Measuring gerrymandering by recovering individuals' preferences and turnout costs

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Abstract

Legislative maps are often evaluated along dimensions of proportionality (the alignment between parties' seat shares and their state- or nation-wide vote shares) and competitiveness (the fraction of contests with uncertain winners). Since a map is intended to be used for multiple elections, policy-makers want to accurately predict how it will perform on these dimensions in the future. Doing this is difficult because future elections will differ from past ones due to changes in the demographic composition of the electorate and as a result of electoral shocks to preferences and turnout costs. Citing this uncertainty, the U.S. Supreme Court recently ruled that the judicial system is incapable of adjudicating claims of partisan gerrymandering. In this paper, I develop a method for predicting the uncertainty in a map's performance due to these factors. The method relies on a structural voting model, which describes the preference and turnout decisions of a potential voter. The model decomposes an election into (i) a set of candidate qualities and (ii) individual-level utility parameters. I assess map performance in two steps. First, I examine the effect of electoral shocks by simulating alternative values of the candidate qualities and utility parameters. Second, I investigate the influence of demographic changes by re-running the simulations using different electorates. I apply the method to rich data from the 2008 to 2018 general elections in North Carolina and show that it allows credible and precise evaluations of maps. I also show that the method is better than existing approaches at predicting gerrymandering outcomes in excluded elections.

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1 Introduction

In the U.S., a candidate wins a seat in a state or federal legislature by gaining the most votes within a geographic district. Under this district-based system, key features of representation are influenced by the district configuration, or what's known as the legislative map. Notably, the legislative map can influence (i) how well the composition of the legislature reflects voters' choices and (ii) the extent to which residents can exert pressure on legislators through voting and campaigning. Correspondingly, analysts wish to be able to evaluate maps on dimensions of *proportionality* (the alignment between a party's share of legislative seats and its share of the state- or nation-wide vote) and *competitiveness* (the frequency of close and/or uncertain district races). In the popular discourse, legislative maps are said to be *gerrymandered* when they perform poorly on these dimensions.[1]

There is widespread agreement that proportionality and competitiveness are important characteristics of map quality.[2] However, there is disagreement as to whether it is possible to credibly *score* maps on these dimensions–to determine the degree to which a map is proportional or competitive. Measuring proportionality and competitiveness is of significant public interest. Maps are periodically redrawn, and stakeholders would like to select maps that perform well on these characteristics. In addition, maps are often challenged in court, and cases center on assessing whether a map is sufficiently gerrymandered to require being revised.

The reason it is difficult to score maps on proportionality and competitiveness is because we observe only a small number of elections, and a map's performance is likely to vary across election realizations. In particular, elections can differ in turnout and in preferences for parties or candidates. This variation can be both common to all potential voters in a state or specific to particular regions or demographic groups.[3] Variation in either the statewide swing or in the geographic distribution of votes can both alter a map's performance. The problem is even more acute because maps are intended to be used for multiple elections. Thus, policymakers want to understand a map's *future* performance.[4] Future elections will differ from those that have been observed due not just to variation in preferences and turnout, but also to changes over time in the demographic composition of the electorate. Citing this uncertainty, the U.S. Supreme Court recently ruled that the judicial system is incapable of determining which maps are gerrymandered.[5] As a result, maps can no longer be challenged in federal court.

1. Specifically, maps that perform poorly on proportionality and competitiveness are known, respectively, as *partisan* and *bipartisan* gerrymanders. A separate type of gerrymandering concerns maps that disadvantage members of a particular racial group. This type, known as *racial* gerrymandering, is not the focus of the present paper.

2. See, e.g., Browning and King (1987), Gelman and King (1994), Coate and Knight (2007), Friedman and Holden (2008), Fryer and Holden (2011), and Chambers, Miller, and Sobel (2017), among others.

3. For instance, midterm and presidential elections differ significantly in turnout across an entire state. In addition, turnout can vary by region due to bad weather (e.g., Fujiwara, Meng, and Vogl (2016)). Similarly, a recession or a charismatic top-ticket candidate can cause a common shift in preferences; meanwhile, local economic shocks or changes in a party's policy platform can sway preferences for certain groups of potential voters.

4. In a notable recent case, the District Court for the Middle District of North Carolina created a standard for proving unlawful gerrymandering that required plaintiffs to show "that the dilution of the votes of supporters of a disfavored party [...] is likely to persist in subsequent elections" (Common Cause v. Rucho 2018).

5. In a 5-4 majority opinion, Chief Justice Roberts wrote, "asking judges to predict how a particular districting map will perform in future elections risks basing constitutional holdings on unstable ground outside judicial expertise" (Rucho

In this paper, I examine whether gerrymandering outcomes in future elections can be predicted well enough to allow comparing maps. To do this, I combine a new methodology for measuring gerrymandering with richer data than has been used previously in the literature. The method for measuring gerrymandering centers on constructing plausible *counterfactual* elections. These are elections that have either a different electorate or different preference and turnout shocks. Once these are obtained, an analyst can record a map's performance in each of them. This allows the analyst to predict performance in election scenarios that haven't been observed and to understand the uncertainty in gerrymandering outcomes associated with the map. The method has two components. First is a structural model of voting that decomposes an election into (i) a set of candidate qualities and (ii) individual-level preferences for parties and costs of turning out. Second is a simulation procedure that constructs the counterfactual elections by drawing values of the model coefficients and/or altering the set of potential voters. In order to restrict the analysis to plausible counterfactuals, I fit the model in multiple elections and calculate the across-election mean and variance of coefficients. In the simulations, I then draw from distributions that use these values. Similarly, I adjust the set of potential voters in order to reflect the electorate in a desired year.

The method draws on a series of papers in economics and political science that attempt to measure gerrymandering by simulating counterfactual elections (Gelman and King 1994; Coate and Knight 2007; Fryer and Holden 2011; Geruso, Spears, and Talesara 2019). The existing approaches all work directly with aggregate vote shares. By contrast, the method developed in this paper is based on a micro-founded voting model with endogenous turnout.[6]

As an empirical illustration, I use the method to evaluate legislative maps from North Carolina. I generate predictions of map quality using data from the 2008 to 2018 general elections in that state. I show first that the method is credible in that gerrymandering outcomes in excluded elections fall within my prediction intervals. I next show that the predictions are precise enough to allow comparing alternative maps. I then examine whether requiring that districts be geographically compact is likely to improve map quality. Finally, I show that my method generates more accurate gerrymandering predictions than existing approaches.

The paper makes use of rich data that is now available on elections. Specifically, I work with three kinds of data. First, I have access to the North Carolina voter file, which is an administrative database on the universe of registered residents of the state. I have snapshots of this database at the time of each of the 2008 to 2018 general elections. The data includes demographics, address, and history of party registration and turnout. It also includes a unique identifier that allows me to link registrants across years. Thus, I observe each registrant's turnout decision in each election. Second, I have precinct-level vote shares for a large number of contests on the ballot. Finally, I have individual-level survey data for a random sample of North Carolina registrants. This data is from the Cooperative Congressional Election Study (CCES). It reveals a respondent's preference choices on the highest-profile contests in

v. Common Cause 2019).

6. I provide a detailed comparison of my method with the existing approaches in Appendix A2.

the election, and it also provides validated turnout decisions. The data used in the paper is increasingly available in all states. I focus on North Carolina because it provides the easiest access to its voter file.

Next, the voting model describes a potential voter's decision problem in an American general election. The potential voter receives utility from revealing her preferences and must pay a cost to turn out to vote. She faces a ballot with a bundle of contests. The model focuses on partisan contests, such as the races for U.S. President or NC Governor, which are defined as those in which each candidate is affiliated with a political party. Partisan contests offer three options: Democrat D, Republican R, or Abstain A, with candidates for third parties grouped with the abstain option. The potential voter determines her preferred choice on each of the contests and decides whether to submit her choices by turning out. Potential voters differ in preferences for parties and in the costs of turning out, and candidates differ in quality. Specifically, a potential voter i is defined by three election-specific parameters. Partisanship, Δ_{it}, measures the extent to which i prefers the Republican to the Democratic party. Political efficacy, λ_{it}, captures i's willingness to participate in the political process by choosing a major-party candidate versus abstaining. Finally, turnout costs, c_{it}, refer to i's difficulty in submitting a ballot.[7] I explain individuals' utility parameters using a large set of covariates, including individuals' demographics and party of registration. I explain candidate qualities using contest fixed effects.

The model generates predictions for individual-level preference and turnout probabilities, which are then transformed and/or aggregated in order to be comparable with outcome data. Specifically, the model makes predictions for (i) individual-level turnout decisions of all registrants, (ii) individual-level turnout and preference choices of survey respondents, and (iii) precinct-level vote shares. Estimates of model coefficients, $\hat{\theta}_t$, are obtained by maximizing a joint quasi-likelihood.

The model is identified mostly from cross-sectional variation in how precinct vote shares and individual turnout decisions vary with covariates. The survey data helps to identify the selection coefficient, which governs the extent to which utility from revealing preferences influences turnout. This coefficient is also identified in part via cost instruments, which are variables that are assumed to impact a potential voter's cost of turning out but not to affect her preferences.[8] The model allows potential voters to have a component of partisanship that is unexplained by covariates but known to the individual at the time of the turnout decision. Thus, it allows for a limited form of selection in turnout on unobservables. Finally, most of the variation used in identifying preferences is from contests that are common to all registrants in the state, such as races for U.S. President, U.S. Senate, or NC Governor. Since all registrants face the same candidates in these contests, the registrants' choices are fully comparable. By contrast, the model also includes U.S. House races, which vary by district. Conditions in these races may reflect or cause regional shocks to individuals' utility parameters. In order to avoid this, I include district fixed effects in the covariates used to explain $(\lambda_{it}, \Delta_{it}, c_{it})$. Thus, contest fixed effects in the U.S. House races

7. Turnout costs are defined broadly to include all components of one's utility from turning out other than that from revealing preferences on partisan contests. Thus, these include both traditionally conceived costs, such as traveling to the polls, accessing childcare, or having the necessary documentation, as well as other benefits from voting, such as utility from non-partisan and local races or from fulfilling one's sense of duty to turn out.

8. The cost instruments that I use are rainfall on election day and the distance from a registrant's home to the nearest early-voting location.

are identified by differences in a district's voting between the U.S. House race and the other contests.[9]

The model closely fits the data. For each of the 2008-2018 elections, I estimate the model on two-thirds of precincts and predict outcomes for the excluded one third. Depending on the election, the model predicts 94-97% of the variation in precinct vote shares. It also correctly classifies individuals' choices in survey data in almost 80% of cases. I find that selection on unobservables exerts a small effect on preference probabilities. Thus, a model without this feature would perform similarly well.

After estimating the model in each of the 2008-2018 elections, I simulate counterfactual elections in three steps. First, I pool the preference and cost parameters across years and use a regression to decompose them into individual fixed effects and covariate-level, election-specific shocks. Second, I calculate the across-election mean and variance of the shocks; and finally, third, I construct counterfactual elections by combining the individual fixed effects with random draws of the shocks. Once I obtain the counterfactual elections, I can measure gerrymandering for any legislative map by aggregating predicted votes according to the map's districts. For each counterfactual election, I record the predicted winner and two-party vote share of the district-level races and the predicted seat and statewide vote shares for each party. I then evaluate gerrymandering by summarizing these quantities. First, I examine proportionality by plotting the "seats-votes curve", which shows how each party's seat share varies with its statewide vote share (Tufte 1973). I calculate a number of statistics related to this curve, including (i) the predicted seat shares for two-party vote shares of 0.5, (ii) the average predicted seat shares over a given range of vote shares, and (iii) the predicted vote shares for seat shares of 0.5. Separately, I show competitiveness by plotting the range of simulated vote shares for each district. Finally, I examine whether results are sensitive to changes in the demographic composition of the electorate by altering the sample of potential voters and repeating the procedure.

Before providing empirical results, I first assess whether the method's predictions for a map's proportionality are credible. Specifically, the predictions for proportionality amount to a set of confidence intervals for the seat shares that a party may obtain under each share of the two-party statewide vote. I assess the credibility of the predictions by running the procedure on a subset of elections and computing prediction intervals for proportionality outcomes in excluded elections. I calculate the proportionality outcomes by aggregating votes in the contests in the excluded elections according to the districts of a number of recently used legislative maps. The outcomes that I predict are (i) the Republican seat share conditional on knowing the statewide two-party vote share and (ii) the difference between district and state two-party vote shares. I find that these outcomes fall within the predictions intervals at the appropriate rates.

I then use the procedure to evaluate legislative maps. I show that recently used maps strongly favor Republicans. For instance, I predict that the U.S. House map used from 2012-2014 would provide Republicans 74% of seats when they win half the statewide two-party vote. The 95% confidence interval for this value is 60-77%. For the NC Senate and NC House maps used during these years, Republicans would be expected to win 64% and 63% of seats, with confidence intervals of 57-68% and 55-67%,

9. I also include covariates related to the closeness of state legislative races.

respectively.

I next examine whether requiring districts to be geographically compact is likely to generate less biased maps. I first show that map-makers are able to draw maps that are both compact and biased. In particular, I give the example of the U.S. House map used in North Carolina during 2016-2018. I show that this map is both relatively compact and highly favorable towards Republicans. The reason this is achievable is because the U.S. has a significant urban-rural divide in political preferences (Chen and Rodden 2013). Thus, a map-maker can pack a large fraction of a party's supporters into a small number of districts by drawing districts that are either entirely urban or rural. Finally, I examine whether compactness requirements would be more successful if maps were drawn algorithmically rather than by politically motivated agents. I use the algorithm of Saxon (n.d.) to construct U.S. House maps that score highly on various compactness measures. I analyze two representative maps and show that one is unbiased, while the other slightly benefits Republicans. I conclude that this algorithm shows promise, but that analysts should still directly examine a map's proportionality.

I conclude the paper by comparing my gerrymandering predictions with those of two simpler approaches. Specifically, I compare R-squared and mean absolute error for predicting district two-party vote shares in excluded elections, conditional on knowing the statewide two-party vote share. The other methods that I consider are an approach based on the "uniform swing assumption" of Butler (1951) and the method of Geruso, Spears, and Talesara (2019). The uniform swing assumption is that a percentage point change in the statewide vote share will cause the same percentage point change within each district. The method of Geruso, Spears, and Talesara (2019) is the most general of the strategies that simulate counterfactual elections based on models of aggregate vote shares. I find that all methods have strong predictive power, suggesting that most of the variation in district vote shares across elections is due to common shocks. However, my method is the most accurate. My method generates an R-squared of 0.976 and a mean absolute error of 1.6 percentage points. The uniform swing and Geruso, Spears, and Talesara (2019) methods provide R-squared of 0.949 and 0.940 and mean absolute error of 2.4 and 2.6 percentage points, respectively.

The paper relates to two strands of literature. First, it contributes to a large literature on measuring gerrymandering. As discussed, my paper is most similar to papers that try to measure gerrymandering by simulating counterfactual elections (Gelman and King 1994; Coate and Knight 2007; Fryer and Holden 2011; Geruso, Spears, and Talesara 2019). My paper contributes to this literature by modeling individual behavior, rather than aggregate vote shares. Another body of work develops quantities that relate to proportionality and can be measured in a single election. Examples include the "efficiency gap" of Stephanopoulos and McGhee (2015) and "the median versus the mean" of McDonald and Best (2015). My paper is complementary to this literature in that these quantities can be calculated in each of my counterfactual elections. Finally, there is a recent literature that aims to algorithmically recover the set of permissible maps (Cho and Liu 2016; DeFord, Duchin, and Solomon 2019; Fifield et al. 2019; Saxon, n.d.). These are maps that are geographically contiguous, have equal populations, and obey additional requirements, such as scoring sufficiently high on compactness measures. My method can be used jointly with this literature in that it allows evaluating each of the maps on proportionality and competitiveness.

Finally, the paper relates to a growing literature in economics that applies structural models to voting. Papers in this literature include Degan and Merlo (2011), Levonyan (2016), Knight (2017), Merlo and de Paula (2017), Kawai, Toyama, and Watanabe (2018), Gillen et al. (2019), and Ujhelyi, Chatterjee, and Szabo (2019), among others. My paper contributes to these by modeling a larger number of relevant features of American elections. Specifically, my model is the first to jointly incorporate a turnout decision, multiple contests on the ballot, and the option to abstain from answering a question.

The rest of the paper proceeds as follows. In Section 2, I discuss the institutional context and the data. In Section 3, I present the model and explain estimation and identification. In Section 4, I test the model's prediction quality, and I characterize the 2008 to 2018 elections. In Section 5, I detail the simulation, and, in Section 6, I measure gerrymandering.

2 Institutional context and data

2.1 Background on gerrymandering in the U.S.

Gerrymandering is a controversial issue in the United States because legislative maps are frequently redrawn. Maps are required to be redrawn at the beginning of each decade, upon publication of the U.S. Census. This process, known as redistricting, is meant to adjust for population changes that occur during the intervening ten years. Maps are also sometimes redrawn mid-decade in response to court orders. The federal government gives responsibility for drawing maps to the states and imposes limited restrictions on how they do so. It requires only (i) that a map's districts be equal in population (Wesberry v. Sanders 1964; Reynolds v. Sims 1964) and (ii) that some of the districts be configured so as to give political sway to racial minorities (Thornburg v. Gingles 1986; Shaw v. Reno 1993).[10] In most states, map-drawing is controlled by politicians, such as by the legislature and governor or by the legislature alone (Brennan Center 2010). Driven by concerns over gerrymandering, an increasing number of states have shifted responsibility for map-drawing to independent commissions.[11]

In recent years, there has been an increase in data and statistical expertise that can be used in making maps. Data sources include census demographics, precinct-level vote counts, and detailed individual-level data on potential voters. Datasets on potential voters are based on state voter files, which are lists that states maintain of all registered residents. The information in the voter file varies by state, but generally includes a registrant's name, age, gender, address, and history of turnout and party registration; in some states, it also lists the registrant's race/ethnicity (McDonald 2015). Private vendors, such as Catalist or L2, harmonize states' voter files and add extensive additional information.

10. In a series of cases, the U.S. Supreme Court has grappled with whether the U.S. Constitution forbids partisan gerrymandering. In a 5-4 majority opinion in Rucho v. Common Cause (2019), Chief Justice Roberts sidestepped the issue and ruled that the difficulty in measurement means that partisan gerrymandering is not justiciable in federal court: "asking judges to predict how a particular districting map will perform in future elections risks basing constitutional holdings on unstable ground outside judicial expertise". Importantly, maps can still be challenged in state courts.

11. Another way that states try to counter gerrymandering is by mandating that districts meet certain standards, such as requiring them to be compact or to follow community boundaries.

The additional information includes data for non-registrants, as well as covariates related to occupation, religion, credit score, and consumer behavior, among other topics (Hersh 2015). The richness of the newly available data appears to have allowed for more precise map-drawing: researchers examining several decades of maps have found that those enacted in the 2011 redistricting cycle were among the most gerrymandered on record (Stephanopoulos and McGhee 2015).[12]

2.2 Map-drawing in North Carolina

North Carolina is an interesting setting in which to evaluate legislative maps because its recent maps have been the subject of repeated court battles. In North Carolina, maps are drawn by the state legislature and cannot be vetoed by the governor (Levitt 2019). The legislature draws maps for the U.S. House (13 districts), the NC Senate (50 districts), and the NC House (120 districts). Maps were drawn by a Democratic-controlled legislature during the 2001 redistricting cycle and by a Republican-controlled legislature during the 2011 cycle. The maps enacted in 2011 were immediately challenged in federal and state court. The courts ultimately found the maps to be *racial* gerrymanders and ordered that they be redrawn. A Republican-controlled legislature redrew the U.S. House map in advance of the 2016 election and the NC House and NC Senate maps prior to the 2018 election.[13] The revised maps were again challenged in court, this time on grounds of *partisan* gerrymandering. As part of its larger decision in Rucho v. Common Cause (2019), the U.S. Supreme Court rejected the challenge to North Carolina's U.S. House map. However, in a separate case, a state court struck down the NC House and NC Senate maps and ordered that they be redrawn prior to 2020.

2.3 Data

A second reason that I focus the empirical analysis on North Carolina is that it makes its data readily accessible. In the paper, I work with three datasets: (i) individual-level data on North Carolina registrants, (ii) individual-level survey data, and (iii) precinct-level vote data.

The dataset on North Carolina registrants is a panel that includes observations for the individuals registered in the state at the time of each of the 2008 to 2018 general elections. The data includes rich covariates on the registrants and indicates whether a registrant turned out to vote. To create this dataset, I first obtain snapshots of the North Carolina voter file during the 2008-2018 elections. These snapshots are provided by the North Carolina election authority, the NC State Board of Elections (NC SBE). Similar to other states' voter files, they list the name, age, gender, race/ethnicity, and address of all individuals registered in the state at the given point in time. The data includes a unique identifier that allows me to link registrants across elections. I also use this identifier to merge the snapshots

12. Redistricting in 2011 was also distinct from prior cycles in having a heavier emphasis on partisan, rather than bipartisan, gerrymandering. In an effort known as Project Redmap, the Republican State Leadership Committee sought to influence redistricting in swing states by investing heavily in 2010 state legislative races. It helped gain Republican control of redistricting in states including Florida, Michigan, North Carolina, Ohio, Pennsylvania, and Wisconsin. It then pressured map-makers to focus on maximizing Republican seat shares (Daley 2016). Democrats did not have a similarly organized operation during the 2011 cycle. However, they have since formed the National Democratic Redistricting Committee in preparation for map-making in 2021.

13. For certain counties, the state legislative maps used in the 2018 election were drawn by a court-appointed special master.

with data from the NC SBE on registrants' histories of turnout and party registration. This latter database includes information on each election, including primaries and municipal elections, since 2006. I then add a number of additional covariates, such as the value of the property parcel associated with a registrant's address, Census data on the registrant's block and block group, the distance from the registrant's home to her nearest early-voting location, and rainfall on election day for a 2.5 km square grid. Definitions for all covariates are discussed in the data appendix.

Summary statistics for the data on registrants are provided separately by election in Panel A of Table 1. As can be seen in the table, depending on the election, between 86 and 90 percent of North Carolina's voting-age population was registered.[14] Turnout varies for midterm and presidential elections, with turnout shares of 68 to 69 percent in presidential elections and 43 to 52 percent in midterms. The registrant population is about 70 percent white and 20 percent black, with a growing share of members of other races. It is also split by party, with a declining share of Democrats and an increasing share of unaffiliated registrants. Finally, it has an increasing share of registrants age 60 and over.

Next, the survey dataset provides individual-level information on the preference and turnout decisions of a random sample of respondents. The data comes from the CCES, which is a national survey of American adults that occurs during each general election; I limit the sample to just respondents from North Carolina. The CCES queries a respondent's preferred choice on a number of the "top-ticket" contests in the election, including those for U.S. President, U.S. Senate, U.S. House, and NC Governor.[15] A nice feature of the CCES is that the surveyors match respondents to the Catalist voter file, which allows them to determine whether a respondent is registered and to obtain the respondent's actual, rather than self-reported, party and turnout.

I face a challenge in incorporating the CCES data in the analysis because it does not have all the covariates available in the dataset on registrants. I deal with this issue by matching registered survey respondents to registrants and then using the covariates for the matches. In conducting the merge, I exploit a large number of covariates that exist in both datasets, including zipcode, race, age, and gender, as well as registration party, turnout, and vote method in the year's primary and general elections. I present summary statistics for the survey dataset in Panel B of Table 1. On average, there are about ten potential matches per registered respondent. In the analysis, I deal with multiple matches by generating predictions for each potential match and then averaging over all the potential matches for the respondent. Finally, the CCES includes weights to allow the survey sample to reflect the overall state population. Since this is not my interest, I do not incorporate them.

The last dataset that I use is a list of precinct-level vote counts for all partisan contests in the 2008 to 2018 elections. This data is obtained from the NC SBE. In North Carolina, individuals can

14. In the paper, I assume that the set of potential voters is equal to the registrant population. I do this because I do not have data on citizens who are not registered. Excluding these individuals could confound analysis if registration status responds strongly to political conditions. However, due to the high registration rate, the effect is likely to be small. In fact, the registration rate of interest would use the voting-age *citizen* population as the denominator. This rate would be even higher than the values reported in Table 1.

15. All respondents are interviewed before the election and some are re-interviewed afterward; for those who are re-interviewed, I use the choices from the follow-up survey.

vote (i) on election day at polling places or (ii) prior to election day, either by mail or at early-voting centers. The NC SBE calculates precinct-level vote counts by aggregating votes for all residents of small geographic areas, termed precincts, regardless of voting method. Panel C of Table 1 shows that, during 2008-2018, North Carolina generally had about 2,700 precincts, and the median precinct had close to 3,000 registrants.

2.4 Contests included in the model

This subsection discusses the contests included in the model. As mentioned in the introduction, the model focuses on voting behavior in *partisan* contests, which have a single candidate per party. The set of partisan contests on the ballot varies by election. In addition, in some elections, there are so many partisan contests that it is infeasible for me to include all of them in the model individually.

In Table A1, I display the set of partisan contests in each election. As seen in the table, races for the U.S. House, NC House, and NC Senate occur in all elections. However, the number and identities of the remaining contests in the election vary. Midterm elections may have U.S. Senate races and, beginning in 2018, also include races for state judicial seats. Presidential elections involve a large number of contests, with 15 in total in 2008, 13 in 2012 and 20 in 2016. These include both high-profile races, such as those for U.S. President and NC Governor, and less salient ones, such as that for NC Auditor. I reduce the number of contests to a more manageable level by averaging precincts' vote shares in the less salient races. Specifically, I include the following contests in the model individually: the U.S. President, the U.S. Senate, the U.S. House, the NC Governor, and the NC Supreme Court; and I average vote shares for (i) the NC Attorney General and the NC Secretary of State and (ii) all other North Carolina state offices. I select the contests to include individually as those with the smallest share of voters who leave the question blank (i.e., who choose neither a major- nor third-party candidate). With the exception of the NC Supreme Court, these contests match those that are queried in the CCES. Next, I average vote shares for the NC Attorney General and the NC Secretary of State separately from those for the remaining state offices because I believe these contests have an intermediate degree of salience.[16] Importantly, I exclude races for the NC House and NC Senate. This is because a large fraction of these races are contested only by one party.[17] I account for these races by controlling for characteristics of them as covariates in the model. I discuss the consequences of incorrectly specifying the set of contests to include in the model in Section 3.4.3.

Table 2 presents information on statewide vote shares by election. Panel A displays vote shares for each contest included in the model, while Panel B provides summary statistics. The values in Panel B are shown in a version that weights all contests in the election equally and in one that reflects the averaging used to construct the contests included in the model. Panel B shows that the averaging does not seem to misrepresent the election, as the mean and standard deviation of vote shares for the contests used in the model are similar to those for all contests weighted equally. Finally, the table also shows

16. Indicative of this, in certain years, the CCES asks a subset of respondents about races for the NC Attorney General and the NC Secretary of State. It never asks about races for the remaining state offices.

17. I show the share of contested races by election and legislative chamber in Table A2.

that North Carolina is a competitive state, with contests' vote shares often evenly split by party.

2.5 Proportionality in recent elections

I next provide initial evidence on gerrymandering in North Carolina. In Table 3, I show quantities related to proportionality for the legislatures elected in the 2008-2018 elections. Specifically, I display the average statewide two-party vote share for Republicans over the contests in the election, as well as Republicans' seat shares in each legislative chamber. The table shows that seat shares often differ substantially from vote shares. In 2008, Republican vote shares exceeded their seat shares, while in 2010, the partisan advantage varied by chamber. By contrast, following the 2011 redistricting cycle, Republicans consistently benefited from disproportionate seat shares. During this period, Republicans never received more than 53% of the average statewide two-party vote. By contrast, in the U.S. House, they gained a minimum of 69% of seats. Similarly, in the NC House and NC Senate, they gained respective minimums of 62% and 66% of seats during 2012-2016, before gaining 54% and 58% under revised maps in 2018.

2.6 Descriptive evidence on voting behavior

Before turning to the model, I present descriptive evidence on two questions regarding voting behavior. First, I examine whether an election's vote shares are likely to depend on turnout. To get at this, I use the survey data and compare preference shares for voters (respondents who turned out) and non-voters (respondents who stayed home). The comparison is presented in Table A3, which shows values for voters in Panel B and non-voters in Panel C. The table illustrates that non-voters are much more likely to choose the abstain option. For instance, in 2008, the share choosing to abstain was on average 5% for voters and 23% for non-voters. In other years, gaps are similarly large. By contrast, it is not clear from the data whether voters and non-voters on average have different partisan leans.

Second, I investigate the extent to which voters distinguish candidates from political parties. Tables 2 and A1 indicate that voters pay some attention to candidates, as they show that there is significant variation in statewide vote shares across the different contests in an election. For instance, in 2008, the Democratic candidate for NC Attorney General received 58% of the statewide vote, while that for NC Commissioner of Agriculture obtained only 45%. (In the presidential race, Barack Obama received 49%.) However, values in Table 2 suggest that this variation may be declining over time, with the standard deviation of statewide vote shares falling from 0.03 in 2008 to 0.01 in 2018. In Table 4, I probe this question further by calculating the fraction of the variation in precinct-level vote shares that is predicted by precinct and question effects. The table shows that during 2008-2018 voters focused increasingly on party: R-squared from predictions using just precinct effects rises from 0.88 in 2008 to 0.99 in 2018. Additionally, after 2010, there was limited heterogeneity in vote shares beyond precinct and question effects: in each of the 2012 to 2018 elections, these generate R-squared values of over 0.98.

3 Model

I next present a structural model of a registrant's preference and turnout decisions. I first introduce the model and then discuss the parametric assumptions in greater detail. Finally, I describe how the model can be estimated and provide intuition on identification.[18]

3.1 Framework

The model describes registrant i's decision problem in election t. The registrant faces a ballot with a bundle of partisan contests. I use $\mathcal{Q}_{it}$ and Q_{it} to denote the set and number of contests in the bundle, respectively. Some of the contests are faced by all registrants in the state, such as those for U.S. President and NC Governor; I refer to these as state-level contests. Others, such as those for U.S. House or the North Carolina legislatures, differ by the district in which the registrant lives; I call these district-level contests. I let q index a contest in a particular election: for instance, the contest for U.S. President in 2008 or that for the 12th U.S. House district in 2010.

