status online, and whether voters issued provisional ballots can check their ballot status online. The five indicators are binary and can be summed together to create a score ranging from 0 to 5. As in 2008, for a state to receive credit for having any website tool, the resource must be a statewide tool available through an official state website such as the secretary of state's, and it must have been available before the election being scored.⁴⁰

4.20 Voting wait time

4.20.1 Data source

Survey of the Performance of American Elections / Cooperative Election Study

The time voters wait to cast ballots is a highly visible measure of voting convenience. Although long lines can indicate excitement surrounding an election, significant variation in polling place lines across communities can suggest the presence of factors that make it easier or harder for some to vote. Long lines at the polls became so politically salient that President Barack Obama appointed the Presidential Commission on Election Administration following the 2012 election, citing stories of hours-long waiting times in that election as the motivation.

4.20.2 Coding convention

In 2008 and 2012 the wait time indicator was based solely on answers to a question in the Survey of the Performance of American Elections that was asked of all voters who cast a ballot in person, either on Election Day or during early voting. The question asked was: “Approximately how long did you have to wait in line to vote?” Answers to the question are given as intervals by respondents. We recoded the responses to the midpoint of the respective interval, using the mapping in [Table 32](#).

Table 32: Wait Time to Vote Categories

Survey Code	Category	Recorded as
1	Not at all	0 minutes
2	Less than 10 minutes	5 minutes
3	10 to 30 minutes	20 minutes
4	31 minutes to 1 hour	45 minutes
5	More than 1 hour	See Below
6	Don't know	Missing

The survey contained an open-ended question for those answering “more than 1 hour,” requesting the respondent to supply the exact amount of time spent waiting in line. For those who supplied an exact time, we recoded the response to reflect the exact time. For the remaining respondents, we recoded the waiting time answer to be the mean of all the respondents who gave the “more than 1 hour” answer in that particular election year.

Beginning with 2014, the SPAE began asking respondents who had voted “by mail” whether they had returned their ballot in person, or had taken it to a physical location and dropped it off. These voters were asked the following question: “Once you got to where you dropped off your ballot, how long did you have to wait before you could deposit your ballot and leave?” The response categories were the same as those used for in-person voting.

Starting in 2014, we combine the answers from the in-person wait time question and the mail wait time question to create a wait time measure for three states where voting is now predominantly via mail: Colorado, Oregon, Washington, Utah, and Hawaii.

4.20.3 *Reliability of the measure*

Reliability pertains to the ability of a measure to be estimated consistently, when measured at different times or using different methods. The SPAE was first conducted for the 2008 presidential election, then again in 2012, 2014, 2016, and 2020; it was not conducted for the 2010 and 2018 midterm election. Therefore, the ability to test the reliability of the measure using only the SPAE is limited, but growing. Because of the policy interest in the length of waiting times at the polls, we have used other data sources, in addition to the SPAE, to gauge the reliability of this measure. The “waiting time” question was originally asked on the 2006 Cooperative Congressional Election Study (CCES) and asked again in 2008, 2012, 2014, 2016, 2018 and 2020. This allows us to use responses to the CCES to augment our exploration of this measure’s reliability. We begin with the SPAE responses in 2008, 2012, 2016, and 2020. The average wait time to vote exhibits a strong right skew for 2008, 2012, 2016, and 2020. Because of the right skew in the distribution of wait times, any scatterplot that compares values across two years will be misleading in that the bulk of observations will be clumped around the origin, with our eye drawn toward the outliers with extremely large values. To deal with this right skew, it is common to transform the measures by taking logarithms. Figure 33 shows the scatterplot among states from the 2008, 2012, 2016, and 2020 SPAE wait time estimates, plotting the variable on log scales.

The Pearson correlation coefficient describing the relationship between the four years ranges from 0.24 to 0.73. The strongest correlation, 0.73, is between 2008 and 2016. The weakest correlation, 0.24, is between 2012 and 2020, and despite its small size, it is still positive and statistically significant.

The wait time question was also asked in the 2008, 2012, 2014, and 2016 CCES, which allows us to compare results obtained across two different surveys (the SPAE and the CCES) at the same time. The scatterplots in Figure 34 show the different estimates from these two surveys, again after taking the logarithm of both variables. The Pearson correlation coefficient describing the relationship between the methods are very high, especially for the presidential election years. The correlation for the 2016 data is 0.761.