Registrant i's decision problem is to determine her preferred choice on each partisan contest on the ballot and to decide whether to turn out to vote. Partisan contests offer three options: Democrat D, Republican R, or abstain A. Without loss of generality, utilities for each option can be written in terms of efficacy, λ_{itq}, and partisanship, Δ_{itq}:

$$
\begin{aligned}
U_{itqD} &= \lambda_{itq} - \frac{1}{2}\Delta_{itq} \\
U_{itqR} &= \lambda_{itq} + \frac{1}{2}\Delta_{itq} \\
U_{itqA} &= 0.
\end{aligned}
$$

It can be seen that Δ_{itq} measures the difference in utilities gained by i from the Republican versus the Democrat. By contrast, λ_{itq} measures the difference between i's average utility from the major-party candidates versus abstaining. The decision problem for question q is illustrated graphically in Figure 1. As shown in the figure, the efficacy and partisanship parameters divide registrants into three groups, corresponding to the available choices. Registrants with high efficacy, λ_{itq}, are likely to prefer one of the major party candidates; however, if they are weakly partisan, $|\Delta_{itq}| \approx 0$, they can be marginal between D and R. By contrast, registrants with extreme partisanship, $|\Delta_{itq}| \gg 0$, can only be marginal between choosing their preferred party and abstaining. Further, as an individual becomes more partisan, abstaining requires a more negative value of λ_{itq}.

On each question, i chooses the option that provides the greatest utility. She then decides whether to turn out by aggregating the utilities she receives from the entire bundle of questions and comparing this value to the costs of going to the polls and submitting a ballot. The turnout decision occurs before i completes her ballot. Thus, it depends on i's expectation of her utility from revealing preferences, rather than on the realized value.

18. The model is similar to some used in health economics; for instance, Limbrock (2011). He models patients' prescription drug choices conditional on their choice of HMO or non-HMO insurance plans.

3.2 Functional forms for preferences

I impose the following functional forms for preference parameters:

$$\lambda_{itq} = \lambda_q + X_{it}' \cdot \lambda_t^X + \epsilon_{itq,\lambda}$$
$$\Delta_{itq} = \Delta_q + X_{it}' \cdot \Delta_t^X + \sigma_t \cdot e_{it} + \epsilon_{itq,\Delta}.$$

Here, λ_q and Δ_q are question fixed effects, X_{it} is a vector of covariates of i in t, and λ_t^X and Δ_t^X are vectors of election-specific coefficients. For notational convenience, I abbreviate $X_{it}' \cdot \lambda_t^X$ as $\lambda_{X,t}$, and similarly for $\Delta_{X,t}$. Next, e_{it} is a scalar that captures a component of i's partisanship in t that is not explained by covariates and that applies to all contests in the election; I assume $e_{it} \overset{iid}{\sim} N(0,1)$. As a simplification, I do not include a corresponding unobservable for efficacy. Finally, I define $\epsilon_{itq,\lambda} \equiv \frac{1}{2}(\check{\epsilon}_{itqD} + \check{\epsilon}_{itqR}) - \check{\epsilon}_{itq,A}$ and $\epsilon_{itq,\Delta} \equiv \check{\epsilon}_{itqR} - \check{\epsilon}_{itqD}$, where $\check{\epsilon}_{itqj}$ is assumed to be i.i.d. and Type-1 Extreme Value (T1EV) with location 0 and scale 1. This means $\epsilon_{itq,\Delta}$ and $\epsilon_{itq,\lambda} \pm \frac{1}{2}\epsilon_{itq,\Delta}$ are logistic random variables with location 0 and scale 1. Utilities for question q can then be re-written as:

$$\begin{aligned} U_{itqD} &= \lambda_q + \lambda_{X,t} + \epsilon_{itq,\lambda} - \frac{1}{2}(\Delta_q + \Delta_{X,t} + \sigma_t \cdot e_{it} + \epsilon_{itq,\Delta}) \\ U_{itqR} &= \lambda_q + \lambda_{X,t} + \epsilon_{itq,\lambda} + \frac{1}{2}(\Delta_q + \Delta_{X,t} + \sigma_t \cdot e_{it} + \epsilon_{itq,\Delta}) \\ U_{itqA} &= 0. \end{aligned} \tag{1}$$

The model distinguishes between question- and registrant-specific components of preferences. λ_q can be thought of as the contest's importance or salience: contests with higher λ_q induce more registrants to prefer one of the major parties. Δ_q captures the relative popularity of the contest's candidates: $\Delta_q > 0$ induces more registrants to prefer R to D. By contrast, $\lambda_{it} \equiv \lambda_{X,t}$ and $\Delta_{it} \equiv \Delta_{X,t} + \sigma_t \cdot e_{it}$ are components of preferences that vary by registrant and that apply in all contests. Finally, $\epsilon_{itq,\lambda}$ and $\epsilon_{itq,\Delta}$ are residuals that vary for registrants by question and that thus have no predictive power for choices on other questions. I discuss the functional forms further in Section 3.4.

3.3 Functional forms for turnout

I next explain the structure imposed on the turnout decision. I assume that when deciding whether to turn out, i observes her individual-level preference parameters, $(\lambda_{it}, \Delta_{it})$, as well as question effects for each partisan contest on the ballot, $(\lambda_q, \Delta_q)_{q \in \mathcal{Q}_{it}}$; however, she does not observe her idiosyncratic question-specific shocks, $(\epsilon_{itq})_{q \in \mathcal{Q}_{it}}$ for $\epsilon_{itq} \equiv (\epsilon_{itq,\lambda}, \epsilon_{itq,\Delta})$. She thus decides whether to turn out by comparing her expected utility from revealing preferences, averaged over $(\epsilon_{itq})_{q \in \mathcal{Q}_{it}}$, with her costs of submitting a ballot.

For a single question, i's expected utility is the expected value of the utility of her (unknown) preferred option on the question. Due to the assumption of T1EV errors for $\check{\epsilon}_{itqj}$, this is the logit inclusive value:

$$\mathrm{E}[\max_j U_{itqj}|q, X_{it}, e_{it}; \theta_t] = \log(\sum_{j\in\{D,R,A\}} \exp[u_{itqj}]),$$

where u_{itqj} is the component of U_{itqj} that excludes ϵ_{itq}.[19] The independence of ϵ_{itq} across questions means that there is also a simple form for i's expected utility from revealing her preferences on the entire ballot. Specifically, expected utility from the bundle $\mathcal{Q}_{it}$ is the sum of the expected utilities from the individual questions:

$$\begin{aligned}\mathrm{E}[\sum_{q\in\mathcal{Q}_{it}} \max_j U_{itqj}|\mathcal{Q}_{it}, X_{it}, e_{it}; \theta_t] &= \sum_{q\in\mathcal{Q}_{it}} \mathrm{E}[\max_j U_{itqj}|q, X_{it}, e_{it}; \theta_t] \\ &\equiv EU_{it}.\end{aligned}$$

Finally, write i's costs of turning out as $Z_{it}{}' \cdot c_t^Z + \epsilon_{it,TO}$, where Z_{it} is a vector of covariates that affect i's costs in t and $\epsilon_{it,TO}$ is assumed to be i.i.d. and logistic with location 0 and scale 1. Utilities for turning out, TO, versus staying home, SH, can thus be written:

$$\begin{aligned}U_{it,TO} &= \alpha_t \cdot EU_{it} + Z_{it}{}' \cdot c_t^Z + \epsilon_{it,TO} \\ U_{it,SH} &= 0,\end{aligned} \tag{2}$$

with the registrant choosing the more preferred option. Consistent with the previous notation, I abbreviate $Z_{it}{}' \cdot c_t^Z$ as $c_{Z,t}$. The coefficient α_t captures selection. It measures the effect of expected utility from partisan contests on utility from turning out. Specifically, it benchmarks expected utility relative to idiosyncratic cost shocks, $\epsilon_{it,TO}$: if the standard deviation of the cost shocks is large relative to expected utility, then α_t will be small in magnitude.[20]

3.4 Discussion

I next discuss the parametric assumptions in more detail.

3.4.1 Preference utilities

The specification for preference utilities, equation (1), makes a few simplifications. First, the model does not allow interactions between question effects, (λ_q, Δ_q), and registrant characteristics, X_{it}. Instead, question effects are assumed to apply uniformly for all registrants. There are a number of cases where this assumption may be expected to fail. For instance, non-white candidates may provide differing utility to white and non-white registrants, conditional on the registrants' preference parameters, $(\lambda_{it}, \Delta_{it})$. I have experimented with interacting covariates with the question effects; however, I find that the interactions provide little additional predictive power. In cases where they are seen to matter, they can be easily

19. I.e., $u_{itqA} \equiv 0$, $u_{itqD} \equiv U_{itqD} - (\epsilon_{itq,\lambda} - \frac{1}{2}\epsilon_{itq,\Delta})$, and $u_{itqR} \equiv U_{itqR} - (\epsilon_{itq,\lambda} + \frac{1}{2}\epsilon_{itq,\Delta})$.

20. If one were to impose $\alpha_t > 0$, then the turnout decision could be equivalently formulated with $U_{it,SH} = 0$ and $U_{it,TO} = EU_{it} + \check{c}_{Z,t} + \sigma_t^{TO} \cdot \epsilon_{it,TO}$, where $\sigma_t^{TO} = \alpha_t{}^{-1}$ and $\check{c}_{Z,t} = c_{Z,t} \cdot \alpha_t{}^{-1}$. This parameterization highlights that the model allows the standard deviation of the cost shocks to vary flexibly.

included.

Similarly, I do not allow the magnitude of individual-level preference parameters, $(\lambda_{it}, \Delta_{it})$, to vary across questions. Formally, this is equivalent to not allowing a question-specific scale parameter, σ_q, on $\check{\epsilon}_{itq} \equiv (\check{\epsilon}_{itqD}, \check{\epsilon}_{itR}, \check{\epsilon}_{itA})$. Thus, for instance, an important or close race in which few individuals prefer A influences utility only additively, through λ_q. As a result, the race's importance increases utility for all registrants equally, regardless of the registrants' partisanship or efficacy. This is in contrast with the calculus of voting model (Downs 1957; Riker and Ordeshook 1968), which was recently expanded upon in Kawai, Toyama, and Watanabe (2018). In that model, a potential voter's sense of pivotality multiplies the difference in her utilities from the major-party candidates. As a result, close races have a larger effect on utility for more extreme partisans. As before, this assumption could be relaxed if it were found to improve the model's fit.

Finally, the model does not include precinct-level residuals. Instead, errors are assumed to be independent by registrant, e_{it}, or by registrant and question, ϵ_{itq}. As I explain later, I attempt to capture precinct-level heterogeneity by including precinct-level covariates and regional fixed effects. Excluding precinct-level residuals is convenient in that it allows me to use a likelihood for estimation, rather than a GMM approach; in my setting, which involves both aggregate- and micro-level data, a large number of observations, and a selection step, I find the likelihood much easier to work with.[21]

3.4.2 The role of σ_t

The standard deviation of e_{it}, σ_t, plays two roles in the model. First, it determines the relative importance of residuals at the level of the registrant versus the registrant and question. If residuals matter relatively more at the level of the registrant, then registrants who have a stronger-than-predicted preference for D or R on one question will also have one on other questions. This role of σ_t is illustrated graphically in Figure 2. In the figure, registrants A and B have the same covariate values, $X_{At} = X_{Bt}$, but $e_{At} < e_{Bt}$. The two panels show the distribution of possible partisanship values, Δ_{itq}, for A and B in a question in which $\epsilon_{itq,\Delta}$ has not yet been realized. In the first panel, σ_t is small and the densities for A and B have considerable overlap. Thus, there is a significant probability of $\epsilon_{itq,\Delta}$ realizations that involve A's preference for R being stronger than B's. By contrast, in the second panel, with larger σ_t, B's preference for R is stronger than A's under most $\epsilon_{itq,\Delta}$ realizations.

Second, σ_t scales the $(\lambda_{X,t}, \Delta_{X,t})$ and (λ_q, Δ_q) parameters. This is shown for partisanship in Figure 3. The figure plots the distribution of partisanship in two elections, t and t', for a group of registrants with the same covariates. The green line represents the distribution of partisanship in election t, when $\Delta_{X,t} = 2.5$ and $\sigma_t = 3.5$, while the blue line is for election t', with $\Delta_{X,t'} = 1.04$ and $\sigma_{t'} = 0$. The shaded areas represent the share of registrants who prefer D to R. The preference parameters are chosen such

21. This is in contrast with many industrial organization papers that make use of aggregate data. These papers often use a GMM methodology that involves orthogonalizing precinct-level errors with respect to covariates, following Berry, Levinsohn, and Pakes (1995). While this approach has been shown to work with large-scale aggregate data (Conlon and Gortmaker 2019), I found it difficult to apply in my setting, which involves both aggregate- and micro-level data. In particular, the optimal moments for the micro data would be the score of the likelihood of the individual choices, conditional on the precinct-level errors. Optimizing the GMM objective function would thus require calculating the derivative of the score, or second derivatives, in each iteration. This is computationally costly.

that in Panel 1, under $\Delta_q = 0$, the share of registrants who prefer D is the same in both elections. This panel shows that σ_t influences the magnitude of $\Delta_{X,t}$. Since $\sigma_t \neq \sigma_{t'}$, equality of preference shares requires $\Delta_{X,t} \neq \Delta_{X,t'}$. Specifically, the election with larger σ_t will have greater (lesser) $\Delta_{X,t}$ if the share who prefer R is greater (less) than 0.5. In addition, σ_t scales Δ_q; it influences the fraction of registrants who switch choices in response to a given change in question effects. This is seen in Panel 2, under $\Delta_q = -2.5$. Since $\sigma_{t'} < \sigma_t$, a larger share of registrants in t' switch to preferring D when the Democratic candidate becomes more popular. Similar results hold for $\lambda_{X,t}$ and λ_q.

The discussion highlights that the preference parameters only have meaning in a relative sense. Large magnitudes of $\lambda_q + \lambda_{X,t}$ and $\Delta_q + \Delta_{X,t}$ compared to unobservables indicate that registrants with the given covariate values are likely to make the same choices. Large magnitudes of σ_t indicate that most of the residual variation in preferences pertains to registrants in all questions, rather than being question-specific noise.

3.4.3 Turnout

The main challenge in modeling turnout is correctly specifying the bundle of contests that the registrant considers when deciding whether to turn out. If this set is misspecified, then expected utility will include measurement error. I discussed how I selected contests in Section 2.4. Measurement error could occur due to incorrectly specifying either the identity or number of contests in the bundle. Measurement error due to incorrectly specifying the identity of contests is likely to be limited. First, we have strong prior beliefs that certain contests, such as those for U.S. President or NC Governor, have much higher salience than others, such as that for NC Commissioner of Insurance. Second, I provided evidence in Section 2.6 that question effects are small compared to registrants' preferences for parties.[22] Thus, a registrant's expected utility from one contest is likely to be similar to that from another.

On the other hand, incorrectly specifying the number of contests could generate significant bias. This is because expected utility from the bundle is additive; thus, for instance, specifying that registrants pay attention to six contests when they actually focus only on three would cause the estimate of α_t to be half as large as the true value.[23] In the results, I show evidence that the number of contests is correctly specified. First, α_t coefficients are similar in midterm and presidential elections, despite these having different numbers of contests. In addition, in Section 5.2, I obtain a separate estimate of α_t that is based on variation in a registrant's turnout behavior over time. The value of this estimate is similar to the others.

3.4.4 Selection on unobservables

The model allows for selection on *unobservables*. That is, conditional on covariates, registrants who turn out are permitted to have different preferences from those who stay home. Selection on unobservables

22. In particular, I found that, depending on the election, the average vote share in a precinct explains between 88% and 99% of the variation in precinct vote shares. By contrast, the average vote share in a question explains a maximum of 6.2% of this variation.

23. Multiplying EU_{it} by a scalar and dividing α_t by that same scalar would not affect the model's predictions for turnout in a particular election. However, for the purposes of my simulation, I am interested in calculating the mean and variance of α_t across elections. Thus, obtaining a consistent scaling is important.

will occur if registrants consider expected utility in deciding whether to turn out, $\alpha_t > 0$, and if there are registrant-level unobservable preferences, $\sigma_t > 0$. Since the model does not include a registrant-level unobservable for political efficacy, selection on unobservables is assumed to occur only on unobserved partisanship, e_{it}. Specifically, it implies that the distribution of e_{it} conditional on turning out is not $N(0,1)$.

Selection on unobservables is illustrated for a hypothetical election in Figure 4. The first column of the figure plots $U_{it,TO}$ against e_{it} and the second column shows the density of e_{it} for voters. The hypothetical election involves a single contest q. The figure is drawn for registrants with $\alpha_t = 1$, $\sigma_t = 1$, and $\lambda_q + \lambda_{X,t} = 1$. The three rows of the figure represent different values of $\Delta_q + \Delta_{X,t}$, and the three lines in each plot represent different values of $c_{Z,t} + \epsilon_{it,TO}$. The dashed lines in the first column represent values of e_{it} for which registrants do not turn out.

The figure shows that when the probability of turning out is less than 1, the distribution of e_{it} among voters differs from that among all registrants. The first row presents the case in which registrants are on average indifferent between the parties, $\Delta_q + \Delta_{X,t} = 0$. Here, e_{it} remains mean-zero among voters; however, registrants with small magnitudes of e_{it} do not turn out. As a result, the share of individuals who prefer to abstain is smaller for voters than registrants. Naive estimation based on the choices of voters would thus generate a prediction for $\lambda_q + \lambda_{X,t}$ with a positive bias. The second and third rows present the case where registrants on average prefer one of the parties. As before, the distribution of e_{it} for voters excludes values with small magnitudes. But now, it is also shifted and asymmetric, with more weight placed on values of e_{it} with the same sign as $\Delta_q + \Delta_{X,t}$. Thus, naive estimation based on the voter sample would both overstate the prediction for $\lambda_q + \lambda_{X,t}$ and bias the prediction for $\Delta_q + \Delta_{X,t}$ in the direction of its sign.

3.5 Observed quantities and estimation

I estimate the model by maximizing a joint quasi-likelihood of the data. The data provides three observable quantities: (i) turnout choices for all registrants, (ii) turnout and preference choices for survey respondents, and (iii) precinct-level vote counts. The objective function that I maximize is composed of the exact likelihoods of the survey and turnout data and an asymptotic approximation to the likelihood of the vote data. I describe how to derive these in turn.

First, define some notation. Let $\mathcal{R}_t$ refer to the set of registrants or potential voters in election t, let $\mathcal{S}_t$ be the set of survey respondents, and let $\mathcal{T}_t$ be the set of voters. Also, let $\mathcal{R}_{ht}$ refer to the set of registrants in precinct h in election t, and let $N_{t,\mathcal{R}}$ and $N_{ht,\mathcal{R}}$ be the number of registrants in election t in the state and in h, respectively. Allow corresponding relations for $\mathcal{S}$ and $\mathcal{T}$.

3.5.1 Turnout likelihood

In the turnout data, we observe whether registrants turned out. The likelihood of this data can be calculated as follows. Let to_{it} indicate i's turnout decision: $to_{it} \equiv \mathbb{1}\{i \text{ turns out in } t\}$. Conditional on bundle $\mathcal{Q}_{it}$, covariates Z_{it}, and unobservable partisanship e_{it}, the probability that i turns out takes a logit form:

$$\Pr[to_{it} = 1|\mathcal{Q}_{it}, Z_{it}, e_{it}; \theta_t] = \frac{\exp[u_{it,TO}]}{1 + \exp[u_{it,TO}]} \\ \equiv \mathrm{TO}_{it}, \tag{3}$$

where $u_{it,TO} \equiv U_{it,TO} - \epsilon_{it,TO}$. The probability of turning out conditional only on observables is then the average of (3) over the distribution of e_{it}:

$$\Pr[to_{it} = 1|\mathcal{Q}_{it}, Z_{it}; \theta_t] = \int \Pr[to_{it} = 1|\mathcal{Q}_{it}, Z_{it}, e_{it}; \theta_t]\phi(e)de \\ = \int \mathrm{TO}_{it}\phi(e)de,$$

where $\phi(\cdot)$ indicates the standard normal density. The probability of staying home is 1 minus the probability of turning out. The likelihood of an individual's turnout decision is the conditional-on-observables probability of the option that they select:

$$\Pr[to_{it}|\mathcal{Q}_{it}, Z_{it}; \theta_t] = \int \mathrm{TO}_{it}^{to_{it}}(1 - \mathrm{TO}_{it})^{(1-to_{it})}\phi(e)de, \tag{4}$$

and the log-likelihood of the turnout data is the sum of the log of (4) over all registrants:

$$LL_{TO}(\theta_t) \equiv \sum_{i \in \mathcal{R}_t} \log\left(\Pr[to_{it}|\mathcal{Q}_{it}, Z_{it}; \theta_t]\right).$$

3.5.2 Survey likelihood

The likelihood of the survey data has a slight complication in that some survey respondents are matched with multiple registrants. For the time being, ignore this complication and assume that each respondent s is matched with a single registrant i.

In the survey data, we observe respondents' turnout decisions and their preference choices on a subset of contests on the ballot, $\mathcal{Q}_{it}^S \subset \mathcal{Q}_{it}$. Let p_{itqj} indicate whether i prefers j on question q: $p_{itqj} \equiv \mathbb{1}\{U_{itqj} = \max_k U_{itqk}\}$ for $k \in \{D, R, A\}$. The probability of preferring j given covariates X_{it} and unobservable partisanship e_{it} takes a multinomial logit form:

$$\Pr[p_{itqj} = 1|q, X_{it}, e_{it}; \theta_t] = \frac{\exp[u_{itqj}]}{\sum_{k \in \{D,R,A\}} \exp[u_{itqk}]} \\ \equiv \mathrm{P}_{itqj}.$$

The likelihood of a respondent's survey choices is the product of the conditional-on-e_{it} probabilities of the options they select, averaged over e_{it}:

$$\Pr[to_{it}, (p_{itqj})_{j,q}|\mathcal{Q}_{it}, \mathcal{Q}_{it}^S, Z_{it}; \theta_t] = \int \mathrm{TO}_{it}^{to_{it}}(1 - \mathrm{TO}_{it})^{(1-to_{it})} \prod_{q \in \mathcal{Q}_{it}^S} \prod_{j \in \{D,R,A\}} {\mathrm{P}_{itqj}}^{p_{itqj}}\phi(e)de. \tag{5}$$

Now consider a respondent with multiple matches. For this respondent, the likelihood is the average of (5) over all potential matches. Let $\mathcal{M}_s$ and M_s represent the set and number of matches for respondent s. The log-likelihood of the survey data is then:

$$LL_S(\theta_t) \equiv \sum_{s \in \mathcal{S}_t} \log \left(\frac{1}{M_s} \sum_{i \in \mathcal{M}_s} \Pr[to_{it}, (p_{itqj})_{j,q} | \mathcal{Q}_{it}, \mathcal{Q}_{it}^S, Z_{it}; \theta_t] \right).$$

3.5.3 Vote quasi-likelihood

The vote data consists of precinct-level counts of voters' preference choices on a bundle of contests. The exact likelihood of this data is complex. Given that there are no precinct-level unobservables, voters' preference choices on a single contest q are independent categorical variables that differ in distribution according to the voters' preference probabilities. Thus, vote counts for q are the sum of $N_{ht,\mathcal{T}}$ categorical variables that are independent but not identically distributed.[24] Random variables of this kind have a Poisson-Multinomial distribution, which is impractical to calculate exactly.[25] Further, the joint likelihood of the precinct's vote counts in all contests includes correlation across questions due to the presence of the individual-level error, e_{it}. I deal with these difficulties by using the asymptotic approximation to the joint likelihood of a precinct's vote data.

Let $p_{it} \equiv (p_{itqD}, p_{itqR})'_{q \in \mathcal{Q}_{it}}$ be a vector of i's preference choices for $q \in \mathcal{Q}_{it}$, and let $v_{ht} \equiv \frac{1}{N_{ht,\mathcal{T}}} \sum_{i \in \mathcal{T}_{ht}} p_{it}$ be the vector of observed vote shares in h.[26] h's vector of vote shares is the mean of $N_{ht,\mathcal{T}}$ independent but differently distributed random variables, p_{it}. By the Central Limit Theorem (CLT), this quantity has an asymptotic normal distribution, which becomes the correct distribution as the number of voters in the precinct goes to infinity.[27] The asymptotic normal distribution is calculated using the conditional-on-observables expected values and covariances of voters' preference choices. I define these quantities and then derive the full distribution. Some care must be taken to deal with the fact that voters are a selected sample. In particular, the conditional-on-observables expected value of voter i's preference choice for candidate j on question q is the probability that i prefers j on q conditional on

24. Importantly, it would not be correct to simply create a representative preference probability by averaging values for all voters in a precinct. This is because vote counts are calculated by aggregating the choices of each individual voter, rather than by drawing with replacement from the precinct's set of voters. A multinomial likelihood that assumes drawing with replacement would predict votes to be more dispersed than they are under the true data-generating process. The multinomial likelihood would expect there to be variation across draws in both (i) the preferences of voters conditional on their characteristics and (ii) the characteristics of voters in the draw; in reality, there is only variation due to (i). Another way to see this is that preference shares calculated with and without replacement both have asymptotic normal distributions, but with different variances. The variance for the case of sampling without replacement is the average of the variances for each voter, while that for sampling with replacement depends only on the representative preference probability.

25. Developing accurate approximations of the Poisson-Multinomial distribution is an area of active research, see, e.g., Daskalakis et al. (2016).

26. I include values only for D and R because they fully determine choices and shares for A.

27. A limitation of the asymptotic normal approximation is that the speed of convergence decreases as the mean preference probability among a precinct's voters becomes more extreme. That is, even for moderate sample sizes, the approximation can be poor if the mean preference probability for $j \in \{D, R\}$ approaches 0 or 1. In practice, this does not seem to be an issue, as precincts generally have large numbers of voters.

covariates, Z_{it}, on ballot, $\mathcal{Q}_{it}$, and on turning out. By Bayes rule, this value is:

$$\begin{aligned}
\mathrm{E}[p_{itqj}|q, \mathcal{Q}_{it}, Z_{it}, to_{it} = 1; \theta_t] &= \Pr[p_{itqj} = 1|q, \mathcal{Q}_{it}, Z_{it}, to_{it} = 1; \theta_t] \\
&= \int \Pr[p_{itqj} = 1|q, X_{it}, e_{it}; \theta_t] \cdot \Pr[e_{it}|\mathcal{Q}_{it}, Z_{it}, to_{it} = 1; \theta_t] de \\
&= \int \Pr[p_{itqj} = 1|q, X_{it}, e_{it}; \theta_t] \cdot \frac{\Pr[to_{it} = 1|\mathcal{Q}_{it}, Z_{it}, e_{it}; \theta_t]\phi(e)}{\Pr[to_{it} = 1|\mathcal{Q}_{it}, Z_{it}; \theta_t]} de \\
&= \int \mathrm{P}_{itqj} \cdot \frac{\mathrm{TO}_{it}\phi(e)}{\int \mathrm{TO}_{it}\phi(e)de} de \\
&\equiv \mathrm{P}_{\mathcal{Q}Z,tqj,\mathcal{T}}.
\end{aligned}$$

It is the average of P_{itqj} over the distribution of e_{it} among registrants with $\mathcal{Q}_{it}$ and Z_{it} who turned out. Intuitively, it re-weights the $N(0,1)$ distribution of e_{it} that exists among all registrants with $\mathcal{Q}_{it}$ and Z_{it} by the relative probability that a registrant would turn out under a given value of e_{it}.

Next, collect $\mathrm{P}_{\mathcal{Q}Z,tqj,\mathcal{T}}$ into a vector for all options and contests: $\mathrm{P}_{\mathcal{Q}Z,t,\mathcal{T}} \equiv (\mathrm{P}_{\mathcal{Q}Z,tqD,\mathcal{T}}, \mathrm{P}_{\mathcal{Q}Z,tqR,\mathcal{T}})'_{q\in\mathcal{Q}_{it}}$, and let $\mathrm{P}_{ht,\mathcal{T}}$ be the mean of this vector among voters in h: $\mathrm{P}_{ht,\mathcal{T}} \equiv \frac{1}{N_{ht,\mathcal{T}}} \sum_{i\in\mathcal{T}_{ht}} \mathrm{P}_{\mathcal{Q}Z,t,\mathcal{T}}$. Finally, let $\mathrm{W}_{\mathcal{Q}Z,t,\mathcal{T}}$ be the covariance matrix of voter i's preference choices, p_{it}, conditional on observables:

$$\mathrm{W}_{\mathcal{Q}Z,t,\mathcal{T}} \equiv \mathrm{Var}[p_{it}|\mathcal{Q}_{it}, Z_{it}, to_{it} = 1; \theta_t].$$

In Appendix A1.1, I show that the components of this matrix are the following:

$$\begin{aligned}
\mathrm{Var}[p_{itqj}|q, \mathcal{Q}_{it}, Z_{it}, to_{it} = 1; \theta_t] &= (1 - \mathrm{P}_{\mathcal{Q}Z,tqj,\mathcal{T}}) \cdot \mathrm{P}_{\mathcal{Q}Z,tqj,\mathcal{T}}, \\
\mathrm{Cov}[p_{itqj}, p_{itqk}|q, \mathcal{Q}_{it}, Z_{it}, to_{it} = 1; \theta_t] &= -\mathrm{P}_{\mathcal{Q}Z,tqj,\mathcal{T}}\mathrm{P}_{\mathcal{Q}Z,tqk,\mathcal{T}} \text{ for } k \neq j, \\
\mathrm{Cov}[p_{itqj}, p_{itq'k}|q, q', \mathcal{Q}_{it}, Z_{it}, to_{it} = 1; \theta_t] &= \int \mathrm{P}_{itqj}\mathrm{P}_{itq'k} \cdot \frac{\mathrm{TO}_{it}\phi(e)}{\int \mathrm{TO}_{it}\phi(e)de} de - \mathrm{P}_{\mathcal{Q}Z,tqj,\mathcal{T}}\mathrm{P}_{\mathcal{Q}Z,tq'k,\mathcal{T}} \text{ for } q \neq q'.
\end{aligned}$$

Let $\mathrm{W}_{ht,\mathcal{T}}$ be the average covariance matrix for voters in h: $\mathrm{W}_{ht,\mathcal{T}} \equiv \frac{1}{N_{ht,\mathcal{T}}} \sum_{i\in\mathcal{T}_{ht}} \mathrm{W}_{\mathcal{Q}Z,t,\mathcal{T}}$. Then by the multivariate Lindeberg-Feller CLT (e.g., Hansen (2019), pg. 183), we have:

$$\sqrt{N_{ht,\mathcal{T}}}(v_{ht} - \mathrm{P}_{ht,\mathcal{T}}) \xrightarrow{d} \mathrm{N}(0, \mathrm{W}_{ht,\mathcal{T}}).$$

Thus, we can obtain an approximate likelihood of the vote shares as:

$$v_{ht} \approx \mathrm{N}(\mathrm{P}_{ht,\mathcal{T}}, \mathrm{W}_{ht,\mathcal{T}}/N_{ht,\mathcal{T}}),$$

with the approximation becoming exact as $N_{ht,\mathcal{T}} \to \infty$. The log quasi-likelihood of the vote data is then:

$$LQL_V(\theta_t) \equiv \sum_{h\in\mathcal{H}_t} \log(\phi(v_{ht}; \mathrm{P}_{ht,\mathcal{T}}, \mathrm{W}_{ht,\mathcal{T}}/N_{ht,\mathcal{T}}),$$

where $\mathcal{H}_t$ is the set of precincts in t and $\phi(\,\cdot\,;\mu,\sigma^2)$ is a multivariate normal density with mean μ and variance σ^2.

3.5.4 Estimation

Estimation proceeds by maximizing the sum of the log likelihoods of the turnout and survey data and of the log quasi-likelihood of the vote data:

$$\begin{aligned} LL(\theta_t) &\equiv LL_{TO}(\theta_t) + LL_S(\theta_t) + LQL_V(\theta_t), \\ \hat{\theta}_t &= \arg\max_{\theta_t} LL(\theta_t). \end{aligned}$$

Let $LL_c(\theta_t)$ be the value of the log likelihood for cluster c. A cluster-robust M-estimation asymptotic variance matrix can be estimated as

$$\widehat{\mathrm{Var}}[\hat{\theta}_t] = \left(\sum_{c=1}^{C} \frac{\partial^2 LL_c(\hat{\theta}_t)}{\partial\theta_t\partial\theta_t'}\right)^{-1} \sum_{c=1}^{C} \frac{\partial LL_c(\hat{\theta}_t)}{\partial\hat{\theta}_t} \frac{\partial LL_c(\hat{\theta}_t)}{\partial\hat{\theta}_t}' \left(\sum_{c=1}^{C} \frac{\partial^2 LL_c(\hat{\theta}_t)}{\partial\theta_t\partial\theta_t'}\right)^{-1}$$

(e.g., Cameron and Trivedi (2005), pg. 842). $\hat{\theta}_t$ is consistent and asymptotically normal as the number of clusters, C, goes to infinity.[28]

3.6 Intuition on identification

I next provide intuition on how the model coefficients are identified. First, the registrant-level preference parameters, $(\lambda_{X,t}, \Delta_{X,t})$, are identified from cross-sectional variation in the characteristics of survey respondents and precinct voter populations. Specifically, they are identified in part from how covariates, X_{it}, predict the preference choices of survey respondents (after including question fixed effects and conducting a mixed multinomial logit transformation). They are also identified in part from how voters' covariates predict precinct vote shares (after adding question fixed effects, incorporating a nonlinear transformation that adjusts for selection on unobservables, and aggregating over all voters in the precinct). Next, question effects, (λ_q, Δ_q), are identified from variation across contests. Specifically, they are chosen to capture the across-question differences in survey preference choices and precinct vote shares (after adjusting for the effects of covariates and conducting the appropriate transformations).[29][30]

28. I estimate the model in Python using the *Autograd* automatic differentiation package (Maclaurin 2016).

29. Importantly, question effects for district-level races are not constant throughout the state and instead vary according to geographic districts. This creates a worry that they are confounded by local preference or cost shocks – that is, that they do not solely reflect the electoral conditions of the particular district race, but instead also absorb unobserved characteristics of district registrants. I deal with this issue by including district fixed effects in X_{it} and Z_{it}. Thus, question effects for the district-level races are identified only by the difference in preferences in the district between the district-level race and the other contests. Another distinctive feature of district-level races is that candidates in these races can target their policy platforms to the district's registrants. This means that candidates are likely to be more popular in their own districts than in others, controlling for district observables. It is not clear that this is an issue, since it is the case for all candidates in these races. It implies merely that candidates in district-level races are more popular than they would be if they were forced to adopt a common party platform.

30. The fact that the model includes multiple contests with separate question effects makes the precinct vote shares more powerful in identifying $(\lambda_{X,t}, \Delta_{X,t})$. To see this, consider two precincts, A and B. Suppose that the precincts have the same vote shares on average, but that A's shares are more responsive to changes in question effects. The model will infer that Precinct A has a larger share of moderate voters, while Precinct B is more polarized, with some voters who strongly

The standard deviation of e_{it}, σ_t, is identified by the across-question, conditional covariance of survey preference choices and precinct vote shares. Intuitively, for survey data, if some respondents repeatedly make more partisan choices than other respondents with the same covariates, they will be interpreted as having different draws of $\sigma_t \cdot e_{it}$. The model will adjust σ_t in order to make the patterns of choices more likely. In the same vein, if precincts with similar covariates repeatedly differ in vote shares, then they will be interpreted as having different sets of draws of $\sigma_t \cdot e_{it}$. The model will again adjust σ_t in order to make the conditional covariance in shares more likely. It can do this because of the presence of the conditional covariance terms in the multivariate normal quasi-likelihood.

Next, identification of the selection coefficient, α_t, is somewhat subtle. In my main specification, I set Z_{it} to include all the variables in X_{it}, $X_{it} \subset Z_{it}$. Thus, there is limited variation in EU_{it} in equation (2) that is not collinear with, or explained by, Z_{it}. The residual variation in EU_{it} is due only to unobserved partisanship, e_{it}, and to the linearity restriction on how Z_{it} enters $U_{it,TO}$, $Z_{it}' \cdot c_t^Z$.[31] Consequently, α_t is identified as follows. First, it is identified in the survey data from differences in e_{it} between voters and non-voters; this is recovered via the joint likelihood of a respondent's preference and turnout choices. Intuitively, if respondents who make more partisan choices than others with the same covariates are also more likely to turn out, then α_t will be positive. Second, α_t is identified from "cost instruments", which are variables that are in Z_{it} but not X_{it}; that is, these are variables that are assumed to affect costs but not preferences. Cost instruments are able to identify α_t via their effects on unobserved partisanship, e_{it}. Specifically, cost instruments induce additional registrants to turn out, which changes the distribution of e_{it} in the precinct. The model chooses α_t in order to match vote shares in precincts with differing amounts of induced turnout. For instance, if precincts in which the cost instruments create a large increase in turnout also have larger-than-predicted vote shares for the abstain option, then the model will infer that the marginal voters have values of e_{it} that make them more moderate. It will then increase α_t in order to match this.[32]

Finally, the cost coefficients, $c_{Z,t}$, are identified by how registrants' covariates, Z_{it}, predict their turnout choices, after adding $\alpha_t \cdot EU_{it}$ and applying a mixed logit transformation.

4 Model results

I next provide results from the model. I first discuss the covariates used in estimation and present the model coefficients. I then quantify the magnitude and consequences of selection, and I examine within-election prediction quality. Finally, I briefly characterize the 2008 to 2018 elections.

prefer Democrats and others who strongly prefer Republicans.

31. If X_{it} were a partition of the registrant sample into mutually exclusive groups, then $Z_{it}' \cdot c_t^Z$ could flexibly fit EU_{it} for given e_{it}, and the functional form effect would disappear.

32. Another possible source of identification for α_t is variation in the electoral conditions of district-level races. By including district fixed effects in X_{it} and Z_{it}, I shut down this channel. I have tried a specification in which I control for fixed effects for geographic areas that do not fully align with districts. In this specification, registrants with the same covariates and who live in the same regions but in different districts will have the same values of $c_{Z,t}$ but differing values of EU_{it}. This allows α_t to be identified directly from turnout choices. However, it requires assuming that the effects of being in a particular district operate only through expected utility in the district-level race, not also via costs or through expected utility in the other contests. I find that the estimates of α_t in this alternative specification are generally similar to those in my main specification. Nonetheless, I avoid the alternative specification due to its additional assumptions.

4.1 Covariates and coefficients

The covariates used in the model are listed in Table 5. They include registrants' demographics and party registration, characteristics of registrants' neighborhoods, fixed effects for U.S. House districts, out-of-sample predictions of the utility from turning out, the closeness of registrants' NC House and NC Senate races, and cost instruments. The selection and construction of covariates deserves a number of comments. First, the goal of the model is to best recover individuals' preferences and costs in a given election. Consequently, it is permissible to use covariates that relate to individuals' choices, such as party registration, as well as covariates that incorporate information from future elections. Second, contemporary election data provides a large set of possible covariates; however, the nonlinear nature of the model means that there is a limit to the number that can be feasibly estimated. I attempt to collapse the covariate space by generating out-of-sample predictions of turnout utilities. Specifically, I use a random forest to obtain out-of-sample predictions of registrants' turnout probabilities and then transform these onto an approximate utility scale by taking the log-odds ratio. Predicted turnout utility has strong explanatory power for the turnout decision; in addition, it reveals how preferences vary with an individual's observed propensity of turning out.

The cost instruments that I use are related to rainfall on election day and the distance from the registrant's home to the nearest early-voting location.[33] I use distance to the nearest early-voting location, rather than to the election-day polling place, because early voting locations differ by election, while polling places are relatively fixed. In particular, early-voting locations vary across elections due to budgetary constraints and possibly via strategic efforts at influencing turnout.[34] To reduce worries that the cost instruments may be correlated with unobserved preferences, I residualize them on random forests that use the same covariates as in predicting turnout. In the random forests, I include a large number of covariates, including past and future values of the cost variables.[35] This means that the cost instruments represent the time-varying and unpredictable component of the cost variables.[36][37]

33. Specifically, I calculate an index of rainfall intensity with values for $0 - 1$ mm, $1 - 8$ mm, and more than 8 mm. Also, I deflate distance by the square root of the area of the registrant's census block and take the natural log.

34. Early-voting locations are chosen by the county board of elections and must be approved by the state board of elections. In addition, prior to the 2014 election, some counties had to receive federal pre-clearance before changing early-voting locations, as mandated by Section 5 of the Voting Rights Act. Registrants are allowed to vote at any early-voting location in their county.

35. Examples of covariates include (i) the registrant's party of registration, turnout decision, and vote method in each election, including primaries and municipal elections, from 2006 to 2018; (ii) political choices for other members of the registrant's household, (iii) neighborhood characteristics; and (iv) voting conditions. Voting conditions include past and future values of the cost instruments and past, present, and future values of (i) distance to the election-day polling place, (ii) the hours and locations of other early-voting sites, and (iii) rainfall during early voting. All variables used in the random forest are listed in the data appendix.

36. The specific random forest that I use is a clustered regression forest with honesty (Athey, Tibshirani, and Wager 2019). In my case, this involves dividing North Carolina into ten regions and using data from nine of the regions to make predictions for the excluded one. I incorporate this form of clustering because the cost variables vary geographically. If I did not, they could be fully predicted by unique combinations of neighborhood characteristics.

37. Including covariates based on machine learning creates the potential for regularization bias if the model is not fit using a Neyman-orthogonal score (Chernozhukov et al. 2018). In a linear regression, using a Neyman-orthogonal score is equivalent to residualizing the remaining covariates by the machine learning procedure. In non-linear models, it is more complex. I have estimated an alternate version of the model in which I exclude the out-of-sample predictions. I find that the results are similar, but predictive power is reduced.

Summary statistics for the variables used in the model are shown in Table A4. λ, Δ, and c coefficients are presented in Tables A5-A7. Standard errors are clustered by county.[38] Coefficients for σ, α, and the cost instruments are displayed in Table 6. The table reveals first that σ_t, which represents the standard deviation of unobserved partisanship, is substantial and appears to be growing over time. Second, selection, α_t, is similar across years and has the expected sign.[39] Finally, cost instruments have a small but generally significant effect on turnout.

4.2 Quantifying the magnitude and consequences of selection

I next illustrate the implications of the model coefficients for the magnitude of selection and the consequences of selection on unobserved partisanship. I present results related to the magnitude of selection in Table 7. In order to benchmark effect sizes, the first row of the table presents information on the degree to which registrants differ in the probability of turning out. Specifically, it shows the difference between the 95th and 5th percentiles of each election's distribution of turnout probabilities, TO_{it}. The values indicate that there is significant variation in turnout probabilities: depending on the election, registrants at the 95th percentile are between 93.8 and 98.2 percentage points more likely to turn out than those at the 5th percentile. The remaining rows provide the results for selection. Specifically, they show the effect of shifting a registrant from the 5th to the 95th percentile of an election's expected utility, EU_{it}, distribution, while holding the registrant's costs, $c_{Z,t}$, constant. The rows present the mean, the 10th percentile, and the 90th percentile of this effect across the registrants in an election. The values indicate that expected utility impacts turnout but explains only a small share of the variation in turnout probabilities. Depending on the election, the mean effect size is between 2.5 and 6.2 percentage points. For registrants at the 10th percentile of the distribution, the effect is between merely 0.1 and 0.3 percentage points; while for those at the 90th percentile, it ranges between 5.5 and 13.5 percentage points.

Table 8 provides results related to the consequences of selection on unobserved partisanship, $\sigma_t \cdot e_{it}$. It shows first the effect of e_{it} on a registrant's probability of turning out. It then shows the effect of differences in e_{it} for voters and non-voters on gaps in preferences between these groups. The results for the effect of unobserved partisanship on turnout are presented in Panel A of the table. This effect depends on both the selection coefficient, α_t, and on the standard deviation of unobserved partisanship, σ_t. In order to obtain the results, I calculate the probability that a registrant turns out, TO_{it}, over a grid of e_{it} values between -1.96 and 1.96 (corresponding to the 2.5 and 97.5 percentiles of the standard

38. The covariates constructed by the random forests are generated regressors. Obtaining the correct standard errors thus requires accounting for uncertainty due to both estimating the model and fitting the random forests. In practice, the uncertainty due to the random forests is likely to be small. The random forests are fit using close to 7 million observations and the predictions that they generate have tight confidence intervals. For instance, the standard error for the predicted turnout probabilities is on average 2 percentage points. Consequently, I incorporate only the uncertainty due to estimating the model. One could obtain the correct standard errors by bootstrapping the combined procedure of fitting the random forests and estimating the model. This could be made more computationally manageable by using a bag of little bootstraps (Kleiner et al. 2014).

39. Later in the paper, I obtain a second estimate of selection that uses within-registrant variation in expected utility across elections. I explain this regression fully in Section 5.2. However, it is worth noting now that those coefficients, presented in Table 11, are similar to the ones presented here, which use only cross-sectional variation.

normal distribution). I then calculate the difference between the registrant's maximum and minimum turnout probabilities over this grid. The panel presents the mean, the 10th percentile, and the 90th percentile of the difference for the set of registrants in each election. The results suggest that σ_t is large enough for differences in e_{it} to meaningfully impact turnout probabilities. Depending on the election, the mean effect of shifting registrants from their turnout-minimizing to their turnout-maximizing values of e_{it} is between 2.1 and 5.0 percentage points. The effect is between 0.1 and 0.3 percentage points for registrants at the 10th percentile of the distribution and 5.3 to 11.9 percentage points for those at the 90th percentile.

Finally, in Panels B and C of Table 8, I show the effect that selection on unobserved partisanship has on preference probabilities. In Panel B, I calculate the decrease in a registrant's conditional-on-observables probability of abstaining if the registrant were to turn out rather than stay home. For question q, this value is:

$$\Pr[p_{itqA} = 1 | q, \mathcal{Q}_{it}, Z_{it}, to_{it} = 1; \hat{\theta}_t] - \Pr[p_{itqA} = 1 | q, \mathcal{Q}_{it}, Z_{it}, to_{it} = 0; \hat{\theta}_t]. \tag{6}$$

I average (6) for each registrant over all the questions in the registrant's bundle, $\mathcal{Q}_{it}$, and I then provide summary statistics for this average over the set of registrants in each election. In Panel C, I do the same but for the absolute value of the difference in the probability that a registrant prefers the Republican to the Democratic candidate. The results in Panels B and C indicate that selection on unobserved partisanship does not significantly affect preference probabilities. The 90th percentile of the effect on the probability of abstaining ranges from 0.2 to 0.9 percentage points, while that for the absolute value of the effect on preferring the Republican to the Democrat ranges from 0.7 to 1.6 percentage points.

4.3 Prediction quality within elections

I next examine prediction quality within elections. I first assess out-of-sample prediction quality for turnout and vote data and then inspect prediction quality for preference choices in the survey data.

Table 9 summarizes out-of-sample prediction quality for the administrative data. To calculate these values, I fit the model on two-thirds of the precincts and generate predictions for the excluded one third. The table presents three categories of results. Panel A shows results for turnout outcomes and Panels B and C show results for vote outcomes. In Panel B, the predictions condition on the voter sample in the excluded precincts, while in Panel C they do not. Predictions for precinct vote shares in Panel B are calculated as:

$$\frac{1}{N_{ht,\mathcal{T}}} \sum_{i \in \mathcal{T}_{ht}} \Pr[p_{itqj} = 1 | q, \mathcal{Q}_{it}, Z_{it}, to_{it} = 1; \hat{\theta}_t] = \frac{1}{N_{ht,\mathcal{T}}} \sum_{i \in \mathcal{T}_{ht}} \mathrm{P}_{QZ,tqj,\mathcal{T}},$$

while those in Panel C are:

$$\frac{\frac{1}{N_{ht,\mathcal{R}}} \sum_{i \in \mathcal{R}_{ht}} \Pr[p_{itqj} = 1, to_{it} = 1 | q, \mathcal{Q}_{it}, Z_{it}; \hat{\theta}_t]}{\frac{1}{N_{ht,\mathcal{R}}} \sum_{i \in \mathcal{R}_{ht}} \Pr[to_{it} = 1 | \mathcal{Q}_{it}, Z_{it}; \hat{\theta}_t]} = \frac{\frac{1}{N_{ht,\mathcal{R}}} \sum_{i \in \mathcal{R}_{ht}} \int \mathrm{P}_{itqj} \mathrm{TO}_{it} \phi(e) de}{\frac{1}{N_{ht,\mathcal{R}}} \sum_{i \in \mathcal{R}_{ht}} \int \mathrm{TO}_{it} \phi(e) de}.$$

The table shows a variety of measures of prediction quality. First, the classification rate represents the share of individuals for whom the predicted decision equals the actual choice. For turnout this is: $\frac{1}{N_{t,\mathcal{R}}} \sum_{i \in \mathcal{R}_t} \mathbb{1}\{to_{it} = \text{round}(\Pr[to_{it} = 1 | \mathcal{Q}_{it}, Z_{it}; \hat{\theta}_t])\}$. Next, R-squared measures the fraction of variation in precinct shares explained by the predictions. For turnout, this is:

$$1 - \frac{\text{Var}[to_{ht} - \text{TO}_{ht}]}{\text{Var}[to_{ht}]},$$

where to_{ht} and TO_{ht} are respectively the observed and predicted precinct turnout shares. For votes, R-squared is:

$$1 - \frac{\text{Var}[v_{htqj} - \text{V}^P_{htqj}]}{\text{Var}[v_{htqj}]}$$

for $j \in \{D, R\}$, where V^P_{htqj} is the predicted precinct vote share, either conditional or unconditional on turnout. Finally, mean absolute error is the average absolute difference between observed and predicted shares.

The table shows that the model has strong predictive power within elections. Mean absolute error for precinct turnout shares ranges between 0.9 and 1.8 percentage points. Mean absolute error for vote shares ranges from 2.5 to 3.3 percentage points when conditioning on turnout and is only slightly higher when not conditioning (2.6 to 3.3). For each election after 2008, the model explains over 96% of the variation in precinct vote shares, regardless of the prediction method. Finally, the mean absolute errors for the "state-level shares" provide information on prediction quality when votes are aggregated over all excluded precincts. The maximum of these values is 0.3 percentage points.

Next, I examine how well the model predicts individual preference choices in the survey data. In Figure 5, I plot local linear regressions of respondents' choices versus predicted preference probabilities. The predicted preference probabilities are: $\frac{1}{M_s} \sum_{i \in \mathcal{M}_s} \Pr[p_{itqj} = 1 | q, \mathcal{Q}_{it}, Z_{it}, to_{it}; \hat{\theta}_t]$ for $j \in \{D, R\}$. The figure shows that predictions are approximately unbiased, both for voters and non-voters. Finally, Table 10 presents classification rates for preference choices, broken down by demographic group and turnout status. The classification rates reveal how often the rounded values of the predicted preference probabilities equal respondents' choices. The table shows that the model has significant predictive power. It correctly predicts choices in 78% of cases, with somewhat higher rates for voters (81%) than non-voters (73%).

In order to benchmark the quality of the predictions, I compare the results with those from a regression of precinct vote shares on precinct characteristics. Measures of prediction quality for these regressions are presented for precinct vote shares in Table A8 and for survey preference choices in Table A9. I run the regressions using the same precincts and covariates as in fitting the structural model. To generate predictions of precinct vote shares that condition on turnout, I run the regressions using the mean covariates of a precinct's voters; to generate predictions that do not condition on turnout, I run the regressions using the mean covariates of a precinct's registrants. Finally, to create predictions for survey choices, I multiply the regression coefficients by the mean covariates for the respondent's registrant matches.[40] Comparing the values in Tables 9 and 10 with those in Tables A8 and A9, it is seen that prediction quality is similar for the two methods. The regression obtains slightly higher R-squared for out-of-sample precinct vote shares, while the structural model gains classification rates for survey preference choices that are higher by 2-3 percentage points.[41]

4.4 Characterizing the 2008 to 2018 elections

Finally, I briefly describe the 2008 to 2018 elections. First, Figure 6 provides a graphical representation of the elections by mapping predicted vote margins for each block group. The figure shows that North Carolina's political geography remained stable during the period. However, some rural areas in Appalachia and the southeastern part of the state trended Republican. In Figures 7-9, I present distributions of preference and turnout probabilities for each election by registrants' covariate groups. Figure 7 shows the predicted probability that a registrant prefers the Republican to the Democratic candidate over the contests in each election. The figure shows that partisan preferences differ substantially by registrants' covariates, with Republican and black registrants having notably strong preferences for Republican and Democratic candidates, respectively. Further, it shows that trends in partisan preferences over time are small compared to the fixed variation across covariate groups. Next, Figure 8 displays distributions for the predicted probability that a registrant prefers abstaining to selecting either of the major-party candidates. It shows that registrants with no party affiliation, registrants that are neither black nor white, and registrants age 18-30 are most likely to abstain. Finally, Figure 9 exhibits predicted turnout probabilities. It shows that all groups are less likely to turn out in midterms than in presidential races. However, the gaps are smallest for registrants age 60 and over.

In a last exercise, I examine how trends in utility parameters and demographics during 2008-2018 influenced observed vote shares. Results are presented in Figure 10. The plots in the figure show mean two-party vote shares in actual and counterfactual versions of the 2008-2018 elections. The plot in the first row of the figure shows values for actual elections and reveals that there was no trend in vote shares over the period. The plots in the second row show values for counterfactual elections that hold fixed either demographics or utility parameters.[42] Specifically, in the first plot in the row, I combine the model coefficients from the specified elections with the registrant sample from 2008. In the second plot, I combine the electorates from the specified elections with the model coefficients from 2008. These plots show that the stability in North Carolina's vote shares was due to countervailing trends in demographics and utility parameters: holding demographics constant, the state would have become more Republican; meanwhile, fixing model coefficients, it would have trended Democratic.

40. I also set all predictions that are less than 0 or larger than 1 to 0 or 1, respectively.

41. The relative strength of the structural model in predicting survey choices may be due either to its micro-founded nature or to the fact that it uses survey data in estimation while the regression does not.

42. I detail the procedure for constructing counterfactual elections in Section 5.

5 Simulation

I next discuss how the model estimates can be used for counterfactual simulations. The simulations involve predicting preferences, turnout, and votes in unobserved elections and then aggregating the votes by the districts of the legislative map under consideration.

Before conducting the simulations, I pool registrants' preference and cost estimates over all years and run regressions to decompose them into individual fixed effects and election-specific shocks. I make the simplifying assumption that individual-level, unobserved partisanship, e_{it}, is independent by registrant across elections. This means that the dependent variables in the regressions are expected values conditional only on registrants' covariates, not additionally on their turnout decisions.[43] Before running the regressions, I standardize the mean preference parameters, $\delta_t = (\lambda_{X,t}, \{\lambda_q\}_{\mathcal{Q}_t}, \Delta_{X,t}, \{\Delta_q\}_{\mathcal{Q}_t})'$, in order to make them comparable in different years. This is necessary because δ_t depends on the scale, σ_t, of e_{it}. By contrast, I do not need to standardize the turnout parameters, as both σ_t and δ_t influence the conditional-on-covariates expected utility from revealing preferences, $\mathrm{E}[EU_{it}|\mathcal{Q}_{it}, X_{it}; \theta_t]$. After running the regressions, I calculate the across-election variances of the election-specific shocks. I conduct simulations by combining draws of shocks and e- and ϵ-residuals with the individual fixed effects of the electorate in a given election.

5.1 Standardizing preference parameters

As discussed in Section 3.4.2, σ_t influences the across-question conditional covariance of preference choices. For given σ_t, δ_t then adjusts to match the conditional expectation of preference choices. Consequently, if σ_t changes across elections, then δ_t will as well, even if conditional preference probabilities do not. I disentangle these factors by transforming δ_t into a space with zero across-question conditional covariance; that is, with $\sigma_t = 0$. In this space, there is a one-to-one mapping between transformed coefficients, $\tilde{\delta}_t$, and preference probabilities. Following results in Berry (1994) and Berry, Levinsohn, and Pakes (1995), one can then reverse the transformation in order to recover the across-question conditional covariance implied by a given σ_t.

The standardization process involves separately transforming individual- and question-level preference parameters. The individual-level preference parameters are conditional-on-covariates expected values of efficacy and partisanship in election t. For $\delta \in (\lambda, \Delta)$, these are:

$$\mathrm{E}[\delta_{it} + \delta_q | \mathcal{Q}_t, X_{it}; \theta_t] = \delta_{X,t} + \mathrm{E}[\delta_q | \mathcal{Q}_t; \theta_t], \tag{7}$$

where $\mathcal{Q}_t$ is the set of all contests in t, including state-level contests faced by all registrants and U.S.

43. For instance, in calculating net turnout utility, I use the conditional-on-covariates expected utility $\mathrm{E}[EU_{it}|\mathcal{Q}_{it}, X_{it}; \theta_t] = \int EU_{it}\phi(e)de$, rather than the expected value conditional on covariates and turnout, $\mathrm{E}[EU_{it}|\mathcal{Q}_{it}, Z_{it}, to_{it}; \theta_t] = \int EU_{it} \Pr[e|\mathcal{Q}_{it}, Z_{it}, to_{it}]de$. This assumption is reasonable because the covariates for a given election include turnout history in other elections. Thus, expected values of e_{it} given turnout decisions tend to cancel out across elections. In particular, I find that individual fixed effects explain only 15% of the variation in e_{it}. The assumption also significantly simplifies the simulation. First, it means predictions for registrant i in counterfactual elections involve draws of e_{it} from a $N(0, 1)$ distribution, not a complicated posterior. Second, it simplifies the process for standardizing the mean preference parameters, which I discuss in Section 5.1.

House contests that differ by district. In the remainder of the paper, I index the U.S. House contest in district d as USH_d. [44] The question-level preference coefficients come in two groups. The first are mean-deviations of question effects for state-level contests and the average U.S. House contest, $\mathrm{E}[\delta_{\text{USH}_d}|\mathcal{Q}_t;\theta_t]$:

$$\dot{\delta}_q \equiv \delta_q - \mathrm{E}[\delta_q|\mathcal{Q}_t;\theta_t]; \tag{8}$$

and the second are deviations of question effects for specific U.S. House contests from their mean:

$$\dot{\delta}_{\text{USH}_d} \equiv \delta_{\text{USH}_d} - \mathrm{E}[\delta_{\text{USH}_d}|\mathcal{Q}_t;\theta_t], \tag{9}$$

I detail the specific process for transforming the preference parameters in Appendix A1.2. I obtain transformed coefficients $\tilde{\delta}_{it}$ corresponding to the parameters in equation (7) and $\tilde{\dot{\delta}}_q$ and $\tilde{\dot{\delta}}_{\text{USH}_d}$ corresponding to the parameters in equations (8) and (9), respectively.

5.2 Pooled regressions

I next discuss the regressions used to decompose parameters into individual fixed effects and election-specific shocks. I pool observations across years and run separate regressions for parameters related to efficacy, partisanship, and turnout utility. Importantly, some of the covariates used in the explanatory model, such as party of registration and predicted turnout utility, relate to individuals' endogenous behaviors, rather than to their immutable characteristics. I exclude these covariates from the regressions and allow their effects to either (i) be captured by the fixed effects and exogenous covariates or (ii) form part of the residuals. Let $Z_{it,0} \subset Z_{it}$ be the set of exogenous covariates for i in t, and similarly for $X_{it,0} \subset X_{it}$.

For efficacy and partisanship, I regress the transformed individual-level parameters, $\tilde{\delta}_{it} = (\tilde{\lambda}_{it}, \tilde{\Delta}_{it})$, on individual fixed effects, $\tilde{\delta}_i$, and exogenous covariates, $X_{it,0}$, allowing the coefficients on the covariates, $\tilde{\delta}_t^{X_0}$, to vary by year:

$$\tilde{\delta}_{it} = \tilde{\delta}_i + X_{it,0}{}' \cdot \tilde{\delta}_t^{X_0} + r_{it,\tilde{\delta}}. \tag{10}$$

For the turnout utility regression, the dependent variable is the conditional-on-observables expected value of utility from turning out:

$$\mathrm{E}[U_{it,TO}|\mathcal{Q}_{it}, X_{it};\theta_t] \equiv \alpha_t \cdot \mathrm{E}[EU_{it}|\mathcal{Q}_{it}, X_{it};\theta_t] + c_{Z,t}.$$

I regress this dependent variable on $\mathrm{E}[EU_{it}|\mathcal{Q}_{it}, X_{it};\theta_t]$, individual fixed effects, c_i, and exogenous covariates, $Z_{it,0}$, again allowing the coefficients on the covariates, $\tilde{\delta}_t^{Z_0}$, to vary by year:

$$\mathrm{E}[U_{it,TO}|\mathcal{Q}_{it}, X_{it};\theta_t] = \alpha_W \cdot \mathrm{E}[EU_{it}|\mathcal{Q}_{it}, X_{it};\theta_t] + c_i + Z_{it,0}{}' \cdot c_t^{Z_0} + r_{it,c}. \tag{11}$$

Consistent with prior convention, I abbreviate $X_{it,0}{}' \cdot \tilde{\delta}_t^{X_0}$ and $Z_{it,0}{}' \cdot c_t^{Z_0}$ as $\tilde{\delta}_{X_0,t}$ and $c_{Z_0,t}$, respectively.