Finally, following the 2014 election, the North Carolina State Board of Elections (NCSBOE) conducted a survey of its county election officials, asking for the experiences of counties with voter wait times in 2014.⁴¹ The NCSBOE summarized the wait time information they received back into three categories, 0-30 minutes, 30-60 minutes, and 60+ minutes. The appendix to the report issued by the NCSBOE indicated the distribution of in-person wait times in each county, for both Election Day and early voting.

It so happens that in 2014, the SPAE conducted a special study of 10 states, in which an additional 1,000 respondents were surveyed (in addition to the standard SPAE study). North Carolina was included in this “oversample” study. Combining responses from the oversample study with responses from the regular administration of the SPAE means that we

had 1,200 respondents from North Carolina in 2014. This large number of observations allows us to break down responses to the SPAE survey questions into smaller units, such as counties.

[Table 33](#), reports a cross-tabulation of responses given by county officials about how long the lines were to vote in their counties (along the rows), associated with the answers given by SPAE respondents to how long they waited to vote (along the columns). For instance, 136 SPAE respondents lived in a county in which county officials reported that early voting waits were “0-30 minutes.” (See the first row of the early voting table.) Among the 136 respondents who lived in one of these counties, 55.4 percent reported not waiting at all to vote, 33.4 percent waited less than 10 minutes, 12.3 percent for 10 to 30 minutes, 0.9 percent for 31 minutes to 1 hour, and no respondents reported waiting more than one hour to vote. Note that as a general matter, the SPAE respondents who reported that they waited the longest to vote, either in early voting or on Election Day, came from counties in which election officials reported the longest wait.

The consistency of results across years and across different research efforts is evidence of the validity of the question.

4.20.4 *Validity of the measure*

Average wait time is one measure of the ease of voting. On its face, the less time a voter waits to cast a ballot, the more convenient the experience.

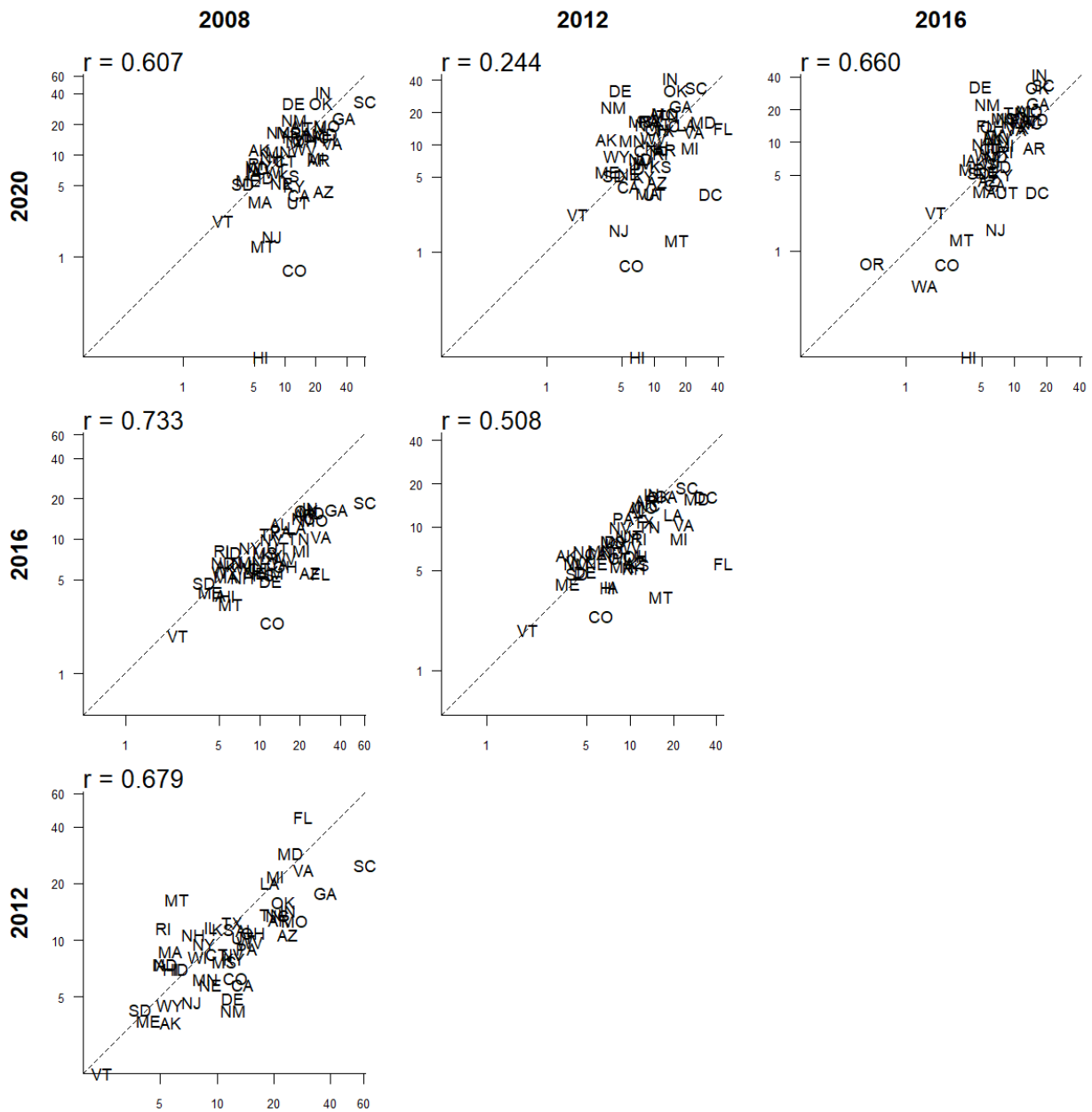
Table 33: Wait Times to Vote in North Carolina in 2014