44. The estimate of $\mathrm{E}[\delta_q|\mathcal{Q}_t;\theta_t]$ is $\frac{1}{Q_t}(\sum_{q\in\mathcal{Q}_t\setminus\text{USH}} \delta_q + \frac{1}{N_{t,\mathcal{R}}}\sum_{i\in\mathcal{R}_t} \delta_{\text{USH}_d})$.

A few comments on the regressions are in order. First, the individual fixed effects can be identified because the regression uses only the exogenous subset of covariates. This is also the main reason why the equations have residuals.[45] Second, I allow the coefficients on the exogenous covariates to vary by year, but I restrict the coefficient on expected utility, α_W, to be constant over time. α_W is a second estimate of selection, or the effect of expected utility from revealing preferences on turnout utility. The first estimate, α_t, was identified cross-sectionally using variation from choices in survey data and from cost instruments that affect the distribution of e_{it} among a precinct's voters. By contrast, α_W is identified using within-individual variation in expected utility over time. Specifically, it measures the effect of changes in an individual's expected utility using variation over time in endogenous covariates, such as party of registration and predicted turnout utility. Estimates for α_W are shown in Table 11. The first row in Panel A shows the main estimates and the other rows show estimates for alternative regression specifications and samples. The table shows that α_W estimates are similar to those for α_t and are robust to specification and sample. Lastly, before running the regressions, I first de-mean $X_{it,0}$, $Z_{it,0}$, and $\mathrm{E}[EU_{it}|\mathcal{Q}_{it}, X_{it}; \theta_t]$ using the grand mean over all years. I do this so that the year-specific coefficients on the constant term are the values of the dependent variable for registrants with covariates and/or expected utility equal to the grand mean.

5.3 Simulation procedure

The simulations proceed as follows. First, I select an electorate in a given year, $\mathcal{R}_t$, with the choice depending on the goal of the simulation. For instance, to evaluate maps proposed for elections in the 2020s, I would use the most recent available electorate, 2018. Next, I calculate the across-election variances of the preference and cost shocks, $(\tilde{\lambda}_t^{X_o}, \tilde{\Delta}_t^{X_0}, c_t^{Z_0})$. These are shown in Table A10. I impose a distribution on these shocks and draw a set of values. In the main results, I use independent normal distributions. I have tried alternative assumptions, such as multivariate normal shocks, and found that results are similar. In order to allow for trends in political conditions, I center the distributions at the values of the shocks in the year of the selected electorate. Thus, if I am using the 2018 electorate, I assume that future elections will involve draws from a distribution with mean equal to the values in the 2018 election and variances equal to those calculated from the 2008 through 2018 elections.

Next, I continue drawing parameters. I draw σ_t and α_t values from independent normal distributions with the 2008-2018 variances and means equal to the values in the year of the selected electorate.[46] I then draw independent and standard normal e_{it} values for each registrant, as well as Q independent values of question effects $\tilde{\dot{\delta}}_q$ from mean-zero normal distributions with empirical variances.[47] Depending on the goal of the simulation, I set $Q = 6$, corresponding to presidential elections, or $Q = 2$, corresponding to midterms. Finally, I draw regression residuals $r_{it} = (r_{it,\tilde{\lambda}}, r_{it,\tilde{\Delta}}, r_{it,c})$. In order to allow for possible

45. In addition, in equation (11), the residuals are partly due to not allowing α_W to vary by t. In equation (10), the residuals are partly because the non-linear standardization process means that $\tilde{\dot{\delta}}_{it}$ is no longer fully linear in X_{it}. However, this effect is small, as $\tilde{\dot{\delta}}_{it}$ is very close to being linear in X_{it}: a regression of $\tilde{\dot{\delta}}_{it}$ on X_{it} generates R-squared values above 0.99.

46. I treat α_W as the equivalent of a realization of α_t for an additional election.

47. $\dot{\delta}_q$ is mean-zero. However, due to the non-linear standardization process, the transformed coefficients are almost, but not exactly, mean-zero.

correlation among residuals, I divide the electorate into groups based on covariate interactions.[48] For each year, I calculate the group and individual components of the residuals: $r_{it} = r_{gt} + \dot{r}_{it}$, with $r_{gt} \equiv \mathrm{E}[r_{it}|gt]$ for group g. I then calculate the variance of these components, and draw independent values of r_{gt} and $\dot{r}_{it}$ from mean-zero normal distributions with the empirical variances.

Finally, I construct counterfactual elections. I combine the simulated coefficients and regression residuals to create $\tilde{\delta}_{it}$ and then calculate associated preference probabilities. I use the Berry, Levinsohn, and Pakes (1995) contraction mapping to recover un-transformed preference parameters, δ_t, for given σ_t. I then combine the preference parameters, e_{it} values, and draws of ϵ errors to calculate preference choices, expected utility, EU_{it}, and turnout decisions. I calculate votes as preferences for registrants who turn out. I then predict gerrymandering outcomes by aggregating the votes by the districts of the map under consideration. I calculate the seat share and statewide two-party vote share for each party and record the winner and two-party vote share in each district. I repeat the process 200 times.

6 Evaluating legislative maps and gerrymandering measures

In this final section, I test and apply the method for measuring gerrymandering. I first examine the credibility of the predictions. I then evaluate legislative maps that were recently used in North Carolina, and I investigate the effect of compactness requirements on map quality. Finally, I compare prediction quality for my method with that for two simpler approaches to measuring gerrymandering.

As previously discussed, the goal in measuring gerrymandering is to accurately predict proportionality and competitiveness in future elections. Gerrymandering outcomes in future elections will differ from those in the past due to demographic changes and electoral shocks. I examine the variability that stems from electoral shocks by simulating counterfactual elections using the process described in Section 5. I summarize the simulations with respect to proportionality by showing the "seats-votes" curve. This figure plots the Republican seat share against the Republican statewide two-party vote share for each contest in the simulated elections. It thus reveals the seat shares that the Republican party may obtain when it receives a given share of the two-party statewide vote. I summarize the simulations with respect to competitiveness by displaying the range of two-party vote shares for each district. Finally, I investigate how changes in demographics can influence gerrymandering outcomes by repeating the analysis under different electorates.

6.1 Testing the credibility of the gerrymandering predictions

The credibility of the gerrymandering predictions hinges on how well the procedure predicts the uncertainty of gerrymandering outcomes in unobserved elections. In particular, the seats-votes curve amounts to a set of prediction intervals for seat shares conditional on the two-party statewide vote share. Thus, a seats-votes curve would be credible if $\tau\%$ of seat shares in unobserved elections fall within the $\tau\%$ intervals. I test this by obtaining seats-votes curves using subsets of the 2008-2018 elections and comparing the prediction intervals with observed seats-votes combinations in excluded elections. For example, to

48. The covariates include indicators for race, gender, and age in ten-year intervals, and quartiles of block density, block group household median income, and block group share college graduates.

predict outcomes in 2018, I fit the model and run the simulations using the 2008-2016 elections, and I construct seats-votes curves for a number of recently used legislative maps.[49] I then take all contests in 2018 and aggregate their votes according to the districts of the legislative maps. For each contest and map, I calculate the Republican share of the two-party statewide vote and the Republican seat share. I then calculate the fraction of 2018 seats-votes combinations that fall within the τ% prediction intervals from the 2008-2016 seats-votes curves, weighting values for each legislative chamber equally. I do this analysis excluding each of the 2008-2018 elections, one at a time.

Results for the test are presented in Panel A of Table 12. The results are summarized for predicting all elections and for predicting just 2008 and 2018.[50] Results are also presented separately for categories termed "Electoral shocks" and "Electoral shocks and demographic changes". As mentioned previously, unobserved elections differ from observed ones due to both (i) differences in electoral shocks and (ii) changes in the demographic composition of the electorate. The prediction intervals incorporate only the uncertainty due to (i). Thus, in the "Electoral shocks" rows, I shut down the effect of demographics and examine whether the intervals have correct coverage for elections with unobserved preference and cost shocks. In order to do this, I do not use votes from the actual contests in the excluded elections as the basis for the seats-votes combinations being predicted. Instead, I use votes from "pseudo" contests that are calculated by combining the model coefficients from the excluded elections with the electorate from the year in which the simulations are centered. For instance, to calculate pseudo 2018 contests, I combine the 2018 model coefficients with the 2016 electorate. By contrast, in the rows for "Electoral shocks and demographic changes", I use the votes from the actual contests. This allows examining the extent to which demographic changes confound the results.

The values in Panel A of Table 12 suggest that the seats-votes curves have approximately correct coverage. For the "All years" and "Electoral shocks" category, 96% of seats-votes combinations in excluded elections fall within the 95% prediction intervals, 90% fall within the 90% intervals, and 88% fall within the 80% intervals. Results are similar when allowing for changes in demographics and when predicting just 2008 and 2018.

A limitation of predicting seats-votes combinations is that, since they vary by contest and map, they are limited in number. I expand the sample size by predicting a quantity that relates to the seats-votes curve but that varies by contest, map, and district. Specifically, seats-votes curves involve predictions for district two-party vote shares conditional on the statewide two-party vote share.[51] Thus, I predict the difference between the district and statewide two-party vote shares.[52] To do this, I use

49. I center the simulations in the election that is nearest to the excluded election. For instance, to predict 2018, I use the 2016 electorate and set means of electoral shocks equal to the 2016 model coefficients. I use the electorate from 2016 rather than 2018 in order to mimic the scenario of predicting 2018 using the information available in 2016. Also, I set the number of contests in the simulated elections equal to the number in the excluded election. For instance, to predict 2018, I use $Q = 3$.

50. I distinguish the results for 2008 and 2018 from those for the other years because these are the only elections that occur either entirely before or after the other elections.

51. To be precise, they involve predicting the fraction of districts in which the Republican two-party vote share is greater than 0.5, conditional on the statewide two-party vote share.

52. This test follows Gelman and King (1994).

a similar procedure as before, but with this alternative outcome. Results are presented in Panel B of Table 12. They again show that the procedure has approximately correct coverage. In Figures A1 and A2, I provide a visual summary of the results for 2008 and 2018, respectively. The figures plot 90% prediction intervals for district-minus-state vote shares for each district and show values from the actual and pseudo contests in the 2008 and 2018 elections. Consistent with the results in Panel B of Table 12, the figures reveal that the pseudo and actual votes generally fall within the prediction intervals.

6.2 Evaluating recent legislative maps in North Carolina

I next evaluate the proportionality and competitiveness of recently used maps in North Carolina. Figure 11 shows seats-votes curves for maps that were used for the U.S. House, the NC Senate, and NC House during the 2000s and 2010s. Each plot represents the districts from a different map. The plots are calculated by running simulations that use the 2010 electorate and set means of electoral shocks equal to the 2010 model coefficients. The simulations set $Q = 2$ or $Q = 6$ with equal probability, thus reflecting variation due to midterm and presidential elections.[53] I choose to center the simulations in 2010 in order to reflect the perspective of a map-maker during the 2011 redistricting process. The plots can be interpreted as follows. Each dot represents a single contest. The value of the dot on the horizontal axis is the Republican two-party statewide vote share in the contest, and the value on the vertical axis is the the share of seats Republicans would win if seats were allocated according to the votes in the contest. The plots have three colors of dots. Blue dots are for observed contests in the 2008-2018 elections. Green dots are for contests in simulated elections that use the 2010 electorate and the observed 2008-2018 model coefficients. Finally, gray dots are for contests in simulated elections that use the 2010 electorate and simulated coefficients. The plots also include predicted values from a local linear regression and a set of local quantile regressions to represent the mean and 95% confidence interval of seat shares for a given two-party statewide vote share.

Figure 11 reveals that the maps differ visibly in proportionality, with those used after the 2011 redistricting cycle being more biased than those used before. This contrast is especially pronounced for the U.S. House. Consistent with the results in Table 12, the figure also shows that demographic changes did not significantly alter the relationship between seats and votes during the period: values for contests in the observed elections, which do not hold demographics fixed, fall within the range of the simulations, which do. Next, I explore the effects of demographic changes more fully by modifying the simulations to be centered in 2016.[54] In Figure 12, I plot local linear and local quantile regressions for seats-votes curves centered in 2010 and 2016. The figure shows that demographic changes during the period did not substantively alter conclusions regarding proportionality: the curves for the two years are similar, especially for vote shares close to 0.5.

Next, I use the curves in Figure 12 to quantify proportionality for each map under the 2010 and 2016 sets of simulations. Results are presented in Tables 13-15. The results present the mean (corre-

53. In contrast with Section 6.1, these simulations use data from all of the 2008-2018 elections.

54. The legislature was ordered by a court to re-draw the state legislative maps for the 2018 election. By centering the simulations in 2016, I adopt the perspective of these map-makers.

sponding to the local linear regressions) and 2.5 and 97.5 percentiles (corresponding to the local quantile regressions) of the listed quantities over the simulated contests. First, I calculate the Republican seat shares predicted by the curves for a Republican two-party vote share of 0.5. These results are presented in Panel A of the tables. Next, I calculate the average of the predicted Republican seat shares over two-party vote shares between 0.45 and 0.55. These results are shown in Panel B of the tables. Finally, I calculate the two-party vote shares that the curves predict Republicans would need in order to obtain a legislative majority. These results are in Panel C of the tables. The results indicate that the maps used before the 2011 redistricting process were reasonably unbiased, while those used afterward favored Republicans. For instance, under the 2010 electorate, the U.S. House map used from 2002-2010 is predicted to give the Republican party just over 50% of seats when it receives a two-party vote share of 0.5. The 95% confidence interval ranges from 45% to 62%. By contrast, the maps used from 2012-2014 and 2016-2018 are predicted to give Republicans 73-74% of seats for the same evenly split two-party vote share. These maps have confidence intervals of between 60-61% and 77%. Results are mostly unchanged when simulations are centered on the 2016 electorate. Results for the other measures also tell a similar story.

Last, I explore how the maps differed in competitiveness. In Figure 13, I display 90% confidence intervals for Republican two-party vote shares in each district, based on the simulations centered in 2010. Consistent with the seats-votes curves, each plot is for the districts in a different map. In addition to the confidence intervals, the plots show blue and green dots, corresponding to district vote shares for observed contests from the 2008-2018 elections and for simulated contests that use the 2010 electorate and the 2008-2018 model coefficients. The figure shows that districts differ significantly in competitiveness. In particular, the first row of the figure shows that the U.S. House maps used in 2012-2014 and 2016-2018 gained additional seats for Republicans by packing Democratic-leaning voters into three highly uncompetitive districts. The 90% confidence intervals for these districts (the first three in the figure) are all well below 0.5, suggesting that Democrats are predicted to almost always win. By contrast, the 90% confidence intervals for the ten remaining districts all intersect 0.5, indicating that they have less certain outcomes.

6.3 The effect of compactness requirements

I next investigate the effect of compactness requirements on map proportionality. Forcing map-makers to draw districts that are geographically compact is a common suggestion for how to combat gerrymandering.[55] However, the relationship between compactness and proportionality is unclear. I start by examining this relationship for historical U.S. House maps in North Carolina. I then assess proportionality for two U.S. House maps created using an algorithm that maximizes compactness.

In Figure 14, I show the U.S. House maps used in North Carolina during the 2000s and 2010s. The figure shows that the 2016-2018 map is reasonably compact, while the 2002-2010 and 2012-2014 maps are not.[56] However, I found in Section 6.2 that the 2002-2010 map has small partisan bias, while both

55. See, e.g., the discussion in Niemi et al. (1990), Fryer and Holden (2011), and Saxon (n.d.).

56. The 2016-2018 map was drawn by the legislature in response to a court order, and the legislature may have made it

the 2012-2014 and 2016-2018 maps significantly favor Republicans. (In addition, both the 2012-2014 and 2016-2018 maps feature three uncompetitive districts, while the 2002-2010 map has only one.) These results suggest that a non-compact map is not necessarily indicative of partisan gerrymandering; moreover, it is possible for map-makers to draw compact maps that are nonetheless biased.

In Figure 15, I explore how map-makers can draw compact and biased maps. This figure displays the 12th U.S. House district from the 2012-2014 and 2016-2018 maps. In the figure, I color census blocks by the blocks' average vote margins from the 2008-2010 elections. The figure shows that North Carolina residents are clustered geographically by political preferences, with urban areas favoring Democrats and rural areas supporting Republicans. The 12th district from the 2012-2014 map (outlined in black) is long and jagged. It attempts to maximally absorb Democratic-leaning registrants by connecting the urban areas of Charlotte, Greensboro, and Winston-Salem. By contrast, the 12th district in the 2016-2018 map (outlined in green) mostly follows the boundaries of Mecklenburg County, and is much more compact. Nonetheless, this county, which includes Charlotte, is heavily Democratic. Thus, even though the new district has fewer Democratic-leaning registrants than the old one, it still swallows a large number. This makes the remaining districts more favorable to Republicans and helps them gain disproportionate seat shares. Residential sorting by political preferences is a common feature across the U.S. (Chen and Rodden 2013). Consequently, there are likely many settings in which it is possible to draw compact and biased maps.

Finally, I assess proportionality for U.S. House maps that are constructed using an algorithm that maximizes compactness. This algorithm is from Saxon (n.d.). It is well known that the large number of possible maps means that is infeasible to discover a single *maximally* compact map. Instead, the algorithm recovers sets of *highly* compact maps. In addition, there are multiple definitions of compactness that can be used as the objective function. I deal with these issues by selecting two representative maps from the sets returned by the algorithm. One of the maps is constructed using the Power Diagrams method, which minimizes the average physical distance between registrants in a district (Fryer and Holden 2011). The other is built using the Isoperimeter Quotient (IPQ) method, which involves maximizing the ratio of the area of a district to that of a circle with equal perimeter (Polsby and Popper 1991). The maps are shown in Figure 16. Seats-votes curves are presented in Figure 17, and summary statistics for proportionality measures are in Table 16. The results indicate that the Power Diagrams map is unbiased. Under this map, the Republican party is expected to win 51% of seats when it obtains half the two-party statewide vote, with a confidence interval of 39% to 62%. By contrast, the IPQ map slightly disadvantages Democrats. For this map, Republicans are expected to win 56% of seats under an even statewide vote, with a confidence interval that ranges from 44% to 68%. These results suggest that algorithmically created maps are likely to perform better than those drawn by politicians. However, they can still exhibit bias.

compact in an attempt to thwart future court challenges.

6.4 Comparisons with simpler approaches to measuring gerrymandering

As a final exercise, I compare prediction quality for the method developed in this paper with that from two simpler approaches to measuring gerrymandering. These include (i) a method based on the "uniform swing" assumption of Butler (1951), and (ii) the approach of Geruso, Spears, and Talesara (2019), which is the most general of the simulation-based methods that rely on aggregate vote shares. To conduct the comparison, I predict district two-party vote shares in excluded elections conditional on knowing the statewide two-party vote share. As discussed in Section 6.1, this outcome is closely related to the seats-votes curve and varies by contest, map, and district. The analysis in Section 6.1 involved examining the *credibility* of the predictions by testing whether outcomes in excluded elections fall within the prediction intervals at the appropriate rates. In this section, I instead assess the *accuracy* of the predictions, by calculating their mean absolute error and R-squared. Consistent with the analysis in Section 6.1, I use information in all elections except the excluded election to make predictions for the excluded election. Also, I predict district vote shares for each contest in the excluded elections and for each legislative map used in North Carolina since 2010.

I create the predictions as follows. First, for my method, I aggregate the simulations from Section 6.1 according to the districts of a particular map.[57] For each district, I then run a local linear regression of the district's two-party vote shares in the simulated contests on the contests' statewide two-party vote shares. I then record the predicted value of the district's two-party vote share at the statewide two-party vote share of each contest in the excluded election. Next, the uniform swing assumption is that a percentage point change in the two-party statewide vote share will cause the same percentage point change within each district. To generate predictions using this method, I aggregate votes in each contest in the included elections according to the district of interest. I then shift the district's vote shares in the included contests based on the uniform swing assumption and average over them. Finally, I calculate the values of this average at the statewide 2-party vote shares for the contests in the excluded election. Last, the Geruso, Spears, and Talesara (2019) approach involves constructing counterfactual elections using only data on aggregate vote shares. To implement this method, I regress precinct two-party vote shares in the excluded elections on (i) county fixed effects, (ii) contest fixed effects, and (iii) interactions of the year with precinct averages of exogenous covariates of registrants.[58] I then construct counterfactual elections using the procedure described in Section A2.3. Once I obtain the counterfactual elections, I generate predictions by fitting a local linear regression of a district's vote shares in the simulated contests on the contests' statewide vote shares, as I did for the paper's main method.

Results are presented in Table 17. They are shown separately for predicting outcomes in all years and for predicting just 2008 and 2018. In addition, they are shown both for outcomes that are based on "pseudo" contests, which control for changes in the demographic composition of the electorate, and for

57. For instance, to predict district vote shares in 2018, I use the simulations based on the 2008-2016 elections.
58. These covariates, $X_{it,0}$, are listed in Table A10.

those that are based on the actual contests, which don't.[59] The results indicate that all methods have strong predictive power and that my method performs the best. For the specification that does not adjust for changes in demographics, my method generates an R-squared of 0.976 and a mean absolute error of 1.6 percentage points, averaged over all years. For the uniform swing and Geruso, Spears, and Talesara (2019) methods, R-squared is 0.949 and 0.940 and mean absolute error is 2.4 and 2.6 percentage points, respectively. Results for the specification that adjusts for demographics are similar. Finally, results for predicting just 2008 and 2018 are slightly worse, but still highly accurate.[60]

Finally, in Figures A3-A5, I show graphically how district vote shares are expected to vary with state vote shares. Specifically, for each U.S. House district, I plot district and state two-party vote share for contests from simulations centered in 2010. Figure A3 presents districts from the 2002-2010 map, A4 shows them for the 2012-2014 map, and A5 is for the 2016-2018 map. The plots include a line of best fit, as well as district vote shares for actual and pseudo 2008-2018 contests.[61] The plots show that the best fit line explains much of the variation in district vote shares, illustrating how my method has strong predictive power. Further, if the uniform swing assumption were accurate, then the best-fit lines would all have slopes of 1. It can be seen that this is not the case. However, for a number of districts, it is not far off.

7 Conclusion

This paper introduced a new method for measuring gerrymandering. The method is distinct from the prior literature in relying on a structural model of voting behavior. The model recovers estimates of individuals' preferences and turnout costs and can incorporate information from different forms of data. In addition to providing the model, the paper developed a simulation procedure that captures uncertainty in gerrymandering outcomes that results from electoral shocks to preferences and turnout costs. One can additionally account for uncertainty due to changes in demographics by manually altering the characteristics of the sample of potential voters. In the paper, the method is applied to North Carolina. With minor modifications to account for institutional differences, it can be applied to other states as well. Doing this would have real-world benefits, as maps are set to be redrawn in 2021.

The model has uses beyond measuring gerrymandering. By recovering preferences for the entire electorate, it can be useful for understanding the effects on vote outcomes of changes in voting conditions. For instance, in North Carolina, it would be interesting to understand how natural disasters, such as hurricanes, change the composition of the voter sample and thus influence vote outcomes. Similarly, one can use the estimates to examine how changes in turnout costs, such as expansions or contractions in early voting, influence vote outcomes. Next, since the model generates longitudinal predictions of individuals' preferences and turnout costs, it can be useful for understanding how external shocks affect these parameters. Finally, the results in the paper can be used to classify the competitiveness

59. See Section 6.1 for a complete discussion.

60. E.g., R-squared of 0.965 and mean absolute error of 1.9 percentage points for my method in the specification that does not adjust for demographics.

61. The pseudo 2008-2018 contests combine the 2008-2018 model coefficients with the 2010 electorate.

of individual districts. In other work, I am using these features to examine effects on turnout and preferences of being redistricted into legislative districts of varying competitiveness.

Tables and Figures

Table 1: Summary statistics for registrants, survey respondents, and precincts

	2008	**2010**	**2012**	**2014**	**2016**	**2018**
A. Registrants						
1. Registration						
Voting-age (≥ 18) population	6,982,283	7,292,935	7,469,158	7,650,810	7,863,122	8,082,975
Number of registrants	6,318,345	6,255,853	6,700,603	6,660,255	6,971,628	7,147,553
Registrants as a share of voting-age population	0.90	0.86	0.90	0.87	0.89	0.88
2. Turnout						
Voters as a share of registrants	0.69	0.43	0.68	0.44	0.68	0.53
3. Demographics						
Race/ethnicity shares						
White	0.73	0.73	0.71	0.71	0.69	0.68
Black	0.22	0.22	0.23	0.23	0.23	0.22
Other	0.05	0.05	0.06	0.07	0.08	0.09
Share female	0.55	0.55	0.55	0.55	0.55	0.55
Age						
Mean	47.1	48.0	47.7	48.3	48.3	48.8
Share 18 to 30	0.21	0.20	0.21	0.21	0.22	0.21
Share 60 and over	0.25	0.26	0.27	0.28	0.29	0.30
Party registration shares						
Democrat	0.46	0.44	0.43	0.42	0.39	0.38
Republican	0.32	0.32	0.31	0.31	0.31	0.30
Other/unaffiliated	0.23	0.24	0.26	0.28	0.30	0.32
Mean of parcel value per registrant ($)	74,504	75,012	75,658	77,172	80,630	83,423
4. Means of block and block group characteristics						
Population density in block (pop. / sq. km)	1,070	1,009	1,160	1,180	1,214	1,201
Household median income in block group (2010 $)	51,787	50,171	48,721	50,117	51,330	51,763
Share college graduates in block group	0.28	0.28	0.29	0.30	0.31	0.32
5. Means of cost instruments						
Distance to closest early-voting location (km)	5.71	6.50	5.58	5.76	5.00	6.16
Election-day precipitation (mm)	7.87	0.00	0.00	0.14	0.00	4.27
B. Survey respondents						
Number of respondents	941	1,556	1,704	1,743	2,004	1,813
Number of registered respondents	829	1,380	1,522	1,513	1,678	1,521
Registered respondents as a share of respondents	0.88	0.89	0.89	0.87	0.84	0.84
Voters as a share of registered respondents	0.83	0.64	0.74	0.52	0.68	0.63
Avg. number of registrant matches per registered respondent	9.7	10.3	8.2	10.6	7.8	9.9
C. Precincts						
Number of precincts	2,692	2,692	2,692	2,692	2,704	2,729
Median number of registrants per precinct	2,800	2,758	2,995	2,972	3,111	3,206

Notes: The table presents summary statistics for registrants, survey respondents, and precincts by year. The sample includes allocated values. Data on registrants is based on the 2008-2018 NC voter files, the NC One Map property database, U.S. Census data, and PRISM climate data. Counts for the voting-age population for 2010-2018 are from the 2018 Annual Estimates of the Resident Population, PEPAGESEX. Counts for 2008 are from the 2008 ACS 1-year estimates. The variable "parcel value per registrant" is the value of the property parcel associated with the registrant's address divided by the average number of registrants living on the parcel during 2008-2018. Parcel values are in dollars; however, due to constraints in the underlying data, the exact year of denomination is unknown. In addition, as a result of the skewness of parcel values, this variable is winsorized at the 1st and 99th percentiles. Data on survey respondents is from the CCES. "Number of respondents" presents the total number of survey respondents in North Carolina for the given election. "Number of registered respondents" lists the number of respondents who were matched by the CCES enumerators to observations in the Catalist voter file. I subsequently merged registered respondents to the North Carolina voter file using covariates that overlap in the two datasets. "Avg. number of registrant matches per registered respondent" captures the number of potential North Carolina registrants matched to each registered survey respondent. Finally, the "Median number of registrants per precinct" is weighted by registrant. See text and the data appendix for additional notes and variable descriptions.

Table 2: Summary statistics for vote shares in partisan contests

Contest	2008			2010			2012			2014			2016			2018		
	Dem.	*Rep.*	*Abstain*	*Dem.*	*Rep.*	*Abstain*	*Dem.*	*Rep.*	*Abstain*	*Dem.*	*Rep.*	*Abstain*	*Dem.*	*Rep.*	*Abstain*	*Dem.*	*Rep.*	*Abstain*
A. Contests in the model																		
US President	0.49	0.49	0.02	-	-	-	0.48	0.50	0.02	-	-	-	0.46	0.49	0.05	-	-	-
US Senate	0.52	0.43	0.05	0.42	0.54	0.04	-	-	-	0.47	0.48	0.05	0.45	0.50	0.05	-	-	-
US House Of Representatives	0.53	0.44	0.04	0.45	0.53	0.02	0.49	0.47	0.04	0.42	0.53	0.05	0.45	0.51	0.04	0.47	0.49	0.04
NC Governor	0.49	0.46	0.05	-	-	-	0.42	0.54	0.04	-	-	-	0.48	0.48	0.03	-	-	-
NC Supreme Court Associate Justice	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.48	0.49	0.03
Avg. of NC Attorney Gen. and NC Sec. of State	0.56	0.39	0.05	-	-	-	0.51	0.44	0.05	-	-	-	0.49	0.47	0.05	-	-	-
Avg. of other NC state-level contests	0.48	0.45	0.07	-	-	-	0.48	0.46	0.05	-	-	-	0.44	0.49	0.07	0.48	0.48	0.04
B. Summary statistics																		
All contests																		
Mean	0.50	0.44	0.06	0.43	0.54	0.03	0.48	0.47	0.05	0.44	0.51	0.05	0.45	0.49	0.06	0.48	0.48	0.04
Standard deviation	0.03	0.03	0.02	0.02	0.00	0.01	0.03	0.04	0.01	0.03	0.03	0.00	0.02	0.02	0.02	0.01	0.02	0.02
Contests in the model																		
Mean	0.51	0.44	0.05	0.43	0.54	0.03	0.48	0.48	0.04	0.44	0.51	0.05	0.46	0.49	0.05	0.48	0.49	0.04
Standard deviation	0.03	0.03	0.02	0.02	0.00	0.01	0.03	0.04	0.01	0.03	0.03	0.00	0.02	0.02	0.01	0.01	0.01	0.01

Notes: The table presents summary statistics on statewide vote shares in partisan contests. Panel *A* lists the shares for the contests used in the model, some of which are averages of multiple contests. Panel *B* shows the mean and standard deviation separately for all contests and for those used in the model. Vote shares are listed individually for all contests in Table A1. *Abstain* includes votes for third-party candidates.

Table 3: Seat shares in North Carolina legislative chambers

	2008	**2010**	**2012**	**2014**	**2016**	**2018**
A. Mean two-party Republican vote shares						
All contests	0.47	0.55	0.50	0.53	0.52	0.50
Contests in explanatory model	0.46	0.55	0.50	0.53	0.52	0.50
B. Two-party Republican seat shares						
US House Of Representatives	0.38	0.46	0.69	0.77	0.77	0.77
NC Senate	0.40	0.62	0.66	0.68	0.70	0.58
NC House of Representatives	0.43	0.57	0.64	0.62	0.62	0.54

Notes: The table presents (i) two-party statewide vote shares and (ii) seat shares for Republicans by election. During 2008-2018, every legislative seat was held by a Democrat or a Republican.

Table 4: Out-of-sample R-sq from predicting vote shares using precinct and question effects

Specification	**2008**	**2010**	**2012**	**2014**	**2016**	**2018**
Precinct-party fixed effects	0.881	0.882	0.933	0.954	0.976	0.990
Precinct-party and question-party fixed effects	0.943	0.931	0.980	0.980	0.988	0.995

Notes: The table presents out-of-sample R-squared values from predicting precinct vote shares using precinct and question effects. Specifically, I predict precinct h's vote share for party $j \in \{D, R\}$ on question q' using either (i) the average of h's shares for j on other contests in the election, $\frac{1}{Q-1}\sum_{q \neq q'} v_{htqj}$, or (ii) the sum of (i) and the difference between the statewide shares for j on q' and on other contests, $v_{tq'j} - \frac{1}{Q-1}\sum_{q \neq q'} v_{tqj}$. Here, Q is the number of contests in the election and v_{htqj} and v_{tqj} are respectively the precinct and statewide vote shares for j on q. In calculating statewide shares, I remove votes from precinct h. To calculate question effects for district-level contests, I use district-wide, rather than statewide, shares. Finally, I calculate out-of-sample R-squared as $1 - \frac{\mathrm{Var}[v_{htqj} - \mathrm{V}^P_{htqj}]}{\mathrm{Var}[v_{htqj}]}$, where V^P_{htqj} is the predicted vote share. This approach is an out-of-sample version of a regression using precinct-party and question-party fixed effects.

Table 5: Covariates included in the model

A. Demographics and party
Race: black
Race: other non-white
Registered Democrat
Registered Republican
Female
Age (years)
Age (years) times Democrat
Age (years) times Republican
White; Democrat; age 60 or over
Parcel value per registrant (20 groups)
B. Party changes
Democrat in t and Unaffil. (1) or Republican (2) in t-4 to t+4
Unaffil. in t and Democrat in t-4 to t+4
Unaffil. in t and Republican in t-4 to t+4
Republican in t and Unaffil. (1) or Democrat (2) in t-4 to t+4
C. Block and block group characteristics
Ln: population density in block (pop. / sq. km)
Ln: household median income in block group (2010 $)
Share college graduates in block group
D. Predicted turnout utility
Predicted turnout utility times non-white
Predicted turnout utility times white
Predicted turnout utility times lean Democratic
Predicted turnout utility times lean Republican
E. Interactions between registrant and precinct characteristics
High-education precinct
Non-white registrant times high-education precinct
Democrat times high-education precinct
Republican times high-education precinct
Age (years) times high-education precinct
F. Characteristics of registrants' NC House and NC Senate races
Average closeness
G. U.S. House district fixed effects
13 districts
H. Residualized cost variables
Ln: distance to nearest early-voting location / block length
Intensity of election-day rainfall (3 groups)

Notes: The table lists the covariates included in the model. Panels *A*-*G* represent the covariates in X_{it} and Panels *A*-*H* capture the covariates in Z_{it}. The dropped race category is white, and the dropped party registration category is unaffiliated. Precincts are classified as "high education" if the average share of college graduates in registrants' block groups is at least 0.25. The average closeness of a registrant's NC House and NC Senate races is calculated as the average of the natural log of the absolute vote share margin in those races.

Table 6: Coefficients for σ, α, and cost instruments

	2008		2010		2012		2014		2016		2018	
	Coef.	*Std. err.*	*Coef.*	*Std. err.*	*Coef.*	*Std. err.*	*Coef.*	*Std. err.*	*Coef.*	*Std. err.*	*Coef.*	*Std. err.*
A. Ln: standard deviation of e_{it}: $\ln(\sigma_t)$	0.162	0.079	1.341	0.224	0.755	0.078	1.543	0.057	0.877	0.052	2.015	0.074
B. Selection: α_t	0.031	0.005	0.043	0.009	0.023	0.004	0.016	0.004	0.019	0.002	0.006	0.002
C. Cost instruments												
Ln: distance to nearest early-voting location / block length	-0.023	0.009	-0.041	0.019	-0.026	0.009	-0.016	0.012	-0.019	0.009	-0.024	0.011
Intensity of election-day rainfall (3 groups)	-0.039	0.015	-	-	-	-	-	-	-	-	-0.001	0.017

Notes: The table shows selected model coefficients. Standard errors are clustered by North Carolina's 100 counties. There are no coefficients for rainfall intensity in 2010-2016 because there were only trace amounts of election-day rainfall in those years.

Table 7: The magnitude of selection

	2008	2010	2012	2014	2016	2018
The 95-5 difference in turnout probabilities, TO_{it}	0.958	0.982	0.981	0.985	0.938	0.973
The effect of expected utility, EU_{it}, on TO_{it}						
Mean	0.054	0.062	0.046	0.025	0.050	0.031
10th percentile	0.003	0.003	0.001	0.001	0.002	0.003
90th percentile	0.135	0.132	0.117	0.055	0.118	0.057

Notes: The table presents results related to the magnitude of selection. The first row shows the difference between the 95th and 5th percentiles of the distribution of turnout probabilities, TO_{it}, by election. The remaining rows present summary statistics related to the effect of expected utility, EU_{it}, on the probability of turning out. Specifically, I calculate the increase in a registrant's probability of turning out due to shifting the registrant's expected utility from the 5th to the 95th percentile of the election's expected utility distribution, while holding the registrant's costs, $c_{Z,t}$, constant. The table presents the mean, the 10th percentile, and the 90th percentile of this distribution across registrants.

Table 8: The effects of selection on unobserved partisanship, e_{it}

	2008	2010	2012	2014	2016	2018
Panel A: The effect of unobserved partisanship, e_{it}, on turnout, TO_{it}						
Mean	0.021	0.050	0.028	0.023	0.036	0.026
10th percentile	0.001	0.002	0.001	0.001	0.001	0.003
90th percentile	0.053	0.119	0.076	0.054	0.092	0.056
Panel B: The effect of selection on e_{it} on abstaining, P_{itqA}						
Mean	0.001	0.004	0.002	0.002	0.003	0.002
10th percentile	0.000	0.001	0.001	0.001	0.001	0.000
90th percentile	0.002	0.009	0.005	0.005	0.006	0.004
Panel C: The absolute effect of selection on e_{it} on preferring R to D						
Mean	0.005	0.009	0.008	0.005	0.009	0.004
10th percentile	0.002	0.003	0.002	0.002	0.003	0.001
90th percentile	0.008	0.016	0.012	0.007	0.013	0.007

Notes: The table presents results related to the effects of selection on unobserved partisanship, e_{it}. Panel *A* shows the effect of e_{it} on registrants' turnout probabilities, TO_{it}. For each registrant, I calculate turnout probabilities over a grid of e_{it} values between -1.96 and 1.96 (corresponding to the 2.5 and 97.5 percentiles of the standard normal distribution). I then calculate the difference between the maximum and minimum of these probabilities. The values in the table are summary statistics for this difference over all registrants in the election. Panels *B* and *C* show the effect of selection on e_{it} on preference probabilities. To obtain the values in Panel *B*, I calculate the decrease in a registrant's conditional-on-observables probability of abstaining if the registrant were to turn out rather than stay home. The panel presents summary statistics for the average of this value over each question in a registrant's bundle, $\mathcal{Q}_{it}$. Panel *C* presents similar results but for the absolute value of the difference in the probability that a registrant prefers the Republican to the Democratic candidate. See Section 4.2 for a more detailed discussion.

Table 9: Out-of-sample prediction quality for turnout and vote data

	2008	**2010**	**2012**	**2014**	**2016**	**2018**
A. Turnout						
1. Individual choices						
Classification rate	0.869	0.840	0.866	0.843	0.853	0.808
2. Precinct-level shares						
R-squared	0.915	0.933	0.961	0.935	0.964	0.909
Mean absolute error	0.011	0.017	0.010	0.016	0.011	0.018
B. Votes conditional on turnout						
1. Precinct-level shares						
R-squared	0.939	0.965	0.960	0.963	0.962	0.973
Mean absolute error	0.034	0.029	0.029	0.028	0.029	0.027
2. State-level shares						
Mean absolute error	0.001	0.002	0.001	0.001	0.002	0.002
C. Votes unconditional on turnout						
1. Precinct-level shares						
R-squared	0.939	0.963	0.959	0.960	0.961	0.970
Mean absolute error	0.035	0.030	0.030	0.030	0.029	0.028
2. State-level shares						
Mean absolute error	0.001	0.002	0.001	0.001	0.002	0.003

Notes: The table summarizes measures of out-of-sample prediction quality for turnout and vote data. The values are calculated in a two-step process. First, the model is fit on a random sample of two-thirds of the precincts. Second, predictions are created for the excluded precincts and compared with observed outcomes. In Panel *B*, vote share predictions use information on the voter sample in the excluded precincts. In Panel *C*, they do not. Results for precinct-level shares are weighted by the number of registrants in the precinct. "State-level shares" refer to the aggregate shares for all excluded precincts.

Table 10: Prediction quality for preference choices in survey data

Group	**All respondents**	**Voters**	**Non-voters**
All	0.78	0.81	0.73
Race			
Black	0.87	0.91	0.82
Other	0.74	0.76	0.70
White	0.76	0.78	0.71
Age			
18-30	0.76	0.78	0.71
31-59	0.78	0.83	0.73
60+	0.79	0.81	0.75
Party	0.77	0.79	0.68
Democrat	0.78	0.79	0.75
Republican	0.88	0.90	0.83
Unaffiliated	0.69	0.71	0.65

Notes: The table shows classification rates for preference choices in survey data. These are shown separately by demographic group and turnout status. The values include observations in all years. Predictions are calculated in three steps. First, preference probabilities are predicted for each potential registrant match. These are then averaged by survey respondent. Finally, they are rounded to 0 or 1.

Table 11: Selection using within-registrant variation

Regression	Coef.	Std. err.
All exogenous covariates, Z_{it0}		
All elections	0.024	0.001
Presidential elections	0.087	0.002
Midterm elections	-0.001	0.003
Only year effects		
All elections	0.022	0.001
Presidential elections	0.075	0.002
Midterm elections	0.006	0.003

Notes: The table presents selection coefficients from the individual fixed effects regressions. Specifically, it shows α_W coefficients from equation (11). The coefficients in Panel A are for regressions with all the exogenous covariates, as specified in (11). The coefficients in Panel B are for regressions with only indicators for the year. Regressions are shown separately for samples using (i) all elections, (ii) only presidential elections, and (iii) only midterm elections. These regressions have registrant-year sample sizes of $40,054,237$, $19,990,576$, and $20,063,661$, respectively. Standard errors are clustered by North Carolina's 100 counties.

Table 12: The credibility of seats-votes curves

Specification	N	Prediction interval		
		80%	*90%*	*95%*
Panel A: Seats-votes combinations				
All years				
Electoral shocks	216	0.88	0.90	0.96
Electoral shocks and demographic changes	216	0.84	0.91	0.96
2008 and 2018				
Electoral shocks	81	0.81	0.85	0.95
Electoral shocks and demographic changes	81	0.84	0.90	0.96
Panel B: District-minus-state 2-party vote shares				
All years				
Electoral shocks	13,176	0.83	0.92	0.96
Electoral shocks and demographic changes	13,176	0.86	0.93	0.97
2008 and 2018				
Electoral shocks	4,941	0.83	0.90	0.94
Electoral shocks and demographic changes	4,941	0.84	0.90	0.94

Notes: The table presents tests of the credibility of seats-votes curves. The results are calculated by fitting the model and running the simulations using subsets of the 2008-2018 elections and obtaining prediction intervals for outcomes in excluded elections. The values represent the share of outcomes in the excluded elections that fall within the listed prediction intervals. The outcome in Panel A is the Republican seat share conditional on the statewide two-party vote share. The outcome in Panel B is the difference between district and state two-party vote shares. The outcomes are calculated by taking contests in an excluded election and aggregating their votes according to the districts of a particular legislative map. This is done for each of the 2008-2018 elections. The legislative maps considered are those that have been used in North Carolina since 2010; these maps are listed in Tables 13-15. Thus, an observation in Panel A is the unique combination of a contest and map, while one in Panel B is that of a contest, map, and district. Results are weighted equally by legislative chamber.

Prediction intervals are calculated using information from all elections except the excluded election. For instance, to obtain prediction intervals for outcomes in 2018, I construct simulated elections using information from 2008-2016. I center the simulations in the election nearest to the excluded election. For example, to predict 2018, I use the 2016 electorate and set the mean of electoral shocks equal to the 2016 model coefficients. (For predicting 2010-2018, I center the simulations at the election before the excluded election. For predicting 2008, I center the simulations at the election after the excluded election.) Finally, I set the number of contests in the simulated elections equal to the number in the excluded election. For instance, to predict 2018, I use $Q = 3$. For each contest in a simulated election, I calculate the given outcome. I then obtain prediction intervals by calculating the appropriate range of outcomes over the simulations. (For predicting seats-votes combinations, I do this using a local quantile regression.)

Results are summarized for predicting all elections and for predicting just 2008 and 2018. Results are also presented separately for categories termed "Electoral shocks" and "Electoral shocks and demographic changes". The outcomes in the "Electoral shocks" rows allow for variation in excluded elections due to electoral shocks, while those in "Electoral shocks and demographic changes" additionally include variation due to changes in the demographic composition of the electorate. The outcomes in the "Electoral shocks" rows are calculated using votes from "pseudo" contests that combine the model coefficients from the excluded elections with the electorate from the year in which the simulations are centered. The outcomes in the "Electoral shocks and demographic changes" rows are calculated using the votes for the actual contests in the excluded elections.

Table 13: Map proportionality: Historical U.S. House districts

Measure	'02-'10 Districts			'12-'14 Districts			'16-'18 Districts		
	Mean	*LB*	*UB*	*Mean*	*LB*	*UB*	*Mean*	*LB*	*UB*
Panel A: R seat share at R 2-party vote share of 0.5									
2010 simulation	0.53	0.45	0.62	0.74	0.60	0.77	0.73	0.61	0.77
2016 simulation	0.53	0.45	0.62	0.70	0.61	0.77	0.74	0.61	0.77
Panel B: R seat share avg'd over R 2-party vote share in 0.45 to 0.55									
2010 simulation	0.52	0.44	0.62	0.70	0.58	0.76	0.65	0.53	0.74
2016 simulation	0.53	0.45	0.61	0.68	0.55	0.77	0.68	0.58	0.74
Panel C: R 2-party vote share at R seat share of 0.5									
2010 simulation	0.49	0.47	0.52	0.46	0.44	0.48	0.47	0.45	0.49
2016 simulation	0.49	0.46	0.51	0.45	0.43	0.48	0.46	0.44	0.48

Notes: The table show summary statistics related to proportionality for recently used U.S. House maps in North Carolina. Each set of columns represents the map used during the listed time period. "Mean", "LB", and "UB" are respectively the mean, 2.5 percentile, and 97.5 percentile of the given quantity over the simulated elections. These values are calculated using the local linear and local quantile regressions presented in Figure 12. R is an abbreviation for Republican.

Table 14: Map proportionality: Historical NC Senate districts

Measure	'04-'10 Districts			'12-'16 Districts			'18 Districts		
	Mean	*LB*	*UB*	*Mean*	*LB*	*UB*	*Mean*	*LB*	*UB*
Panel A: R seat share at R 2-party vote share of 0.5									
2010 simulation	0.55	0.49	0.60	0.64	0.57	0.68	0.58	0.49	0.64
2016 simulation	0.55	0.52	0.59	0.60	0.55	0.67	0.57	0.52	0.63
Panel B: R seat share avg'd over R 2-party vote share in 0.45 to 0.55									
2010 simulation	0.54	0.47	0.59	0.61	0.55	0.66	0.57	0.49	0.63
2016 simulation	0.55	0.51	0.59	0.60	0.54	0.66	0.57	0.51	0.63
Panel C: R 2-party vote share at R seat share of 0.5									
2010 simulation	0.48	0.46	0.50	0.46	0.44	0.48	0.47	0.46	0.50
2016 simulation	0.47	0.45	0.49	0.45	0.44	0.48	0.47	0.45	0.49

Notes: The table show summary statistics related to proportionality for recently used NC Senate maps. See the notes to Table 13 for additional details.

Table 15: Map proportionality: Historical NC House districts

Measure	'10 Districts			'12-'16 Districts			'18 Districts		
	Mean	*LB*	*UB*	*Mean*	*LB*	*UB*	*Mean*	*LB*	*UB*
Panel A: R seat share at R 2-party vote share of 0.5									
2010 simulation	0.54	0.49	0.58	0.63	0.55	0.67	0.57	0.51	0.61
2016 simulation	0.54	0.51	0.58	0.60	0.53	0.66	0.58	0.53	0.63
Panel B: R seat share avg'd over R 2-party vote share in 0.45 to 0.55									
2010 simulation	0.53	0.48	0.57	0.61	0.53	0.65	0.56	0.50	0.60
2016 simulation	0.54	0.50	0.58	0.59	0.52	0.65	0.57	0.52	0.61
Panel C: R 2-party vote share at R seat share of 0.5									
2010 simulation	0.49	0.47	0.50	0.46	0.45	0.49	0.47	0.46	0.50
2016 simulation	0.48	0.46	0.50	0.46	0.45	0.49	0.47	0.45	0.48

Notes: The table show summary statistics related to proportionality for recently used NC House maps. See the notes to Table 13 for additional details.

Table 16: Map proportionality: Automated U.S. House districts

Measure	Power diagrams			Isoperim. quotient		
	Mean	*LB*	*UB*	*Mean*	*LB*	*UB*
R seat share at R 2-party vote share of 0.5	0.51	0.39	0.62	0.56	0.44	0.68
R seat share avg'd over R 2-party vote share in 0.45 to 0.55	0.50	0.39	0.60	0.53	0.41	0.63
R 2-party vote share at R seat share of 0.5	0.50	0.48	0.52	0.49	0.48	0.51

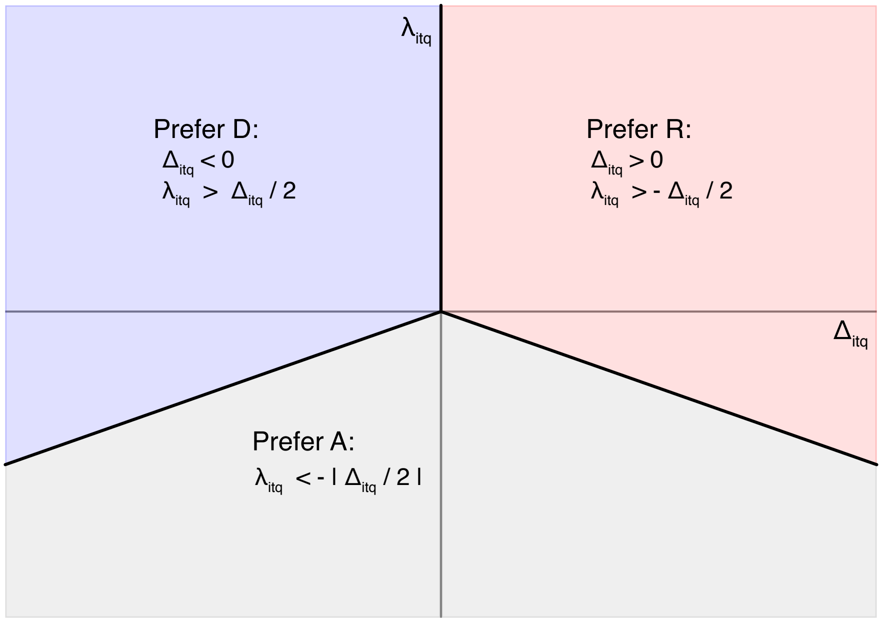
Notes: The table show summary statistics related to proportionality for U.S. House maps constructed using the algorithm of Saxon (n.d.). "Mean", "LB", and "UB" are respectively the mean, 2.5 percentile, and 97.5 percentile of the given quantity over the simulated elections. These values are calculated using the local linear and local quantile regressions presented in Figure 17. Results are calculated using simulations centered in 2010. *R* is an abbreviation for Republican.

Table 17: Prediction quality for alternative approaches to measuring gerrymandering

Method	N	Mean abs. error	R-squared
Panel A: Main method			
All years			
Electoral shocks	13,176	0.017	0.973
Electoral shocks and demographic changes	13,176	0.016	0.976
2008 and 2018			
Electoral shocks	4,941	0.022	0.953
Electoral shocks and demographic changes	4,941	0.019	0.965
Panel B: Uniform swing assumption			
All years			
Electoral shocks	13,176	0.024	0.953
Electoral shocks and demographic changes	13,176	0.024	0.949
2008 and 2018			
Electoral shocks	4,941	0.034	0.914
Electoral shocks and demographic changes	4,941	0.034	0.907
Panel C: Geruso et al. (2019)			
All years			
Electoral shocks	13,176	0.026	0.941
Electoral shocks and demographic changes	13,176	0.026	0.940
2008 and 2018			
Electoral shocks	4,941	0.032	0.912
Electoral shocks and demographic changes	4,941	0.033	0.908

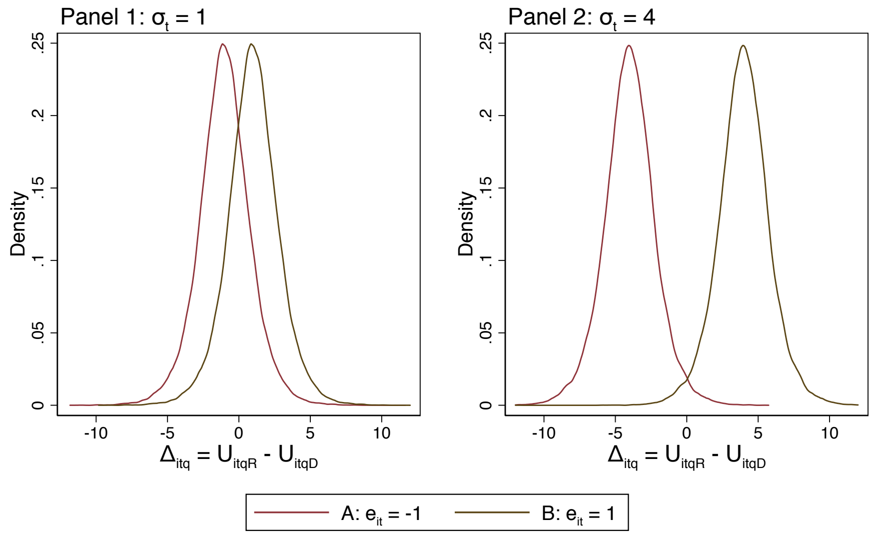
Notes: The table presents mean absolute error and R-squared for predicting district two-party vote shares in excluded elections conditional on knowing the statewide two-party vote share. "Main method" refers to the simulation procedure developed in the present paper. "Uniform swing assumption" and "Geruso et al. (2019)" are alternative approaches to measuring gerrymandering. See Section 6.4 for a discussion of how I obtained predictions. See the notes to Table 12 for the definition of each specification.

Figure 1: Preferences on question q



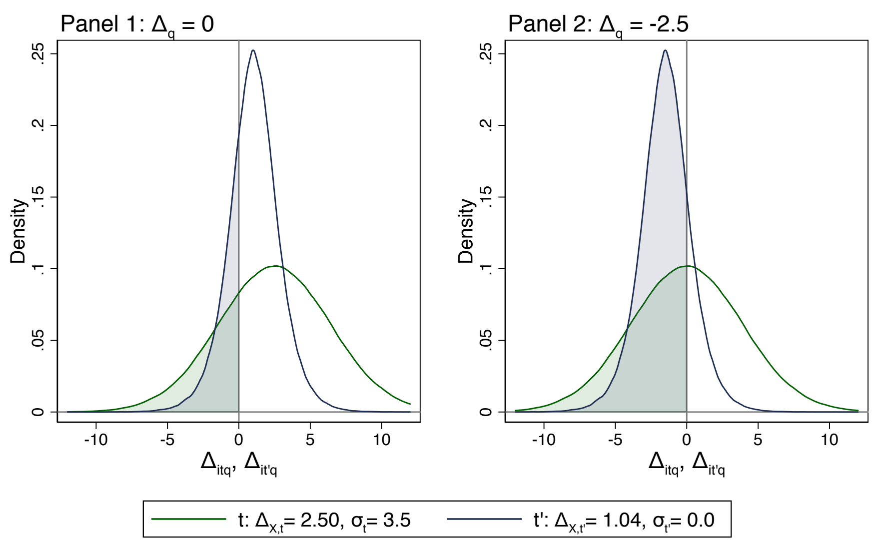
Notes: The figure illustrates registrants' preference choices in relation to their efficacy, λ_{itq}, and partisanship, Δ_{itq}, parameter values. The solid black lines represent parameter values at which individuals are indifferent between two alternatives. The inequalities define the parameter values that imply the given preference.

Figure 2: The effect of σ_t on the density of Δ_{itq} for registrants with the same X_{it}



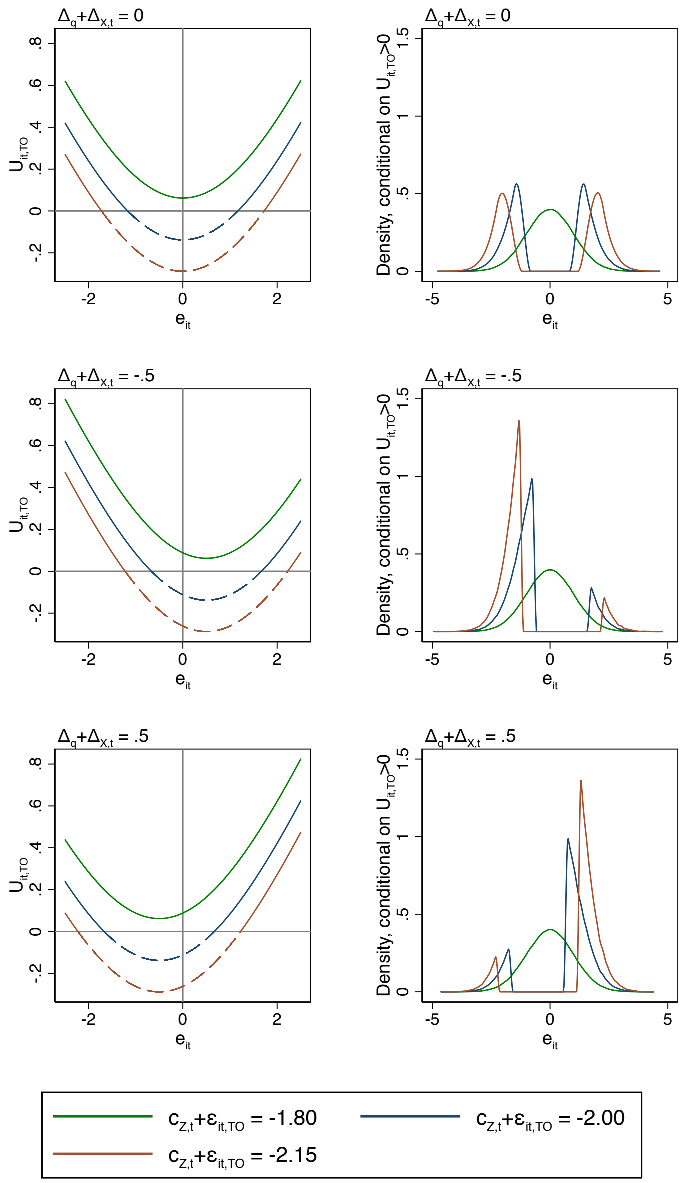
Notes: The figure shows the density of possible $\Delta_{itq} = \Delta_q + \Delta_{X,t} + \sigma_t \cdot e_{it} + \epsilon_{itq,\Delta}$ values for two registrants, A and B, with $X_{At} = X_{Bt}$ and $e_{At} < e_{Bt}$. The values are for a question with $\Delta_q + \Delta_{X,t} = 0$ and in which $\epsilon_{itq,\Delta}$ has not been realized. Panel 1 shows the densities under $\sigma_t = 1$, and Panel B shows them under $\sigma_t = 4$. The figure shows that when σ_t is larger, there is less overlap in Δ_{itq} realizations. That is, there is a higher probability that registrant B's preference for R is stronger than registrant A's.