Election Day						
SPAЕ Response						
NC SBOE category	Not At All	Less than 10 min.	10- 30 min.	30 min - 1hr.	More than an 1 hr.	N
0-30 min.	44.0%	35.1%	20.3%	0.6%	0.0%	128
30-60 min	35.9%	42.7%	14.7%	4.2%	2.5%	97
60+ min	27.0%	37.2%	26.4%	7.9%	1.6%	235
Total	33.6%	37.9%	22.0%	5.1%	1.4%	460

Early Voting						
SPAЕ Response						
NC SBOE category	Not At All	Less than 10 min.	10- 30 min.	30 min - 1hr.	More than an 1 hr.	N
0-30 min.	55.4%	33.4%	12.3%	0.9%	0.0%	136
30-60 min	32.8%	37.4%	19.8%	8.8%	1.2%	114
60+ min	13.9%	31.7%	31.3%	18.2%	4.9%	175
Total	31.9%	33.8%	22.0%	10.0%	2.3%	425

However, one issue that might challenge the validity of this measure is whether survey respondents correctly recall how long they waited in line to vote. Thus far, there have been no studies that relate perceived time waiting in line with actual waiting time. However, the psychological literature on time perception is considerable. A 1979 literature review on time perception by Lorraine Allan, a professor at McMaster University, concluded that, in general, the relationship between perceived and actual time is linear, although the actual parameters describing the relationship vary across settings.⁴² These results suggest that respondents who report waiting in line longer actually did wait in line longer, and that the averages of self-reported waiting times of different groups (based on race, sex, state of residence, and so on) in the survey are likely to reproduce the same relative ranking of the waiting times that were actually experienced by members of those groups.

Figure 33: Wait Times by State



5 Advisory Board

Members of the initial advisory council, convened by Pew, were instrumental in conceptualizing the Elections Performance Index. However, neither they nor their organizations necessarily endorse its findings or conclusions.

Table 35: Initial Elections Performance Index Advisory Council

Board Member	Title	Institution
James Alcorn	Former Deputy Secretary	Virginia State Board of Elections
Pam Anderson	Clerk and Recorder	Jefferson County, CO
Stephen Ansolabehere	Professor of Government	Harvard University
Lonna Rae Atkeson	Professor of Political Science	University of New Mexico
Barry Burden	Professor of Political Science	University of Wisconsin, Madison
Matthew Damschroder	Director of Elections	Ohio Secretary of State's Office
Lori Edwards	Supervisor of Elections	Polk County, FL
Heather Gerken	J. Skelly Wright Professor of Law	Yale Law School
Paul Gronke	Professor of Political Science	Reed College
Kathleen Hale	Professor of Political Science	Auburn University
Carder Hawkins	Former Director of Elections	Arkansas Secretary of State's Office
Kevin Kennedy	Former Director and General Counsel	Wisconsin Government Accountability Board
David Kimball	Professor of Political Science	University of Missouri, St. Louis
Jan Leighley	Professor of Government	American University
John Lindback	Executive Director	Electronic Registration Information Center
Dean Logan	Registrar-Recorder/County Clerk	Los Angeles County
Christopher Mann	Assistant Professor of Political Science	Skidmore College
Joseph Mansky	Elections Manager	Ramsey County, MN
Conny McCormack	Elections Consultant	Independent
Ann McGeehan	Former Director of Elections	Texas Secretary of State's Office
Amber McReynolds	Director of Elections	Denver County, Colorado
Brian Newby	Election Commissioner	Johnson County, KS, Election Office
Don Palmer	Former Secretary and Fellow	Virginia State Board of Elections/Bipartisan Policy Center
Tammy Patrick	Former Federal Compliance Officer	Maricopa County, AZ, Elections Department
Nathaniel Persily	Professor of Law and Political Science	Columbia Law School
Peggy Reeves	Director of Elections	Connecticut Secretary of the State's Office
Angie Rogers	Commissioner of Elections	Louisiana Department of State
Kathleen Scheele	Former Director of Elections	Vermont Secretary of State's Office
Daron Shaw	Professor of Political Science	University of Texas, Austin
Robert Stein	Professor of Political Science	Rice University
Charles Stewart III	Kenan Sahin Distinguished Professor of Political Science	Massachusetts Institute of Technology
Christopher Thomas	Director of Elections	Michigan
Daniel Tokaji	Associate Professor of Law	Ohio State University, Moritz College of Law
Kim Wyman	Secretary of State	Washington

Since the MIT Election Lab took over long-term management of the index, the Lab’s own board of advisors continues to provide guidance through each new iteration of the index. However, neither they nor their organizations necessarily endorse its findings or conclusions.

Table 36: MIT Election Data + Science Lab Board of Advisors

Board Member	Title	Institution
Lonna Rae Atkeson	Professor of Political Science	Florida State University
Barry Burden	Professor of Political Science	University of Wisconsin, Madison
Lori Edwards	Supervisor of Elections	Polk County, FL
Edward Foley	Ebersold Chair in Constitutional Law	Moritz College of Law, The Ohio State University
Bernard Fraga	Associate Professor of Political Science	Emory University
Amanda Grandjean	Director of Elections and Deputy Assistant Secretary of State	Ohio Secretary of State
Paul Gronke	Professor of Political Science	Reed College
Kathleen Hale	Professor of Political Science	Auburn University
Kevin Kennedy	Former Director and General Counsel	Wisconsin Government Accountability Board
Jan Leighley	Professor of Government	American University
Dean Logan	Registrar-Recorder/County Clerk	Los Angeles County
Christopher Mann	Assistant Professor of Political Science	Skidmore College
Amber McReynolds	Governor	Board of Governors, United States Postal Service
Don Palmer (emeritus)	Former Secretary and Fellow	Virginia State Board of Elections/Bipartisan Policy Center
Tammy Patrick	Senior Advisor	Democracy Fund
Peggy Reeves (emeritus)	Director of Elections	Connecticut Secretary of the State’s Office
Daron Shaw	Professor of Government	University of Texas - Austin
Michelle Tassinari	Director and Legal Council	Elections Division, Massachusetts Secretary of State
Christopher Thomas	Former Director of Elections	Michigan
Michael Winn	Director of Elections	Harris County, Texas

6 Endnotes

¹*The Measure of American Elections*. Eds. Barry C. Burden and Charles Stewart III (New York: Cambridge University Press, 2014).

²Heather K. Gerken. *The Democracy Index: Why our Election System Is Failing and How to Fix It* (Princeton University Press, 2009).

³In doing this brainstorming, it immediately became apparent that some indicators could arguably occupy different cells in the table.

⁴Environmental Performance Index, <http://epi.yale.edu>

⁵County Health Rankings & Roadmaps, <http://www.countyhealthrankings.org>

⁶The World Justice Project Rule of Law Index, <http://worldjusticeproject.org/rule-of-law-index>

⁷Kids Count Data Center, <http://datacenter.kidscount.org>

⁸In developing the EPI, the issue of using other aggregation methods was explored with the advisory committee. Among these were methods that gave different weights to different indicators, and methods based on data reduction techniques such as factor analysis. In the end, it was decided that a method that relied on simple averages was the most robust and straightforward. Having all indicators contribute an equal influence to the overall rating is the cleanest approach. It is also the clearest to implement when the data consist of a nontrivial amount of missing data. As the science of election administration develops a more robust empirical basis, and as data collection becomes more complete, there may come a time when the accumulated knowledge could guide alternative approaches to aggregating the data into a bottom-line index number, or even separating out indicators into subindexes.