Figure 3: The effect of σ_t on the scale of $\Delta_{X,t}$ and Δ_q



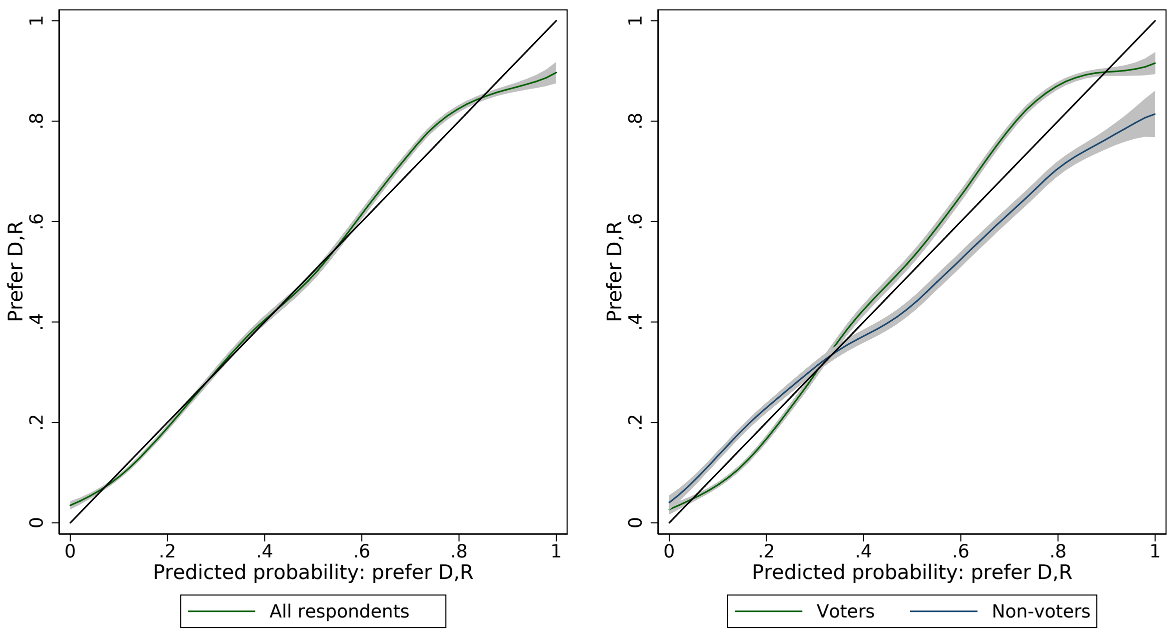
Notes: The figure shows the density of partisanship, Δ_{itq}, in elections t and t' for a group of registrants with the same covariates. The shaded areas indicate registrants who prefer D to R. Parameter values are chosen such that preference shares are the same in t and t' in Panel 1, under $\Delta_q = 0$. Given that $\sigma_t \neq \sigma_{t'}$, equality of preference shares requires that $\Delta_{X,t} \neq \Delta_{X,t'}$. Additionally, $\sigma_{t'} < \sigma_t$ implies that in t' a larger fraction of registrants switch to preferring D when the popularity of the Democrat increases by a given amount. This is seen in Panel 2, where $\Delta_q = -2.5$.

Figure 4: Selection on unobservables



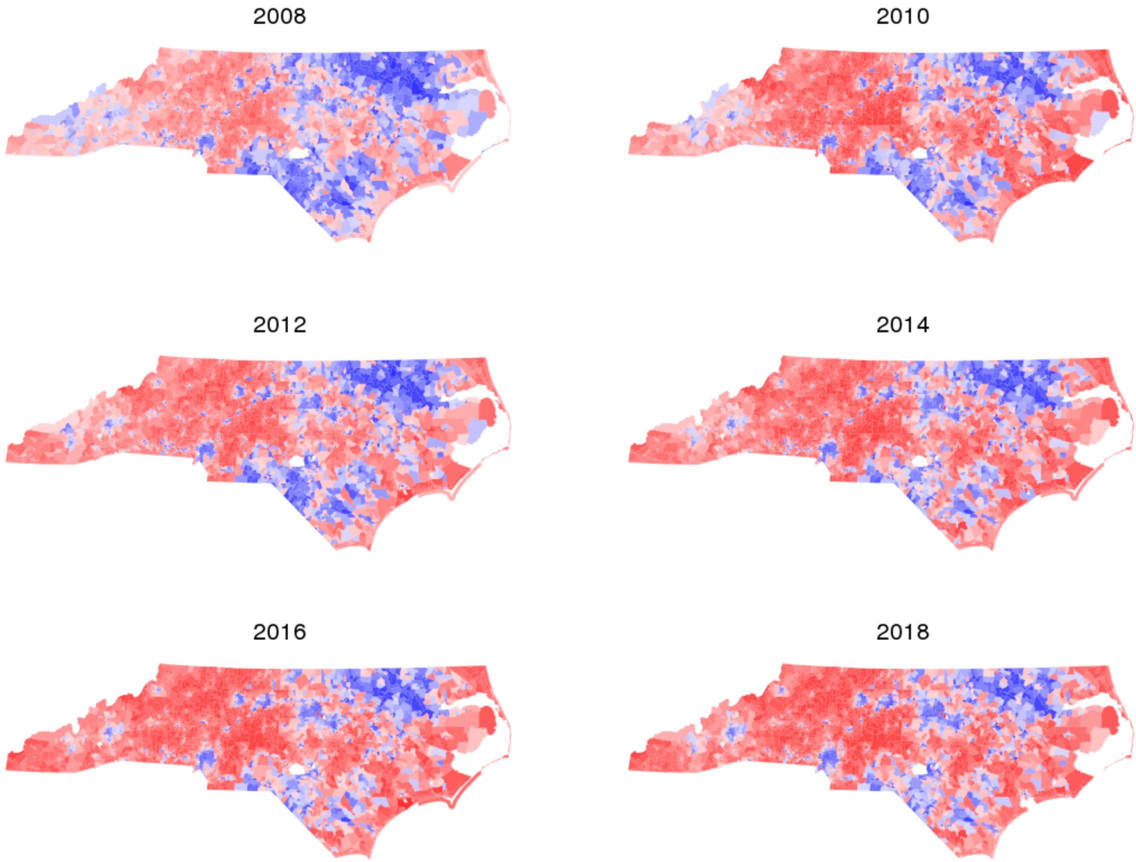
Notes: The figure illustrates selection for a hypothetical election with a single question. The plots are for registrants with $\alpha_t = 1$, $\sigma_t = 1$, and $\lambda_{X,t} + \lambda_q = 1$. The three rows of the figure represent different values of $\Delta_q + \Delta_{X,t}$, and the three lines in each plot represent different values of $c_{Z,t} + \epsilon_{it,TO}$. The dashed lines in the first column represent values of e_{it} for which registrants do not turn out. Selection on unobservables occurs when the distribution of e_{it} for voters differs from that for registrants.

Figure 5: Survey preference choices versus predicted preference probabilities



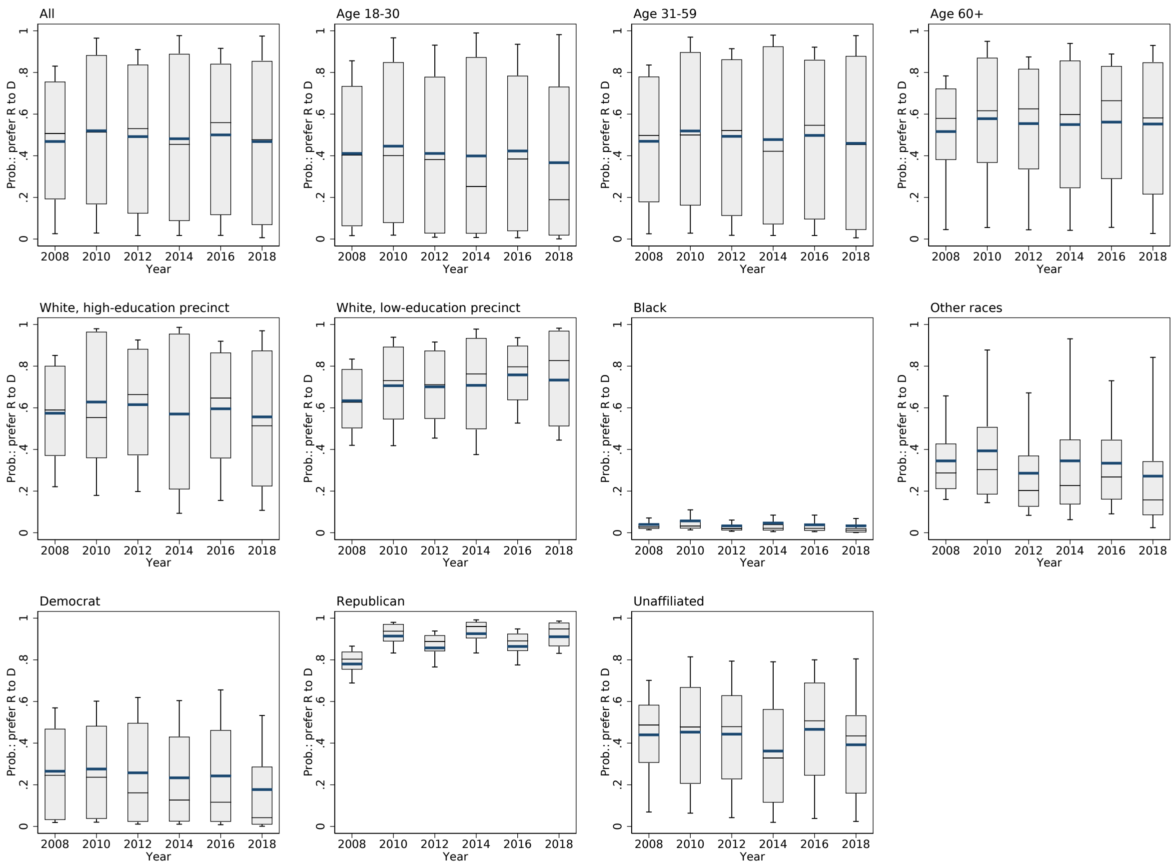
Notes: The figure shows local linear regressions of preference choices in survey data versus predicted preference probabilities. The regressions are shown for all survey respondents and separately for voters and non-voters. Predicted preference probabilities are calculated in two steps. First, predictions are obtained for each potential registrant match, and, second, they are averaged by survey respondent.

Figure 6: Predicted vote margins in block groups by election



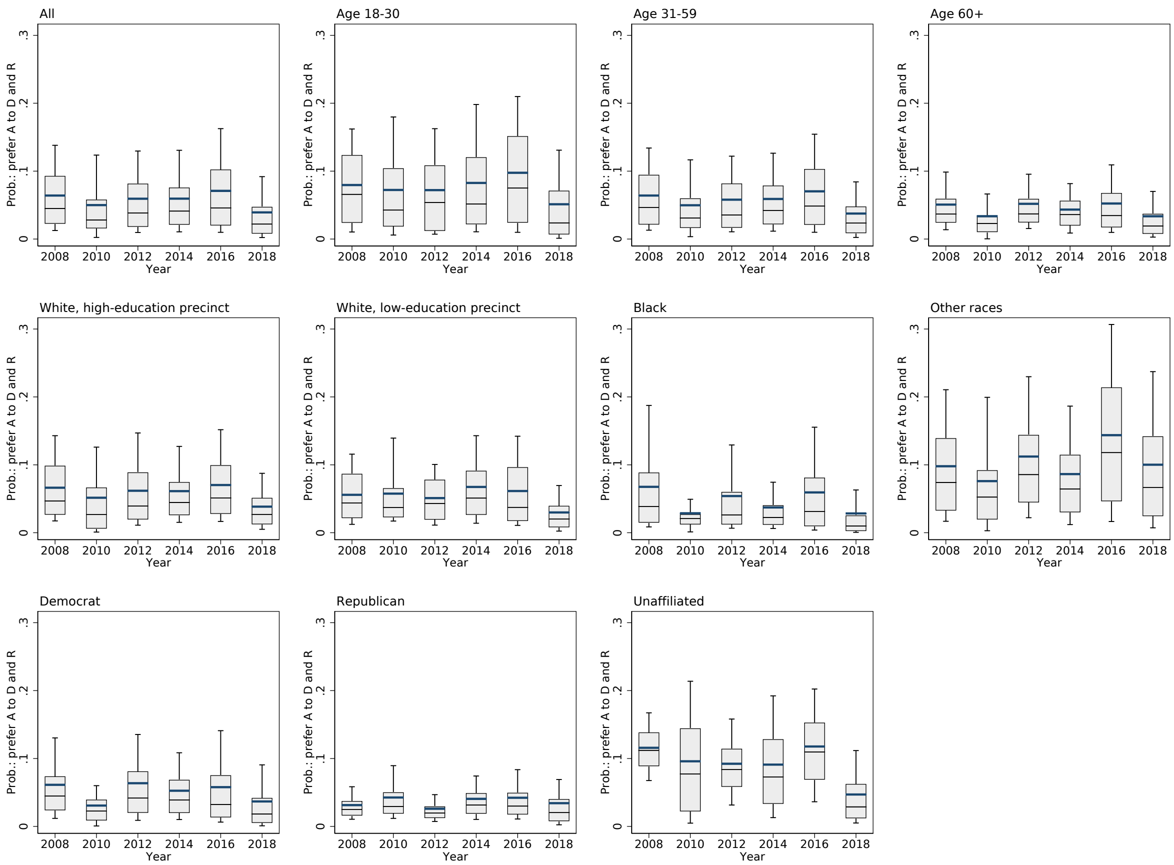
Notes: The map shows predicted vote margins by census block group for each of the 2008-2018 elections. The predicted vote margins are the average of those for all contests in the election: $\frac{1}{Q_t}\sum_q(\mathrm{P}_{btqR,\mathcal{T}} - \mathrm{P}_{btqD,\mathcal{T}})$, where $\mathrm{P}_{btqR,\mathcal{T}}$ is the predicted share of voters in block group b who prefer R to A and D on question q in election t. Block groups with predicted margins favoring Democrats are colored in blue, while those favoring Republicans are shaded red. The intensity of the color represents the magnitude of the predicted margin.

Figure 7: Probabilities of preferring R to D by election



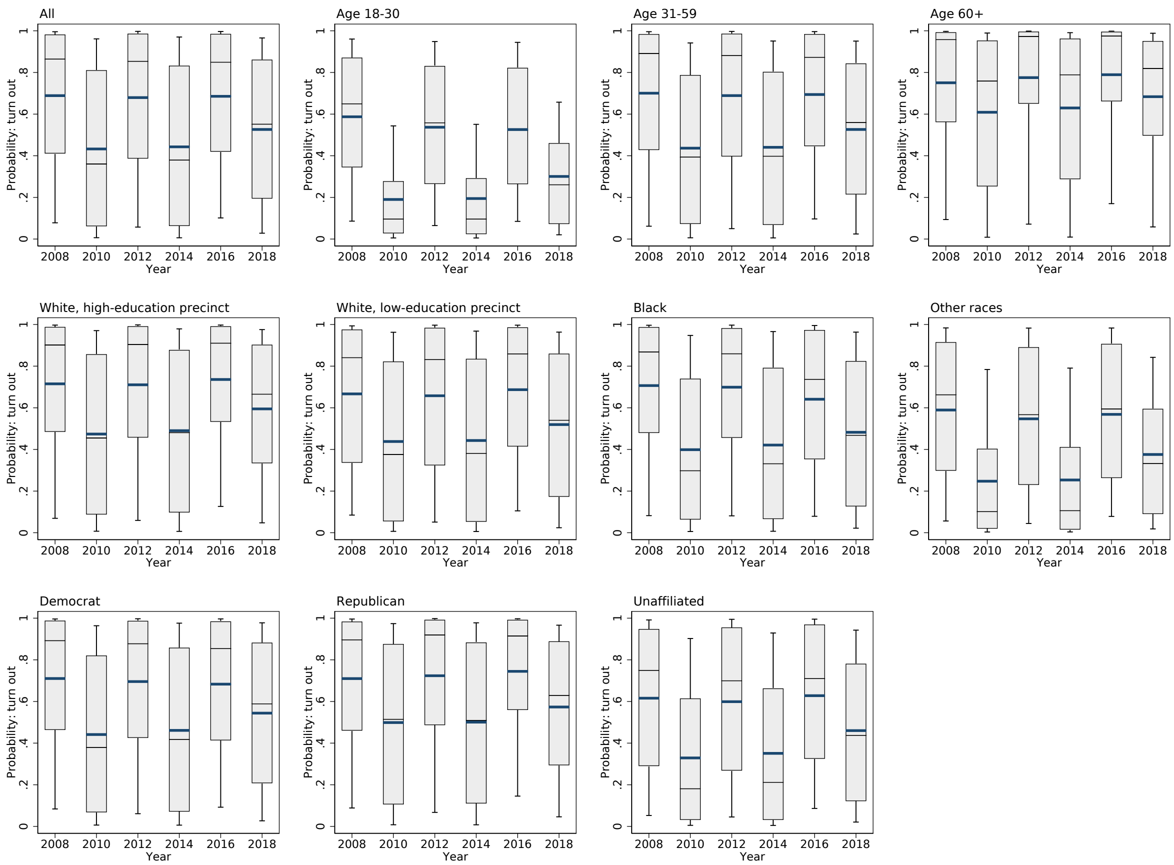
Notes: The figure presents distributions of registrants' predicted preference probabilities by election. Specifically, it shows distributions for the probability that registrant i prefers R to D over all contests in the election: $\frac{1}{Q_t}\sum_q \Pr[U_{itqR} > U_{itqD}|q, \mathcal{Q}_{it}, Z_{it}, to_{it}; \hat{\theta}_t]$. The sample includes all registrants. In the figure, the horizontal blue line represents the mean, the horizontal black line is the median, the box shows the 25th to 75th percentiles, and the vertical line displays the 10th to 90th percentiles.

Figure 8: Probabilities of preferring A to D and R by election



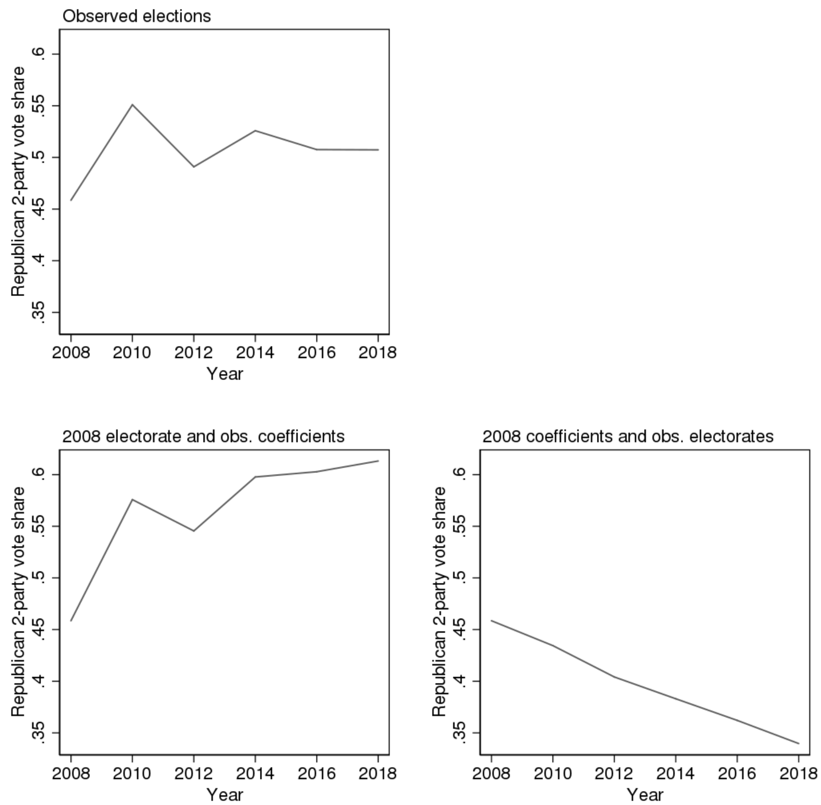
Notes: The figure presents distributions of registrants' predicted preference probabilities by election. Specifically, it shows distributions for the probability that registrant i prefers A to D and R over all contests in the election: $\frac{1}{Q_t}\sum_q \Pr[p_{itqA} = 1|q, \mathcal{Q}_{it}, Z_{it}, to_{it}; \hat{\theta}_t]$. The sample includes all registrants. In the figure, the horizontal blue line represents the mean, the horizontal black line is the median, the box shows the 25th to 75th percentiles, and the vertical line displays the 10th to 90th percentiles.

Figure 9: Probabilities of turning out by election



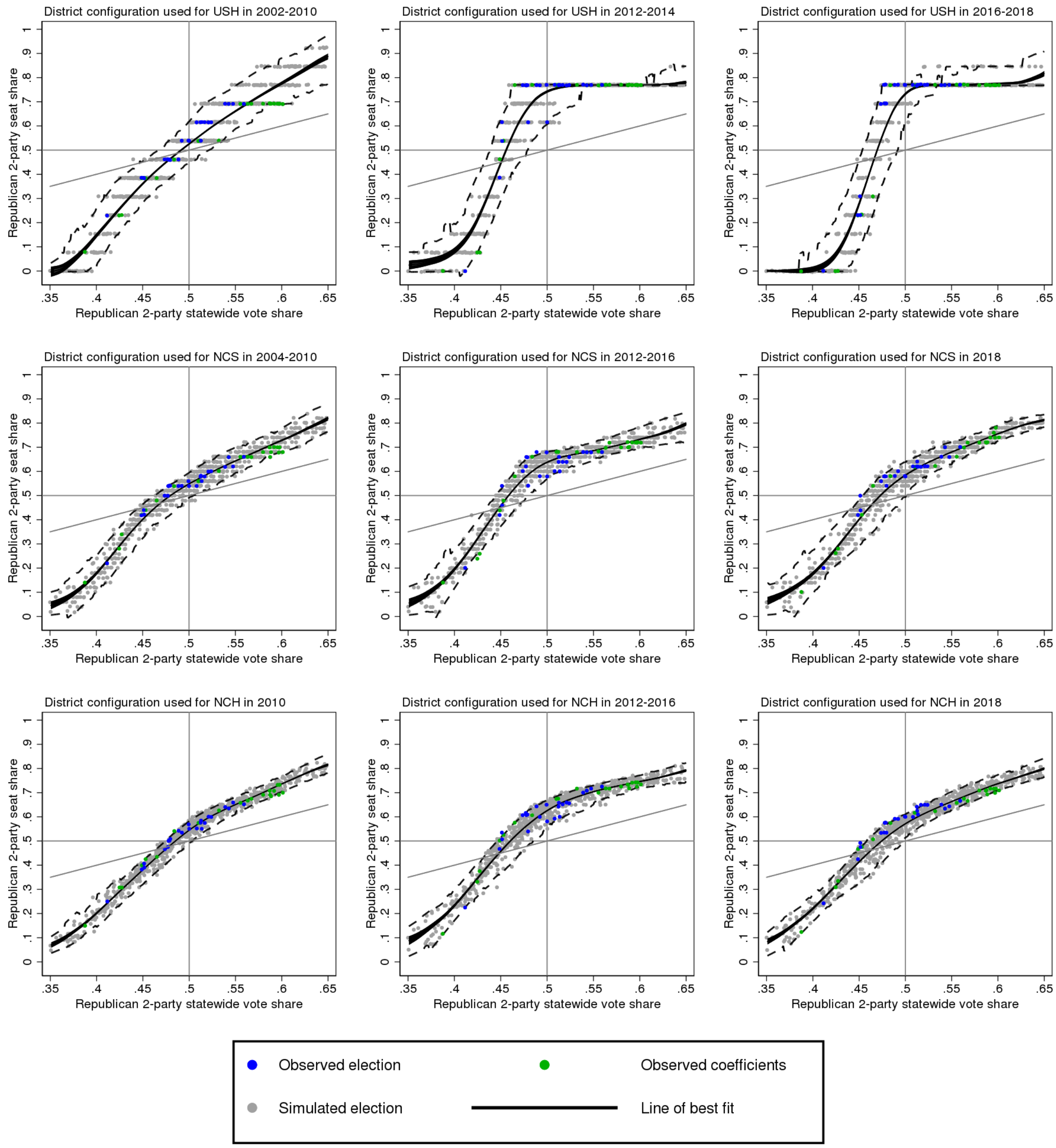
Notes: The figure presents distributions of registrants' turnout predicted probabilities by election. Specifically, it shows distributions for the $\Pr[to_{it} = 1|\mathcal{Q}_{it}, Z_{it}; \hat{\theta}_t]$. The sample includes all registrants. In the figure, the horizontal blue line represents the mean, the horizontal black line is the median, the box shows the 25th to 75th percentiles, and the vertical line displays the 10th to 90th percentiles.

Figure 10: The effects of holding demographics or utility parameters fixed



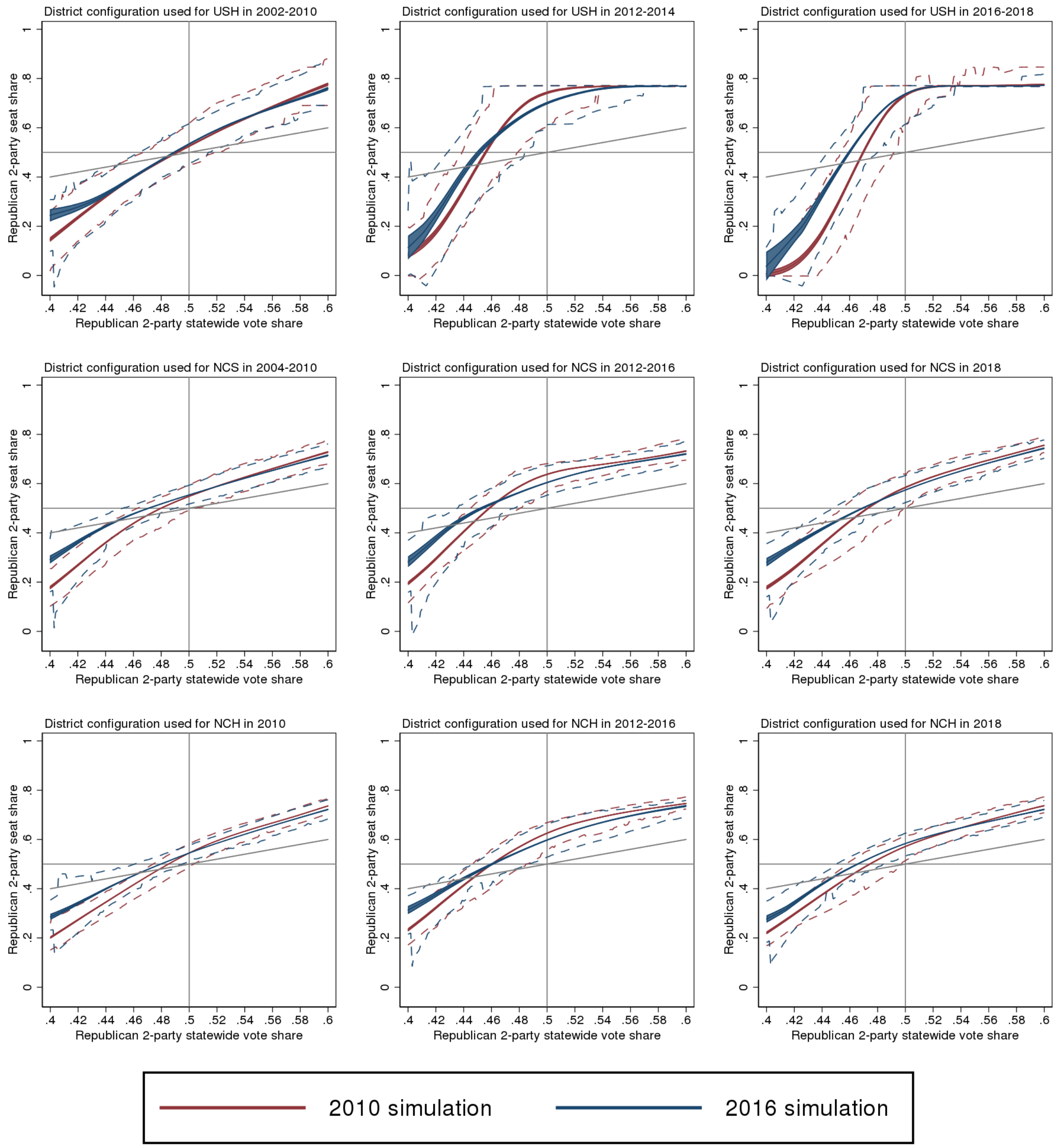
Notes: The figure plots mean Republican two-party vote shares for actual and counterfactual versions of the 2008-2018 elections. The procedure for constructing counterfactual elections is discussed in Section 5. The plot in the first row presents values for actual elections. The first plot in the second row shows values for counterfactual elections that hold demographics fixed. These are constructed by combining the 2008 electorate with the model coefficients from the specified elections. The second plot in the second row is for counterfactual elections that hold utility parameters fixed. These are constructed by combining the 2008 model coefficients with the electorates from the specified elections.

Figure 11: Seats-votes curves for recent North Carolina legislative maps



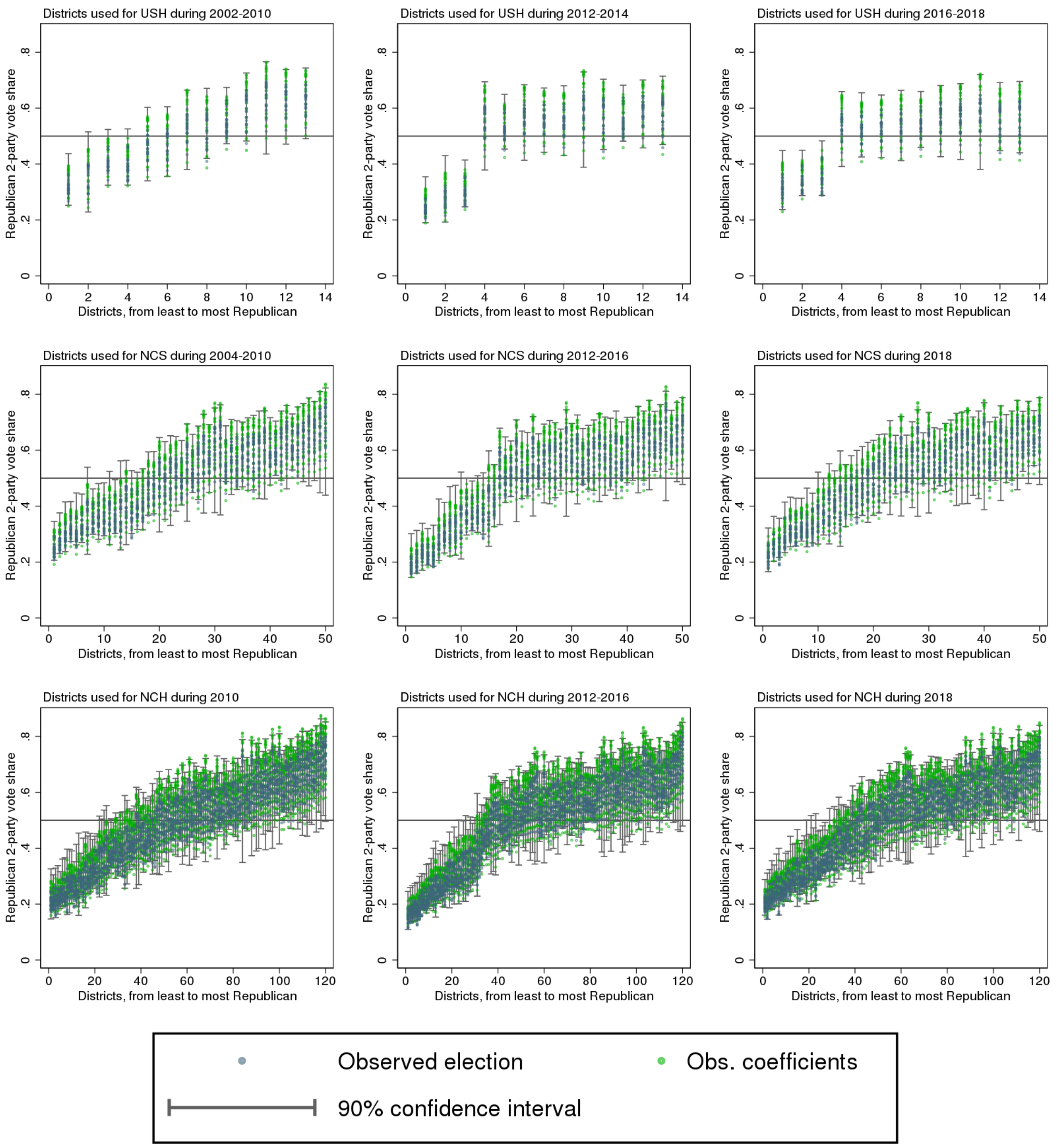
Notes: The figure shows seats-votes curves for recent North Carolina legislative maps. Each dot represents a single contest. The vertical axis shows the share of seats Republicans would obtain if legislative seats were assigned according to the votes in the contest. That is, it exhibits the fraction of districts for which Republicans were the plurality winner in the contest. The horizontal axis shows the statewide 2-party vote share received by Republicans in the contest. Blue dots represent contests from the 2008-2018 elections. Green dots represent contests in simulated elections that use the 2010 electorate and model coefficients from the 2008-2018 elections. Gray dots are for contests in simulated elections that use the 2010 electorate and simulated coefficients. Simulations represented by the gray dots set means of electoral shocks equal to the 2010 model coefficients. They use $Q = 2$ and $Q = 6$ with equal probability. They rely on data from all of the 2008-2018 elections. The dotted lines represent 95% confidence intervals for the Republican 2-party seat share for a given Republican two-party statewide vote share.