⁹As a general matter, we adopted the following rule to decide whether a state would be regarded as missing for the purpose of reporting the value of an indicator: A state was included only if the counties reporting the data necessary to calculate the indicator constituted at least 85 percent of the registered voters in the state. (For North Dakota, which does not have voter registration, we substituted the voting-age population of counties for the number of registered voters.) We picked the 85 percent threshold to ensure that if we were to include data from counties that did not report the necessary data, the overall result for the state would change by only a small amount. In other words, we are confident that the statistics reported here are not overly influenced by the inclusion or exclusion of counties due to concerns about missing data. For states with more than 15 percent missing data (weighted by county registration), we concluded it would be better to exclude them from the presentation than to report an estimated value for these states that was subject to significant revision if the missing data were presented.

¹⁰This is a change from the very first iteration of the EPI. In the first version, we normalized values over 2008 and 2010 together. However given that midterm and presidential election years behave differently, it made sense to create separate presidential and

midterm election scales. One consequence of this rescaling between presidential and midterm years is that some of the overall EPI averages and rank order of states from 2008 and 2010 may be slightly different from in the original release.

¹¹The primary alternative to this approach that we considered was to rank all states for which we had data and then place those states missing data immediately below the state with the lowest ranking. We decided against this strategy for two reasons. First, to do so would overly weight the consideration of missing data in the index. The EPI already has one indicator of the completeness of election administration data that was reported, and it seemed excessive to have this measure intrude into the other measures. Second, after simulating different results that varied different rules about handling states with missing data, we discovered that placing states with missing data tended to elevate the ranking of states with a lot of missing data, which would entirely undo the effect of the data-completeness measure.

¹²A high percentage of respondents are “informants,” that is, respondents within a household who report about the voting behavior of the individual in question.

¹³Government Accountability Office. *Voters With Disabilities: Additional Monitoring of Polling Places Could Further Improve Accessibility*. GAO-09-941 (September 2009), <http://www.gao.gov/assets/300/296294.pdf>

¹⁴In addition to the following categories, there are provisions in the data for “no response,” “refused,” “don’t know,” and “blank or not in universe.” The percentages in the table are weighted by the variable PWSSWGT, which is the “final weight” given to each individual in the survey and is constructed to be proportional to the inverse probability of being included in the survey. Percentages are based on respondents who gave one of these answers, excluding those who refused or said they did not know, did not respond, or were not in the sample universe.

¹⁵Because of the relatively small number of disabled nonvoters in each state, this statement is less likely to be true if we confine this analysis to just one year’s worth of data.

¹⁶Government Accountability Office. *Voters With Disabilities: Additional Monitoring of Polling Places Could Further Improve Accessibility*. GAO-09-941 (September 2009), <https://www.gao.gov/assets/gao-09-941.pdf>

¹⁷These figures are taken from the 2016 Election Administration and Voting Survey Report issued by the U.S. Election Assistance Commission, Table 1. The percentages quoted here for rejection rates due to late arrival and signature problems are clearly underestimates, because about 20% are attributed to an “other” or “not categorized” category.

¹⁸The correlation coefficient was calculated on the logged values, weighting each county by its number of registered voters.

¹⁹According to the 2012 Election Administration and Voting Survey issued by the Election Assistance Commission, at least 1.4 percent of rejected provisional ballots were because the voter had already voted. The actual percentage is likely much higher because fewer than one-third of counties report provisional ballot rejections for this reason.

²⁰In response to the concern over the chain of custody of mail ballots, some jurisdictions have begun to employ programs to track mail ballots as they move through the mail system. One such program was developed by the Denver, Colorado Elections Division, called Ballot TRACE.

²¹The average county with no unreturned absentee ballots in 2008 mailed out 125 absentee ballots; the average county overall mailed out 7,331. The average county with no unreturned absentee ballots in 2010 mailed out 268 absentee ballots; the average county overall mailed out 5,512. The average county with no unreturned absentee ballots in 2012 mailed out 223 absentee ballots; the average county overall mailed out 7,313. The average county with no unreturned absentee ballots in 2014 mailed out 224 absentee ballots; the average county overall mailed out 6,610. The average county with no unreturned absentee ballots in 2016 mailed out 454 absentee ballots; the average county overall mailed out 9,123.

²²U.S. Election Assistance Commission, Uniformed and Overseas Citizens Absentee Voting Act (2008 report), 10, https://www.eac.gov/sites/default/files/eac_assets/1/6/2008_Uniformed_and_Overseas_Citizens_Absentee_Voting_Act_Survey.pdf U.S. Election Assistance Commission, Uniformed and Overseas Citizens Absentee Voting Act (2010 report), 8, https://www.eac.gov/sites/default/files/eac_assets/1/28/EAC%202010%20UOCAVA%20Report_FINAL.pdf U.S. Election Assistance Commission, Uniformed and Overseas Citizens Absentee Voting Act (2012 report), 9, https://www.eac.gov/sites/default/files/eac_assets/1/28/508compliant_Main_91_p.pdf

²³Due to changes in how the EAVS was fielded for the 2016 election, we had to substitute the total ballots submitted by using the sum of the total counted and total rejected.