Figure 12: Comparing seats-votes curves for simulations centered in 2010 and 2016



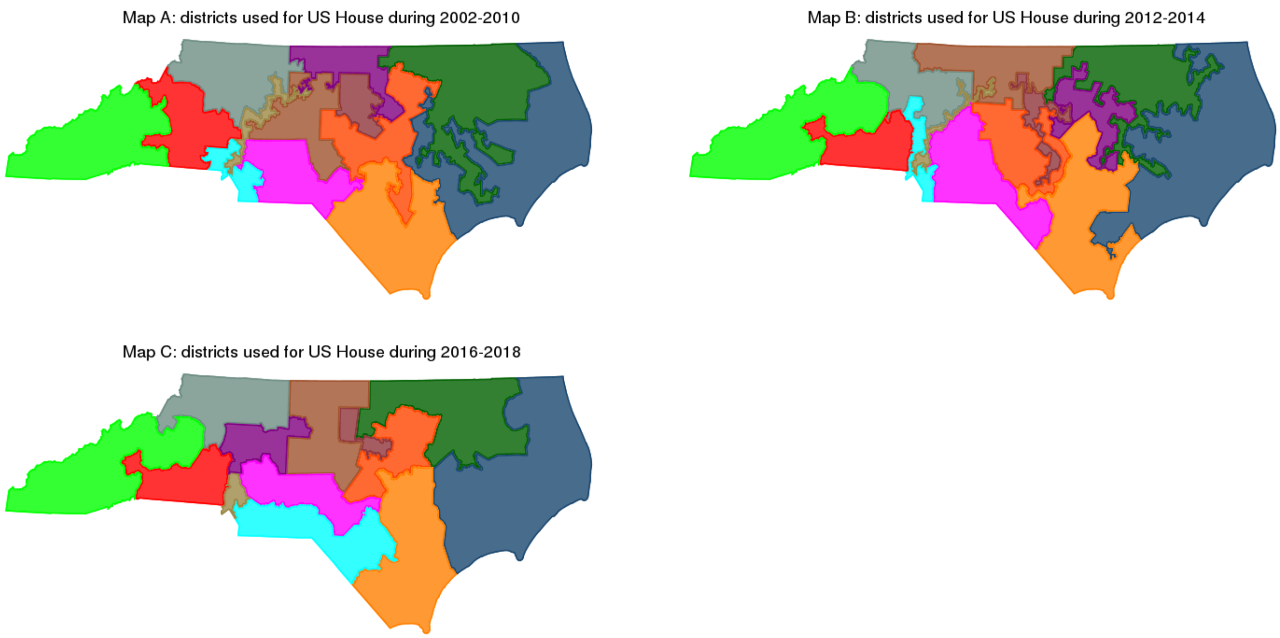
Notes: The figure shows local linear regressions for seats-votes curves using simulations centered in 2010 and 2016. Specifically, for the simulations centered in 2010 (2016), I use the 2010 (2016) electorate and set the mean of electoral shocks equal to the 2010 (2016) model coefficients. The simulations use $Q = 2$ and $Q = 6$ with equal probability and rely on data from all of the 2008-2018 elections. The dotted lines represent 95% confidence intervals for the Republican 2-party seat share for a given Republican two-party statewide vote share.

Figure 13: District competitiveness for recent North Carolina legislative maps



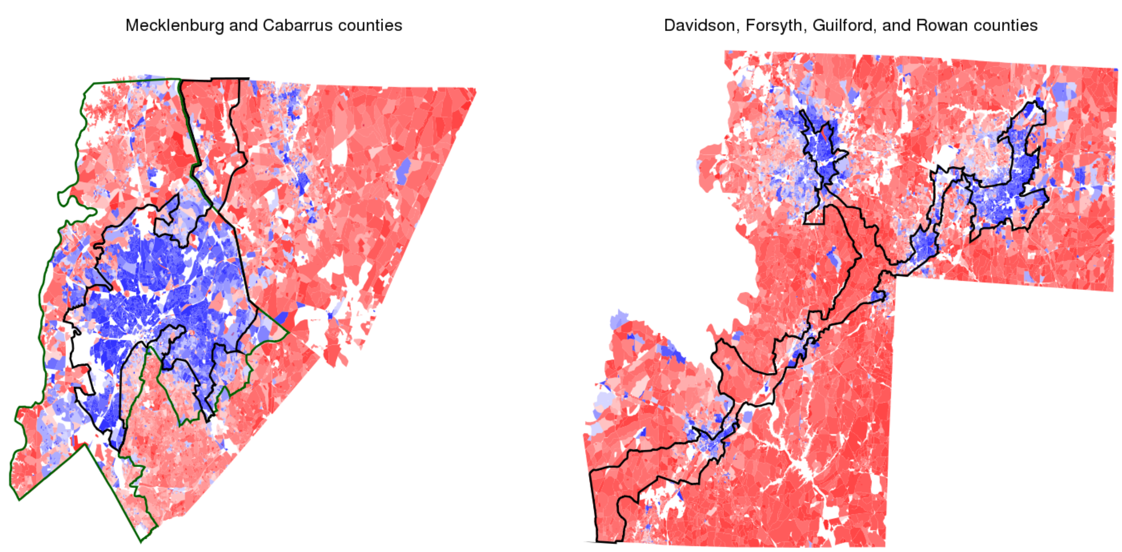
Notes: The figure shows Republican 2-party votes shares for districts in recent North Carolina legislative maps. Blue dots represent district vote shares for contests in the 2008-2018 elections. Green dots show district vote shares for contests in simulated elections that use the 2010 electorate and model coefficients from the 2008-2018 elections. The gray lines are 90% confidence intervals for district vote shares for contests in simulated elections that use the 2010 electorate and simulated coefficients. These simulations set means of electoral shocks equal to the 2010 model coefficients and use $Q = 2$ and $Q = 6$ with equal probability. They rely on data from all of the 2008-2018 elections.

Figure 14: Recent U.S. House maps in North Carolina



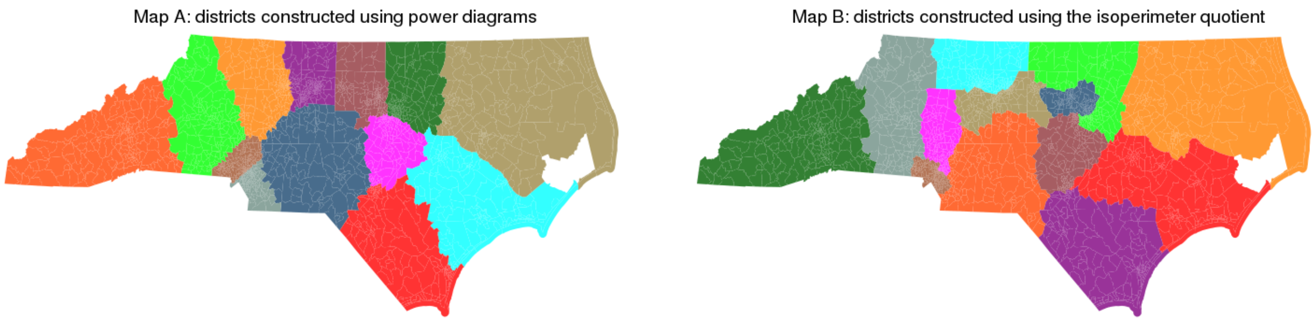
Notes: The figure shows districts for the U.S. House maps used in North Carolina during 2002-2010, 2012-2014, and 2016-2018.

Figure 15: North Carolina's 12th U.S. House district in the 2012-2014 and 2016-2018 maps



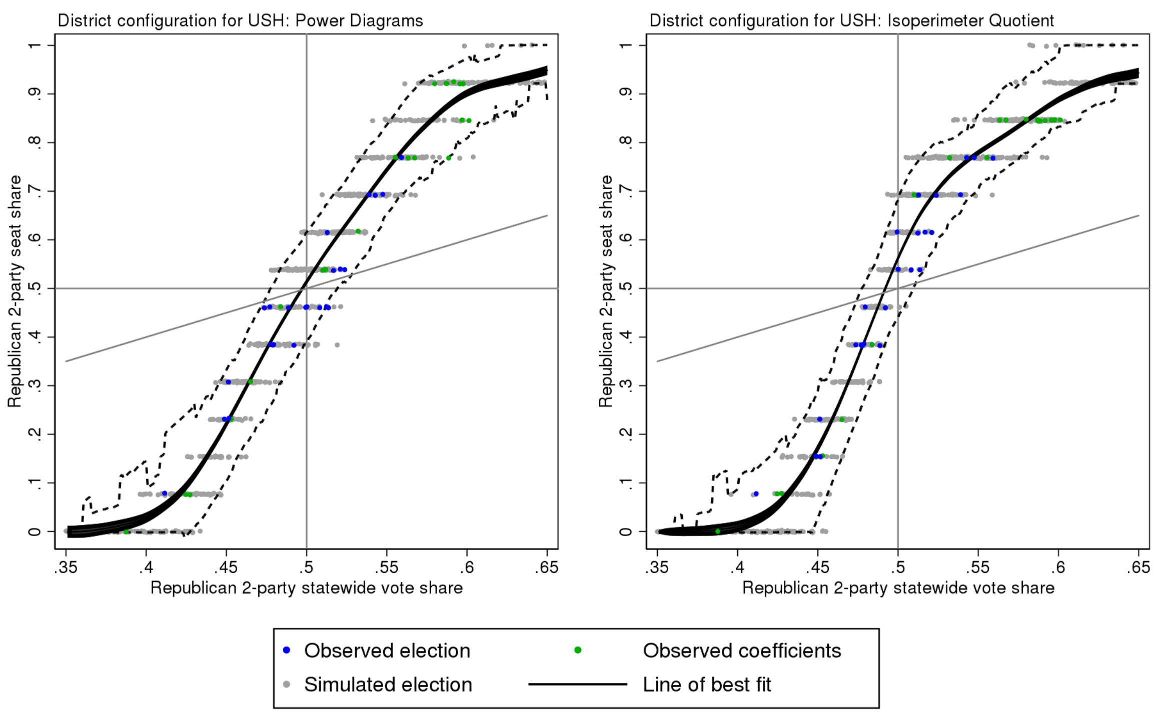
Notes: The map shows predicted vote margins by census block overlaid with boundaries of the 12th U.S. House district for the maps used during 2012-2014 and 2016-2018. The district for the 2012-2014 map is highlighted in black, while that for 2016-2018 is outlined in green. The predicted vote margins are the average of those for all contests in the 2008 and 2010 elections, weighted equally by year: $\frac{1}{2Q_{2008}}\sum_q(\mathrm{P}_{btqR,\mathcal{T}} - \mathrm{P}_{btqD,\mathcal{T}}) + \frac{1}{2Q_{2010}}\sum_q(\mathrm{P}_{btqR,\mathcal{T}} - \mathrm{P}_{btqD,\mathcal{T}})$, where $\mathrm{P}_{btqR,\mathcal{T}}$ is the predicted share of voters in block b who prefer R to A and D on question q in election t. Blocks with predicted margins favoring Democrats are colored in blue, while those favoring Republicans are shaded red. The intensity of the color represents the magnitude of the predicted margin.

Figure 16: Algorithmic U.S. House maps



Notes: The figure shows districts for U.S. House maps constructed using the algorithm of Saxon (n.d.). Map A uses the power diagrams method of Fryer and Holden (2011). Map B uses the isoperimeter quotient method of Polsby and Popper (1991).

Figure 17: Seats-votes curves for algorithmic U.S. House maps



Notes: The figure shows seats-votes curves for U.S. House maps constructed using the algorithm of Saxon (n.d.). The seats-votes curves are created using the procedure described in Figure 11.

References

Athey, Susan, Julie Tibshirani, and Stefan Wager. 2019. "Generalized random forests." *The Annals of Statistics* 47, no. 2 (April): 1148–1178.

Backstrom, Charles, Leonard Robins, and Scott Eller. 1978. "Issues in Gerrymandering: An Exploratory Measure of Partisan Gerrymandering Applied to Minnesota." *Minnesota Law Review* 62, no. 6 (July): 1121–1159.

Berry, Steven T. 1994. "Estimating Discrete-Choice Models of Product Differentiation." *The RAND Journal of Economics* 25 (2): 242–262.

Berry, Steven, James Levinsohn, and Ariel Pakes. 1995. "Automobile Prices in Market Equilibrium." *Econometrica* 63 (4): 841–890.

Brennan Center. 2010. "National Overview of Redistricting: Who draws the lines?" Accessed September 10, 2019. https://www.brennancenter.org/our-work/research-reports/national-overview-redistricting-who-draws-lines.

Browning, Robert X., and Gary King. 1987. "Seats, Votes, and Gerrymandering: Estimating Representation and Bias in State Legislative Redistricting." *Law & Policy* 9 (3): 305–322.

Butler, David E. 1951. *The British General Election of 1950.* Macmillan.

Cameron, A. Colin, and Pravin K. Trivedi. 2005. *Microeconometrics : methods and applications.* Cambridge University Press.

Chambers, Christopher P., Alan D. Miller, and Joel Sobel. 2017. "Flaws in the Efficiency Gap." *Journal of Law & Politics* 33:1–34.

Chen, Jowei, and Jonathan Rodden. 2013. "Unintentional Gerrymandering: Political Geography and Electoral Bias in Legislatures." *Quarterly Journal of Political Science* 8 (3): 239–269.

Chernozhukov, Victor, Denis Chetverikov, Mert Demirer, Esther Duflo, Christian Hansen, Whitney Newey, and James Robins. 2018. "Double/debiased machine learning for treatment and structural parameters." *The Econometrics Journal* 21 (1): C1–C68.

Cho, Wendy K. Tam, and Yan Y. Liu. 2016. "Toward a Talismanic Redistricting Tool: A Computational Method for Identifying Extreme Redistricting Plans." *Election Law Journal* 15 (4): 351–366.

Coate, Stephen, and Brian Knight. 2007. "Socially Optimal Districting: A Theoretical and Empirical Exploration." *The Quarterly Journal of Economics* 122 (4): 1409–1471.

Common Cause v. Rucho. 2018. 318 U.S. District Court, M.D. North Carolina.

Conlon, Christopher, and Jeff Gortmaker. 2019. "Best Practices for Differentiated Products Demand Estimation with pyblp." Working paper.

Daley, David. 2016. *Ratf**ked: The True Story Behind the Secret Plan to Steal America's Democracy.* Liveright Publishing Corporation, A Division of W.W. Norton & Company.

Daskalakis, Constantinos, Anindya De, Gautam Kamath, and Christos Tzamos. 2016. "A size-free CLT for poisson multinomials and its applications." *48th ACM Symposium on Theory of Computing.*

DeFord, Daryl, Moon Duchin, and Justin Solomon. 2019. "A Computational Approach to Measuring Vote Elasticity and Competitiveness." Working paper.

Degan, Arianna, and Antonio Merlo. 2011. "A structural model of turnout and voting in multiple elections." *Journal of the European Economic Association* 9 (2): 209–245.

Downs, Anthony. 1957. "An Economic Theory of Political Action in a Democracy." *Journal of Political Economy* 65 (2): 135–150.

Fifield, Benjamin, Michael Higgins, Kosuke Imai, and Alexander Tarr. 2019. "A New Automated Redistricting Simulator Using Markov Chain Monte Carlo." Working paper.

Friedman, John N., and Richard T. Holden. 2008. "Optimal Gerrymandering: Sometimes Pack, but Never Crack." *The American Economic Review* 98 (1): 113–144.

Fryer, Roland G., and Richard Holden. 2011. "Measuring the Compactness of Political Districting Plans." *The Journal of Law & Economics* 54 (3): 493–535.

Fujiwara, Thomas, Kyle Meng, and Tom Vogl. 2016. "Habit Formation in Voting: Evidence from Rainy Elections." *American Economic Journal: Applied Economics* 8, no. 4 (October): 160–88. doi:10.1257/app.20140533. http://www.aeaweb.org/articles?id=10.1257/app.20140533.

Gelman, Andrew, and Gary King. 1994. "A Unified Method of Evaluating Electoral Systems and Redistricting Plans." *American Journal of Political Science* 38 (2): 514–554.

Geruso, Michael, Dean Spears, and Ishaana Talesara. 2019. *Inversions in US Presidential Elections: 1836-2016.* Technical report. University of Texas Electoral College Study.

Gillen, Benjamin J, Sergio Montero, Hyungsik Roger Moon, and Matthew Shum. 2019. "BLP-2LASSO for aggregate discrete choice models with rich covariates." *Econometrics Journal* 22 (3): 262–281.

Hansen, Bruce E. 2019. "Econometrics." Accessed August 19. https://www.ssc.wisc.edu/~bhansen/econometrics/Econometrics.pdf.

Hersh, Eitan D. 2015. *Hacking the Electorate: How Campaigns Perceive Voters.* Cambridge University Press.

Kawai, Kei, Yuta Toyama, and Yasutora Watanabe. 2018. "Voter Turnout and Preference Aggregation." Working paper.

Kleiner, Ariel, Ameet Talwalkar, Purnamrita Sarkar, and Michael I. Jordan. 2014. "A scalable bootstrap for massive data." *Journal of the Royal Statistical Society: Series B (Statistical Methodology)* 76 (4): 795–816.

Knight, Brian. 2017. "An Econometric Evaluation of Competing Explanations for the Midterm Gap." *Quarterly Journal of Political Science* 12 (2): 205–239.

Levitt, Justin. 2019. "All about redistricting: North Carolina." Accessed September 30, 2019. http://redistricting.lls.edu/states-NC.php.

Levonyan, Vardges. 2016. "What Led to the Ban on Same-Sex Marriage in California?: Structural Estimation of Voting Data on Proposition 8." Working paper.

Limbrock, Frank. 2011. "Pecuniary and Non-Pecuniary Incentives in Prescription Pharmaceuticals: The Case of Statins." *The B.E. Journal of Economic Analysis & Policy* 11 (2).

Maclaurin, Dougal. 2016. "Autograd: Automatic Differentiation for Python." PhD diss., Harvard University: Department of Physics.

McDonald, Michael D. 2015. "Voter list information." Accessed October 1, 2019. http://voterlist.electproject.org/.

McDonald, Michael D., and Robin E. Best. 2015. "Unfair Partisan Gerrymanders in Politics and Law: A Diagnostic Applied to Six Cases." *Election Law Journal* 14 (4): 312–330.

Merlo, Antonio, and Aureo de Paula. 2017. "Identification and Estimation of Preference Distributions When Voters Are Ideological." *The Review of Economic Studies* 84, no. 3 (July): 1238–1263.

Niemi, Richard G., Bernard Grofman, Carl Carlucci, and Thomas Hofeller. 1990. "Measuring Compactness and the Role of a Compactness Standard in a Test for Partisan and Racial Gerrymandering." *The Journal of Politics* 52 (4): 1155–1181.

Polsby, Daniel D., and Robert D. Popper. 1991. "The Third Criterion: Compactness as a Procedural Safeguard against Partisan Gerrymandering." *Yale Law & Policy Review* 9 (2): 301–353. ISSN: 07408048. http://www.jstor.org/stable/40239359.

Reynolds v. Sims. 1964. 377 U.S. Supreme Court.

Riker, William H., and Peter C. Ordeshook. 1968. "A Theory of the Calculus of Voting." *The American Political Science Review* 62 (1): 25–42.

Rucho v. Common Cause. 2019. 588 U.S. Supreme Court.

Saxon, James. n.d. "Reviving Legislative Avenues for Gerrymandering Reform with a Flexible, Automated Tool." *Political Analysis:* 1:23. doi:10.1017/pan.2019.45.

Shaw v. Reno. 1993. 509 U.S. Supreme Court.

Stephanopoulos, Nicholas O., and Eric M. McGhee. 2015. "Partisan Gerrymandering and the Efficiency Gap." *The University of Chicago Law Review* 82 (2): 831–900.

Thornburg v. Gingles. 1986. 478 U.S. Supreme Court.

Tufte, Edward R. 1973. "The Relationship between Seats and Votes in Two-Party Systems." *The American Political Science Review* 67 (2): 540–554.

Ujhelyi, Gergely, Somdeep Chatterjee, and Andrea Szabo. 2019. "None Of The Above." Working paper.

Wesberry v. Sanders. 1964. 376 U.S. Supreme Court.

A1 Mathematical appendix

A1.1 Deriving the asymptotic normal distribution

The mean and covariance of i's preferences conditional on observables and on turning out are as follows:

- $\mathrm{E}[p_{itqj}|q, \mathcal{Q}_t, Z_{it}, to_{it} = 1; \theta_t] = \mathrm{P}_{\mathcal{Q}Z,tqj,\mathcal{T}}$.

- $\mathrm{Var}[p_{itqj}|q, \mathcal{Q}_t, Z_{it}, to_{it} = 1; \theta_t]$

$$\begin{aligned}
=&\mathrm{E}[(p_{itqj} - \mathrm{E}[p_{itqj}|q, \mathcal{Q}_t, Z_{it}, to_{it} = 1; \theta_t])^2|q, \mathcal{Q}_t, Z_{it}, to_{it} = 1; \theta_t] \\
=&\mathrm{E}[(p_{itqj} - \mathrm{P}_{\mathcal{Q}Z,tqj,\mathcal{T}})^2|q, \mathcal{Q}_t, Z_{it}, to_{it} = 1; \theta_t] \\
=&(1 - \mathrm{P}_{\mathcal{Q}Z,tqj,\mathcal{T}})^2 \cdot \Pr[p_{itqj} = 1|q, \mathcal{Q}_t, Z_{it}, to_{it} = 1; \theta_t] \\
+&(\quad - \mathrm{P}_{\mathcal{Q}Z,tqj,\mathcal{T}})^2 \cdot \Pr[p_{itqj} = 0|q, \mathcal{Q}_t, Z_{it}, to_{it} = 1; \theta_t] \\
=&(1 - \mathrm{P}_{\mathcal{Q}Z,tqj,\mathcal{T}})^2 \cdot \mathrm{P}_{\mathcal{Q}Z,tqj,\mathcal{T}} + (-\mathrm{P}_{\mathcal{Q}Z,tqj,\mathcal{T}})^2 \cdot (1 - \mathrm{P}_{\mathcal{Q}Z,tqj,\mathcal{T}}) \\
=&(1 - \mathrm{P}_{\mathcal{Q}Z,tqj,\mathcal{T}}) \cdot \mathrm{P}_{\mathcal{Q}Z,tqj,\mathcal{T}}.
\end{aligned}$$

- $\mathrm{Cov}[p_{itqj}, p_{itqk}|q, \mathcal{Q}_t, Z_{it}, to_{it} = 1; \theta_t]$ for $k \neq j$

$$\begin{aligned}
=&\mathrm{E}[(p_{itqj} - \mathrm{P}_{Ztqj,\mathcal{T}})(p_{itqk} - \mathrm{P}_{Ztqk,\mathcal{T}})|q, \mathcal{Q}_t, Z_{it}, to_{it} = 1; \theta_t] \\
=& - \mathrm{P}_{\mathcal{Q}Z,tqj,\mathcal{T}}\mathrm{P}_{\mathcal{Q}Z,tqk,\mathcal{T}}.
\end{aligned}$$

- $\mathrm{Cov}[p_{itqj}, p_{itq'k}|q, q', \mathcal{Q}_t, Z_{it}, to_{it} = 1; \theta_t]$ for $q \neq q'$

$$\begin{aligned}
=&\mathrm{E}[(p_{itqj} - \mathrm{P}_{Ztqj,\mathcal{T}})(p_{itq'k} - \mathrm{P}_{Ztq'k,\mathcal{T}})|q, q', \mathcal{Q}_t, Z_{it}, to_{it} = 1; \theta_t] \\
=&(1 - \mathrm{P}_{\mathcal{Q}Z,tqj,\mathcal{T}})(1 - \mathrm{P}_{\mathcal{Q}Z,tq'k,\mathcal{T}}) \cdot \Pr[p_{itqj} = 1, p_{itq'k} = 1|q, q', \mathcal{Q}_t, Z_{it}, to_{it} = 1; \theta_t] \\
+&(1 - \mathrm{P}_{\mathcal{Q}Z,tqj,\mathcal{T}})(\quad - \mathrm{P}_{\mathcal{Q}Z,tq'k,\mathcal{T}}) \cdot \Pr[p_{itqj} = 1, p_{itq'k} = 0|q, q', \mathcal{Q}_t, Z_{it}, to_{it} = 1; \theta_t] \\
+&(\quad - \mathrm{P}_{\mathcal{Q}Z,tqj,\mathcal{T}})(1 - \mathrm{P}_{\mathcal{Q}Z,tq'k,\mathcal{T}}) \cdot \Pr[p_{itqj} = 0, p_{itq'k} = 1|q, q', \mathcal{Q}_t, Z_{it}, to_{it} = 1; \theta_t] \\
+&(\quad - \mathrm{P}_{\mathcal{Q}Z,tqj,\mathcal{T}})(\quad - \mathrm{P}_{\mathcal{Q}Z,tq'k,\mathcal{T}}) \cdot \Pr[p_{itqj} = 0, p_{itq'k} = 0|q, q', \mathcal{Q}_t, Z_{it}, to_{it} = 1; \theta_t] \\
=&\int \mathrm{P}_{itqj}\mathrm{P}_{itq'k} \cdot \frac{TO_{it}\phi(e)}{\int TO_{it}\phi(e)de} de - \mathrm{P}_{\mathcal{Q}Z,tqj,\mathcal{T}}\mathrm{P}_{\mathcal{Q}Z,tq'k,\mathcal{T}}.
\end{aligned}$$

A1.2 Standardizing preference coefficients

I transform (7) to (9) by matching quantities that closely follow from their definitions. First, for $\Delta_{X,t} + \mathrm{E}[\Delta_q|\mathcal{Q}_t]$, I match the the probability that a registrant with covariates X_{it} prefers R to D in a hypothetical contest q' in t with mean candidate popularity, $\Delta'_q = \mathrm{E}[\Delta_q|\mathcal{Q}_t]$:

$$\begin{aligned}
\mathrm{P}_{Xtq'RD} &\equiv \Pr[U_{itq'R} > U_{itq'D}|X_{it}, \Delta_{q'}; \theta_t] \\
&= \Pr[\Delta_{X,t} + \Delta_{q'} + \sigma_t e_{it} + \epsilon_{itq',\Delta} > 0|X_{it}, \Delta_{q'}; \theta_t] \\
&= \Pr[\Delta_{X,t} + \Delta_{q'} + \sigma_t e_{it} + \check{\epsilon}_{itq'R} - \check{\epsilon}_{itq'D} > 0|X_{it}, \Delta_{q'}; \theta_t] \\
&= \int \frac{\exp[\Delta_{X,t} + \Delta_{q'} + \sigma_t e_{it}]}{1 + \exp[\Delta_{X,t} + \Delta_{q'} + \sigma_t e_{it}]} \phi(e) de \\
&= \frac{\exp[\tilde{\Delta}_{it}]}{1 + \exp[\tilde{\Delta}_{it}]}.
\end{aligned}$$

Here, the functional form in the fourth line follows from the fact that the difference of two independent T1EV variables is logistic. $\tilde{\Delta}_{it}$ can be interpreted as the value of partisanship that matches the given preference probability under $\sigma_t = 0$. It can be readily seen that every $\mathrm{P}_{Xtq'RD}$ admits a unique $\tilde{\Delta}_{X,t}$, with

$$\tilde{\Delta}_{it} = \log\left(\frac{\mathrm{P}_{Xtq'RD}}{1 - \mathrm{P}_{Xtq'RD}}\right).$$

In fact, as shown in Berry (1994), for every $\bar{\sigma}_t$ there is a unique value of $\bar{\Delta}_{X,t}$ such that

$$\mathrm{P}_{Xtq'RD} = \int \frac{\exp[\bar{\Delta}_{X,t} + \bar{\sigma}_{X,t} e_{it}]}{1 + \exp[\bar{\Delta}_{X,t} + \bar{\sigma}_{X,t} e_{it}]} \phi(e) de.$$

In addition, Berry, Levinsohn, and Pakes (1995) show that $\bar{\Delta}_{X,t}$ can be easily recovered, given $\mathrm{P}_{Xtq'RD}$ and $\bar{\sigma}_t$, via a contraction mapping.