²⁴The correlation coefficient was calculated on the logged values, weighting each county by its number of registered voters.

²⁵See Mark Lindeman and Philip B. Stark, “A Gentle Introduction to Risk-Limiting Audits,” *IEEE Security and Privacy* (March 2012), <http://www.stat.berkeley.edu/~stark/Preprints/gentle12.pdf>

²⁶Steven J. Rosenstone and Raymond E. Wolfinger, “The Effect of Registration Laws on Voter Turnout,” *American Political Science Review* 72 (1) (1978): 22–45; and G. Bingham Powell Jr., “American Voter Turnout in Comparative Perspective,” *American Political Science Review* 80 (1) (1986): 17–43.

²⁷Based on weighting by variable PWSSWGT, which is the “final weight” given to each individual in the survey and is constructed to be proportional to the inverse probability of being included in the survey. Percentages are based on respondents who gave one of these answers, excluding those who refused or said they did not know, did not respond, or were not in the sample universe.

²⁸For a review of the use of the residual vote rate, see Charles Stewart III, “Voting Technologies,” *Annual Review of Political Science* 14 (2011): 353–378. A book that makes extensive use of this measure is Martha Kropf and David C. Kimball, *Helping America Vote: The Limits of Election Reform* (New York: Routledge, 2011).

²⁹Charles Stewart III, “The Performance of Election Machines,” in *The Measure of American Elections*, eds. Barry C. Burden and Charles Stewart III (New York, Cambridge University Press: 2014).

³⁰District of Columbia and Nevada.

³¹Charles Stewart III, Michael Alvarez, Stephen S. Pettigrew, and Cameron Wimpy, “Residual Votes and Abstentions in the 2016 Election,” paper presented at the annual meeting of the Southern Political Science Association, New Orleans, LA, January 4–6, 2018.

³²See Mark Lindeman and Philip B. Stark, “A Gentle Introduction to Risk-Limiting Audits,” *IEEE Security and Privacy* (March 2012), <http://www.stat.berkeley.edu/~stark/Preprints/gentle12.pdf>

³³electproject.org

³⁴Raymond E. Wolfinger and Steven J. Rosenstone, *Who Votes?* (Yale University Press: 1980).

³⁵Glenn E. Mitchell and Christopher Wlezien, “The Impact of Legal Constraints on Voter Registration, Turnout, and the Composition of the American Electorate,” *Political Behavior* 17 (2) (1995): 179–202.

³⁶Robert S. Erikson, “Why Do People Vote? Because They Are Registered,” *American Politics Research* 9 (3) (1981): 259–276.

³⁷According to the EAC’s 2009-10 NVRA report, 25.2 percent of removals from voter registration lists during the 2009-10 election cycle were due to voters “moving from jurisdiction” (Table 4b). This is in contrast with 40.7 percent of removals being because of “failure to vote.”

³⁸For more information about the difference between the VRS numbers and state-reported numbers of registered voters, see The Pew Charitable Trusts, *Election Administration by the Numbers: An Analysis of Available Datasets and How to Use Them*, https://www.pewtrusts.org/~media/legacy/uploadedfiles/pcs_assets/2012/pewelectionsbythenumberspdf.pdf

³⁹In 2012, 7.3 percent of nonregistrants stated they were unregistered for this reason. Although respondents are screened for citizenship status before being asked the questions in the VRS, it is likely that some noncitizens made it past this screen and then reported not registering because they were ineligible. The other main reason for giving this answer is likely that the respondent was unable to register because of a felony conviction.

⁴⁰North Dakota has no voter registration, and provisional ballots are not issued in the state, so it is not evaluated for either the voter registration lookup tool or the provisional ballot lookup tool. Provisional ballots also are not issued in Idaho, Minnesota, and New Hampshire, so they are not evaluated for the provisional ballot lookup tool.

⁴¹North Carolina State Board of Elections, “November 2014: State Board of Elections Analysis of Voter Wait Times.”

⁴²Lorraine G. Allan, "The Perception of Time," *Perception & Psychophysics* 26 (5) (1979): 340–354.