Next, I transform $\lambda_{X,t} + \mathrm{E}[\lambda_q|\mathcal{Q}_t]$ by matching the probability that someone with covariates X_{it} prefers R to A in a hypothetical contest q'' in t with $\Delta_{q''} = -\Delta_{X,t}$ and $\lambda_{q''} = \mathrm{E}[\lambda_q|\mathcal{Q}_t]$:

$$\begin{aligned}
\mathrm{P}_{Xtq''RA} &\equiv \Pr[U_{itq''R} > U_{itq''A}|X_{it}, \Delta_{q''}, \lambda_{q''}; \theta_t] \\
&= \Pr[\lambda_{X,t} + \lambda_{q''} + \epsilon_{itq'',\lambda} + \frac{1}{2}(\sigma_t e_{it} + \epsilon_{itq'',\Delta}) > 0|X_{it}, \Delta_{q''}, \lambda_{q''}; \theta_t] \\
&= \Pr[\lambda_{X,t} + \lambda_{q''} + \frac{\sigma_t}{2} e_{it} + \check{\epsilon}_{itq''R} - \check{\epsilon}_{itq''A} > 0|X_{it}, \Delta_{q''}, \lambda_{q''}; \theta_t] \\
&= \int \frac{\exp[\lambda_{X,t} + \lambda_{q''} + \frac{\sigma_t}{2} e_{it}]}{1 + \exp[\lambda_{X,t} + \lambda_{q''} + \frac{\sigma_t}{2} e_{it}]} \phi(e) de \\
&= \frac{\exp[\tilde{\lambda}_{it}]}{1 + \exp[\tilde{\lambda}_{it}]}.
\end{aligned}$$

Similar to before, $\tilde{\lambda}_{it}$ can be calculated as the log-odds ratio of $\mathrm{P}_{Xtq''RA}$; it is interpreted as the value of political efficacy that matches the given preference probability under $\sigma_t = 0$.

I use a similar approach to transform the de-meaned question effects. The quantities that I match are:

$$\int \frac{\exp[\dot{\Delta}_q + \sigma_{X,t} e_{it}]}{1 + \exp[\dot{\Delta}_q + \sigma_{X,t} e_{it}]} \phi(e) de = \frac{\exp[\tilde{\dot{\Delta}}_q]}{1 + \exp[\tilde{\dot{\Delta}}_q]},$$

and

$$\int \frac{\exp[\dot{\lambda}_q + \frac{\sigma_{X,t}}{2} e_{it}]}{1 + \exp[\dot{\lambda}_q + \frac{\sigma_{X,t}}{2} e_{it}]} \phi(e) de = \frac{\exp[\tilde{\dot{\lambda}}_q]}{1 + \exp[\tilde{\dot{\lambda}}_q]}.$$

A2 How the existing literature simulates counterfactual elections

In this section, I compare my method for simulating counterfactual elections with those of existing papers. My method is similar to that used by Geruso, Spears, and Talesara (2019) and a generalization of those used by Gelman and King (1994) and Coate and Knight (2007).

A2.1 Gelman and King (1994)

Gelman and King (1994) work with aggregate vote shares. They explain district two-party vote shares using the regression:

$$v_{dt} = {X_{dt}}' \cdot \beta_t + \omega_{dt},$$

where v_{dt} is the two-party vote share for Republicans in district d in election t, X_{dt} is a vector of covariates, and β_t is a time-varying coefficient vector. They assume that ω_{dt} is independent and identically normally distributed with mean 0 and variance σ^2: $\omega_{dt} \overset{iid}{\sim} N(0, \sigma^2)$. Thus, the posterior distribution of β_t conditional on the data and on σ^2 is

$$\Pr[\beta_t | X_t, v_t; \sigma^2] = N(\hat{\beta}_t, ({X_t}'X_t)^{-1}\sigma^2),$$

where X_t and v_t collect X_{dt} and v_{dt} over all districts and $\hat{\beta}_t = ({X_t}'X_t)^{-1}{X_t}'v_t$ is the OLS estimate from a regression of v_{dt} on X_{dt}. By using information from multiple elections, Gelman and King assume they can estimate σ^2 without error; thus, they take it as "known". It is calculated as $\sigma^2 = \frac{1}{T}\sum_t \hat{\sigma}_t^2$, where T is the number of elections and $\hat{\sigma}_t^2$ is the OLS "standard error of the regression" in election t: $\hat{\sigma}_t^2 = \frac{1}{D-K}{\hat{\omega}_t}'\hat{\omega}_t$, where D is the number of districts, K is the number of covariates, and $\hat{\omega}_t$ is the vector of regression residuals.

Gelman and King further assume β_{t+1} has the same distribution as β_t. Thus, they simulate district vote shares in election $t+1$ by combining a draw of $\beta_{t+1} \sim N(\hat{\beta}_t, ({X_t}'X_t)^{-1}\sigma^2)$ with D independent draws of $\omega_{dt+1} \sim N(0, \sigma^2)$. They also add a common shock, δ_{t+1}, to allow the simulated elections to have different statewide vote shares. District vote shares in $t+1$ are then: $v_{dt+1} = {X_{dt+1}}'\beta_{t+1} + \delta_{t+1} + \omega_{dt+1}$.

This procedure incorporates uncertainty in future elections due to (i) error in estimating β_t, (ii) swings in state vote shares, and (iii) swings in district-minus-state vote shares that are independent and identically normal. The i.i.d. normal assumption in (iii) is restrictive. First, it forces each district to have the same variance of vote shares across elections. This restriction would be violated if, e.g., districts differ in the share of moderate registrants. Second, the assumption does not allow swings in district-minus-state vote shares to be correlated. This restriction would be violated if, e.g., elections include preference or turnout shocks to registrants in particular regions or demographic groups.

The Gelman and King approach is also used by Fryer and Holden (2011).

A2.2 Coate and Knight (2007)

Coate and Knight (2007) also work with aggregate vote shares. They predict district two-party vote shares using a panel random effects model:

$$v_{dt} = X_{dt}{}' \cdot \theta_1 + \sigma_1 \cdot \xi_d + \exp[\frac{X_{dt}{}'\dot{\theta}_2 + \sigma_2 \cdot \eta_d}{2}] \cdot w_t,$$

where ξ_d and η_d are district-specific random effects that are independent and standard normal, σ_1 and σ_2 are standard deviations of the random effects, θ_1 and θ_2 are vectors of coefficients, and w_t is a common shock. In creating simulated elections, Coate and Knight account for three sources of uncertainty. First, they account for error in estimating the model coefficients. Second, they deal with the fact that districts' values of the random effects are not identified. Finally, they allow elections to have a limited set of vote swings. Coate and Knight deal with the first two sources of uncertainty by fitting the model and drawing random effects in each of 100 bootstrap iterations. They incorporate vote swings by creating elections with different values of w_t. Conditional on the coefficients and random effects from a particular bootstrap iteration, different values of w_t create different district vote shares as governed by $\exp[\frac{X_{dt}{}' \cdot \theta_2 + \sigma_2 \cdot \eta_d}{2}]$.

This method allows districts' vote shares to have different across-election variances. It also allows swings in district-minus-state vote shares to be correlated. However, it imposes strong restrictions on which district vote swings are allowed. In particular, conditional on the model coefficients and random effects, it forces all districts to swing in the same direction.

A2.3 Geruso, Spears, and Talesara (2019)

Geruso, Spears, and Talesara (2019) explain district two-party vote shares using the model:

$$v_{dt} = \alpha_d + X_{dt}{}' \cdot \psi_t + \phi_{dt},$$

where α_d is a district fixed effect, ψ_t is a vector of coefficients that varies by year, and ϕ_{dt} is a district-election error.[62] (Here, X_{dt} is assumed to include an indicator for the election; thus, the model includes "year effects".) Geruso et al. assume the coefficients on the individual covariates, $\{\psi_{t,k}\}_k$ for covariate k, follow independent and mean-zero t-distributions across elections. They assume the district-election errors, ϕ_{dt}, are independent and also follow a mean-zero t-distribution. Their estimation procedure recovers estimates of the district fixed effects, α_d, the across-election variances of the coefficients, $\{\sigma^2_{\psi_{t,k}}\}_k$, and the variance of the district-election errors, $\sigma^2_{\phi_{dt}}$. They then simulate counterfactual elections by combining the fixed effects with a draw of each of the $\psi_{t,k}$ and with D draws of ϕ_{dt}.

This method accounts for uncertainty due to shocks to vote shares that either (i) are correlated by covariates or (ii) are independent by district. It does not account for uncertainty due to estimation

62. In reality, Geruso et al. work with state, rather than district, two-party vote shares. This is because their application concerns the U.S. electoral college, rather than a state's legislative districts. In this discussion, I adapt their procedure to the gerrymandering context.

error. The method allows districts' vote shares to have different across-election variances, as determined by $\sigma^2_{\psi_{t,k}}$. It also allows swings in district-minus-state vote shares to be correlated, as governed by ψ_t.

A2.4 Comparison with my procedure

My procedure is similar to that of Geruso, Spears, and Talesara (2019), but has important differences. First, I simulate utility parameters, rather than aggregate vote shares. Second, I assume coefficients and residuals come from normal distributions, not t-distributions. Finally, I do not set the coefficients to be mean-zero across elections. Setting coefficients to be mean-zero is reasonable in their case because their goal is to understand alternative realizations of past elections. Thus, they allow α_d to represent district d's mean vote share in the period. By contrast, my goal is to simulate future elections. Thus, I attempt to capture trends in coefficients. I do this by drawing from distributions that use means equal to the coefficient values in the most recent election, while still setting variances equal to the across-election variances.

A3 Appendix Tables and Figures

Table A1: Vote shares for all partisan contests

Contest	2008			2010			2012			2014			2016			2018		
	Dem.	*Rep.*	*Abstain*	*Dem.*	*Rep.*	*Abstain*	*Dem.*	*Rep.*	*Abstain*	*Dem.*	*Rep.*	*Abstain*	*Dem.*	*Rep.*	*Abstain*	*Dem.*	*Rep.*	*Abstain*
A. Legislative contests																		
US House Of Representatives	0.53	0.44	0.04	0.45	0.53	0.02	0.49	0.47	0.04	0.42	0.53	0.05	0.45	0.51	0.04	0.47	0.49	0.04
NC Senate	0.44	0.40	0.15	0.38	0.54	0.08	0.41	0.46	0.14	0.40	0.47	0.13	0.38	0.48	0.13	0.49	0.48	0.02
NC House Of Representatives	0.46	0.38	0.16	0.36	0.53	0.11	0.41	0.44	0.15	0.39	0.46	0.15	0.40	0.45	0.15	0.50	0.47	0.03
B. Non-legislative partisan contests																		
US President	0.49	0.49	0.02	-	-	-	0.48	0.50	0.02	-	-	-	0.46	0.49	0.05	-	-	-
US Senate	0.52	0.43	0.05	0.42	0.54	0.04	-	-	-	0.47	0.48	0.05	0.45	0.50	0.05	-	-	-
NC Governor	0.49	0.46	0.05	-	-	-	0.42	0.54	0.04	-	-	-	0.48	0.48	0.03	-	-	-
NC Supreme Court Associate Justice	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.48	0.49	0.03
NC Attorney General	0.58	0.37	0.04	-	-	-	-	-	-	-	-	-	0.48	0.48	0.04	-	-	-
NC Secretary of State	0.53	0.41	0.06	-	-	-	0.51	0.44	0.05	-	-	-	0.50	0.45	0.05	-	-	-
NC Auditor	0.50	0.43	0.07	-	-	-	0.51	0.44	0.06	-	-	-	0.47	0.47	0.05	-	-	-
NC Commissioner Of Agriculture	0.45	0.49	0.06	-	-	-	0.45	0.51	0.05	-	-	-	0.42	0.53	0.05	-	-	-
NC Commissioner Of Insurance	0.48	0.42	0.10	-	-	-	0.49	0.45	0.06	-	-	-	0.47	0.48	0.06	-	-	-
NC Commissioner Of Labor	0.46	0.47	0.06	-	-	-	0.44	0.51	0.05	-	-	-	0.43	0.52	0.05	-	-	-
NC Lieutenant Governor	0.49	0.44	0.07	-	-	-	0.48	0.48	0.04	-	-	-	0.44	0.50	0.06	-	-	-
NC Superintendent Of Public Instruction	0.50	0.43	0.07	-	-	-	0.51	0.43	0.05	-	-	-	0.47	0.48	0.05	-	-	-
NC Treasurer	0.50	0.43	0.07	-	-	-	0.51	0.44	0.05	-	-	-	0.45	0.50	0.06	-	-	-
NC Court Of Appeals Judge (Dietz)	-	-	-	-	-	-	-	-	-	-	-	-	0.43	0.49	0.08	-	-	-
NC Court Of Appeals Judge (Geer)	-	-	-	-	-	-	-	-	-	-	-	-	0.42	0.45	0.12	-	-	-
NC Court Of Appeals Judge (Hunter)	-	-	-	-	-	-	-	-	-	-	-	-	0.42	0.50	0.07	-	-	-
NC Court Of Appeals Judge (Stephens)	-	-	-	-	-	-	-	-	-	-	-	-	0.46	0.47	0.07	-	-	-
NC Court Of Appeals Judge (Zachary)	-	-	-	-	-	-	-	-	-	-	-	-	0.42	0.49	0.08	-	-	-
NC Court Of Appeals Judge Seat 1	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.49	0.48	0.03
NC Court Of Appeals Judge Seat 2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.47	0.49	0.04
NC Court Of Appeals Judge Seat 3	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.47	0.46	0.07

Notes: The table lists statewide vote shares for partisan contests by election. *Abstain* includes votes for third-party candidates.

Table A2: Share of legislative races that are contested

Chamber	2008	2010	2012	2014	2016	2018
US House	1.00	1.00	1.00	0.92	1.00	0.92
NC Senate	0.58	0.76	0.62	0.58	0.64	1.00
NC House of Representatives	0.50	0.64	0.54	0.48	0.50	0.98

Notes: The table presents the fraction of races that were contested for the given chamber and election. Contested races are defined as those that include both a Democratic and a Republican candidate.

Table A3: Preference shares in survey data

Contest	2008			2010			2012			2014			2016			2018		
	Dem.	*Rep.*	*Abstain*	*Dem.*	*Rep.*	*Abstain*	*Dem.*	*Rep.*	*Abstain*	*Dem.*	*Rep.*	*Abstain*	*Dem.*	*Rep.*	*Abstain*	*Dem.*	*Rep.*	*Abstain*
A. All respondents																		
US President	0.44	0.52	0.04	-	-	-	0.51	0.42	0.07	-	-	-	0.51	0.38	0.11	-	-	-
US Senate	0.44	0.48	0.08	0.39	0.45	0.16	-	-	-	0.47	0.37	0.16	0.50	0.40	0.11	-	-	-
US House Of Representatives	0.44	0.46	0.10	0.40	0.43	0.17	0.47	0.40	0.13	0.42	0.36	0.15	0.48	0.38	0.14	0.46	0.37	0.09
NC Governor	0.40	0.49	0.11	-	-	-	0.42	0.48	0.10	-	-	-	0.56	0.36	0.08	-	-	-
Mean	0.43	0.49	0.08	0.39	0.44	0.16	0.47	0.43	0.10	0.45	0.36	0.15	0.51	0.38	0.11	0.46	0.37	0.09
B. Voters																		
US President	0.44	0.53	0.02	-	-	-	0.51	0.45	0.04	-	-	-	0.53	0.38	0.09	-	-	-
US Senate	0.46	0.49	0.05	0.40	0.55	0.05	-	-	-	0.50	0.42	0.08	0.52	0.40	0.08	-	-	-
US House Of Representatives	0.46	0.47	0.07	0.40	0.53	0.07	0.49	0.42	0.08	0.44	0.41	0.06	0.52	0.39	0.10	0.49	0.40	0.05
NC Governor	0.42	0.51	0.07	-	-	-	0.44	0.50	0.06	-	-	-	0.59	0.37	0.05	-	-	-
Mean	0.45	0.50	0.05	0.40	0.54	0.06	0.48	0.46	0.06	0.47	0.42	0.07	0.54	0.38	0.08	0.49	0.40	0.05
C. Non-voters																		
US President	0.44	0.45	0.11	-	-	-	0.52	0.34	0.14	-	-	-	0.46	0.38	0.16	-	-	-
US Senate	0.34	0.42	0.25	0.37	0.28	0.36	-	-	-	0.44	0.31	0.25	0.44	0.39	0.18	-	-	-
US House Of Representatives	0.34	0.40	0.26	0.39	0.26	0.35	0.40	0.33	0.27	0.40	0.30	0.24	0.39	0.36	0.25	0.42	0.32	0.17
NC Governor	0.31	0.38	0.31	-	-	-	0.36	0.44	0.21	-	-	-	0.50	0.35	0.14	-	-	-
Mean	0.35	0.41	0.23	0.38	0.27	0.35	0.43	0.37	0.21	0.42	0.31	0.24	0.45	0.37	0.18	0.42	0.32	0.17

Notes: The table shows preference shares for survey respondents. The sample is limited to registered respondents. Voters are respondents who turned out, as validated by the Catalist voter file. *Abstain* includes votes for third-party candidates.

Table A4: Summary statistics for registrants' covariates

	2008		2010		2012		2014		2016		2018	
	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
Demographics and party												
Race: black	0.22	0.41	0.22	0.41	0.23	0.42	0.23	0.42	0.23	0.42	0.22	0.42
Race: other non-white	0.05	0.21	0.05	0.22	0.06	0.24	0.07	0.25	0.08	0.27	0.09	0.29
Registered Democrat	0.46	0.50	0.44	0.50	0.43	0.50	0.42	0.49	0.39	0.49	0.38	0.48
Registered Republican	0.32	0.47	0.32	0.47	0.31	0.46	0.31	0.46	0.31	0.46	0.30	0.46
Female	0.55	0.50	0.55	0.50	0.55	0.50	0.55	0.50	0.55	0.50	0.55	0.50
Age (years)	47.1	18.2	48.0	18.2	47.7	18.3	48.3	18.3	48.3	18.5	48.8	18.7
Age (years) times Democrat	22.5	27.8	22.4	28.0	21.4	27.6	21.0	27.7	19.8	27.4	19.2	27.3
Age (years) times Republican	15.2	24.3	15.5	24.8	15.3	24.8	15.3	25.1	15.4	25.3	15.5	25.5
White, Democrat, age 60 or over	0.09	0.29	0.09	0.29	0.09	0.28	0.09	0.28	0.08	0.27	0.08	0.26
Parcel value per registrant (20 groups)	10.5	5.7	10.5	5.8	10.6	5.8	10.7	5.8	10.9	5.8	11.1	5.8
Party changes												
Democrat in t and Unaffil. (1) or Republican (2) in t-4 to t+4	0.05	0.28	0.05	0.29	0.05	0.28	0.05	0.29	0.03	0.22	0.02	0.16
Unaffil. in t and Democrat in t-4 to t+4	0.06	0.23	0.06	0.25	0.07	0.26	0.07	0.25	0.07	0.25	0.06	0.23
Unaffil. in t and Republican in t-4 to t+4	0.04	0.20	0.05	0.22	0.07	0.25	0.07	0.26	0.07	0.26	0.06	0.24
Republican in t and Unaffil. (1) or Democrat (2) in t-4 to t+4	0.03	0.21	0.03	0.23	0.04	0.25	0.04	0.26	0.04	0.24	0.03	0.21
Block and block group characteristics												
Ln: population density in block (pop. / sq. km)	5.9	1.7	5.9	1.7	6.0	1.7	6.0	1.7	6.0	1.7	6.0	1.7
Ln: household median income in block group (2010 $)	10.7	0.5	10.7	0.5	10.7	0.5	10.7	0.5	10.7	0.5	10.7	0.5
Share college graduates in block group	0.28	0.20	0.28	0.20	0.29	0.20	0.30	0.21	0.31	0.21	0.32	0.21
Predicted turnout utility												
Predicted turnout utility times non-white	0.39	1.48	-0.29	1.41	0.37	1.54	-0.31	1.54	0.33	1.46	-0.11	1.25
Predicted turnout utility times white	1.15	2.34	-0.35	2.39	1.17	2.60	-0.27	2.43	1.30	2.37	0.23	1.87
Predicted turnout utility times lean Democratic	0.90	2.05	-0.25	1.87	0.79	2.08	-0.20	1.89	0.75	1.93	0.13	1.51
Predicted turnout utility times lean Republican	0.57	1.67	-0.05	1.59	0.68	1.92	-0.01	1.63	0.79	1.86	0.21	1.30
Interactions between registrant and precinct characteristics												
High-education precinct	0.45	0.50	0.45	0.50	0.48	0.50	0.49	0.50	0.51	0.50	0.52	0.50
Non-white registrant times high-education precinct	0.09	0.29	0.10	0.29	0.12	0.32	0.12	0.33	0.14	0.34	0.14	0.35
Democrat times high-education precinct	0.18	0.38	0.18	0.38	0.18	0.39	0.18	0.39	0.18	0.39	0.18	0.39
Republican times high-education precinct	0.15	0.36	0.15	0.36	0.15	0.36	0.16	0.36	0.16	0.37	0.16	0.36
Age (years) times high-education precinct	20.5	25.8	21.4	26.4	22.3	26.5	23.4	26.9	24.3	27.1	24.9	27.4
Closeness of NC House and NC Senate races	-1.06	0.90	-1.29	0.96	-1.08	1.05	-0.99	0.89	-1.02	0.95	-1.67	0.97
Cost instruments												
Ln: distance to nearest early-voting location / block length	-0.02	0.48	-0.01	0.49	-0.02	0.43	-0.01	0.46	-0.01	0.43	-0.02	0.50
Intensity of election-day rainfall (3 groups)	-0.09	0.81	-	-	-	-	-	-	-	-	0.01	0.52
US House district fixed effects												
District 01	0.07	0.25	0.07	0.25	0.08	0.27	0.08	0.26	0.08	0.27	0.08	0.27
District 02	0.07	0.26	0.07	0.26	0.07	0.26	0.07	0.26	0.08	0.27	0.08	0.27
District 03	0.07	0.26	0.07	0.26	0.08	0.26	0.07	0.26	0.07	0.26	0.07	0.26
District 04	0.09	0.29	0.09	0.29	0.08	0.27	0.08	0.27	0.08	0.28	0.08	0.28
District 05	0.07	0.26	0.07	0.26	0.08	0.27	0.08	0.27	0.07	0.26	0.07	0.26
District 06	0.08	0.26	0.08	0.27	0.08	0.27	0.08	0.27	0.07	0.26	0.07	0.26
District 07	0.08	0.27	0.08	0.27	0.08	0.26	0.08	0.27	0.08	0.27	0.08	0.27
District 08	0.07	0.26	0.07	0.25	0.07	0.26	0.07	0.26	0.07	0.26	0.07	0.26
District 09	0.09	0.29	0.09	0.29	0.08	0.28	0.09	0.28	0.08	0.26	0.08	0.26
District 10	0.07	0.26	0.07	0.26	0.08	0.27	0.08	0.26	0.08	0.26	0.07	0.26
District 11	0.08	0.27	0.08	0.27	0.08	0.27	0.08	0.27	0.08	0.27	0.08	0.27
District 12	0.07	0.26	0.07	0.26	0.07	0.26	0.08	0.26	0.08	0.27	0.08	0.28
District 13	0.08	0.27	0.08	0.27	0.08	0.27	0.08	0.27	0.08	0.27	0.08	0.27
Region fixed effects												
Region 01	0.03	0.16	0.03	0.16	0.03	0.16	0.03	0.16	0.03	0.16	0.02	0.16
Region 02	0.08	0.27	0.08	0.27	0.08	0.27	0.08	0.27	0.08	0.27	0.08	0.27
Region 03	0.09	0.29	0.09	0.29	0.09	0.29	0.09	0.28	0.09	0.28	0.09	0.28
Region 04	0.23	0.42	0.23	0.42	0.23	0.42	0.24	0.42	0.24	0.43	0.24	0.43
Region 05	0.15	0.36	0.15	0.36	0.15	0.36	0.15	0.36	0.15	0.36	0.15	0.36
Region 06	0.08	0.27	0.08	0.26	0.08	0.26	0.07	0.26	0.07	0.26	0.07	0.26
Region 07	0.16	0.37	0.16	0.37	0.16	0.37	0.17	0.37	0.17	0.37	0.17	0.37
Region 08	0.09	0.28	0.09	0.28	0.09	0.28	0.09	0.28	0.09	0.29	0.09	0.29
Region 09	0.03	0.17	0.03	0.17	0.03	0.17	0.03	0.17	0.03	0.16	0.03	0.16
Region 10	0.06	0.24	0.06	0.24	0.06	0.24	0.06	0.24	0.06	0.24	0.06	0.24

Notes: The table presents means and standard deviations for registrants' covariates by year. The sample includes allocated values. See Table 5 for the set of covariates used in the model and Table A10 for the set used in the simulations. See text, the notes to Table 1, and the data appendix for variable descriptions.

Table A5: λ_t^X and λ_q coefficients

	2008		2010		2012		2014		2016		2018	
	Coef.	Std. err.	Coef.	Std. err.	Coef.	Std. err.	Coef.	Std. err.	Coef.	Std. err.	Coef.	Std. err.
Demographics and party												
Race: black	-1.09	0.24	0.07	0.29	-0.95	0.27	-0.10	0.23	-0.98	0.31	-0.30	0.44
Race: other non-white	-0.28	0.16	0.01	0.30	-0.55	0.23	0.09	0.18	-0.54	0.19	-0.48	0.26
Registered Democrat	0.84	0.63	-0.27	2.04	1.31	0.57	1.31	0.81	2.15	0.70	3.17	0.61
Registered Republican	2.23	0.51	-0.70	1.42	1.82	1.02	-1.43	1.38	1.71	0.89	-3.05	1.89
Female	0.06	0.08	-0.07	0.18	0.04	0.14	-0.20	0.11	0.28	0.17	-0.29	0.26
Age (years)	0.01	0.01	0.00	0.02	0.03	0.01	0.03	0.01	0.02	0.01	0.05	0.02
Age (years) times Democrat	-0.01	0.01	0.01	0.05	-0.04	0.02	-0.04	0.01	-0.04	0.01	-0.09	0.01
Age (years) times Republican	-0.02	0.01	0.02	0.02	-0.03	0.02	0.01	0.03	-0.02	0.02	0.05	0.03
White, Democrat, age 60 or over	0.82	0.67	0.91	0.79	0.63	0.52	0.88	0.29	0.79	0.40	2.62	0.55
Parcel value per registrant (20 groups)	-0.01	0.01	0.00	0.01	0.00	0.01	0.02	0.01	0.00	0.00	0.02	0.01
Party changes												
Democrat in t and Unaffil. (1) or Republican (2) in t-4 to t+4	0.59	0.34	-0.63	0.26	-0.10	0.24	-0.67	0.14	-0.74	0.20	3.58	1.34
Unaffil. in t and Democrat in t-4 to t+4	-0.60	0.17	0.11	0.69	-0.81	0.27	-0.71	0.51	-0.05	0.30	0.25	0.55
Unaffil. in t and Republican in t-4 to t+4	0.10	0.24	-0.65	0.36	0.28	0.30	-0.96	0.29	-0.32	0.29	-0.03	0.44
Republican in t and Unaffil. (1) or Democrat (2) in t-4 to t+4	1.23	0.77	0.76	0.42	2.23	1.25	1.34	0.61	0.04	0.76	-2.69	1.67
Block and block group characteristics												
Ln: population density in block (pop. / sq. km)	0.00	0.01	-0.02	0.02	0.01	0.02	0.02	0.02	0.00	0.01	0.06	0.02
Ln: household median income in block group (2010 $)	0.20	0.04	0.38	0.09	0.18	0.04	0.37	0.10	0.24	0.03	0.27	0.07
Share college graduates in block group	-0.08	0.08	1.46	0.71	-0.48	0.17	0.75	0.22	-0.02	0.08	0.10	0.17
Predicted turnout utility												
Predicted turnout utility times non-white	0.32	0.08	0.37	0.21	0.35	0.09	0.43	0.13	0.33	0.08	0.39	0.23
Predicted turnout utility times white	0.02	0.05	0.53	0.13	0.07	0.06	0.37	0.11	0.04	0.06	-0.33	0.15
Predicted turnout utility times lean Democratic	0.10	0.05	-0.52	0.16	0.05	0.06	-0.39	0.13	0.09	0.06	0.15	0.19
Predicted turnout utility times lean Republican	-0.07	0.07	-0.51	0.16	-0.10	0.09	-0.29	0.16	0.06	0.10	-0.11	0.17
Interactions between registrant and precinct characteristics												
High-education precinct	-0.40	0.31	-0.56	0.52	0.00	0.31	0.31	0.42	0.20	0.17	0.16	0.35
Non-white registrant times high-education precinct	0.30	0.16	-0.17	0.39	0.11	0.27	0.20	0.29	0.06	0.21	-0.07	0.20
Democrat times high-education precinct	0.09	0.28	-0.08	0.48	0.80	0.39	0.26	0.59	0.12	0.32	1.27	0.67
Republican times high-education precinct	0.29	0.42	-2.23	0.90	1.16	0.50	-0.37	0.56	-0.06	0.31	1.03	0.72
Age (years) times high-education precinct	0.01	0.01	0.02	0.01	-0.01	0.01	-0.01	0.01	0.00	0.00	-0.02	0.01
Closeness of NC House and NC Senate races	0.01	0.01	0.07	0.03	0.01	0.01	0.01	0.02	0.02	0.01	0.03	0.02
US House district fixed effects												
District 02	0.12	0.07	-0.13	0.14	-0.07	0.09	-0.31	0.08	-0.03	0.09	0.01	0.10
District 03	-0.16	0.09	-0.18	0.10	-0.29	0.09	-0.40	0.08	-0.17	0.08	-0.31	0.09
District 04	-0.14	0.07	-0.71	0.26	-0.23	0.07	-0.36	0.07	-0.11	0.08	-0.04	0.11
District 05	-0.17	0.08	-0.19	0.12	-0.22	0.08	-0.41	0.11	-0.17	0.07	-0.43	0.09
District 06	-0.12	0.08	-0.22	0.11	-0.22	0.07	-0.31	0.11	-0.07	0.09	-0.21	0.09
District 07	-0.35	0.08	-0.03	0.09	-0.23	0.09	-0.55	0.09	-0.26	0.08	-0.20	0.09
District 08	-0.15	0.07	-0.02	0.10	-0.22	0.07	-0.47	0.10	-0.16	0.07	-0.48	0.10
District 09	-0.12	0.08	-0.04	0.10	-0.17	0.09	-0.50	0.12	-0.19	0.08	-0.33	0.12
District 10	-0.18	0.08	-0.12	0.12	-0.15	0.08	-0.42	0.07	-0.15	0.07	-0.09	0.12
District 11	-0.27	0.08	-0.52	0.12	-0.31	0.09	-0.43	0.09	-0.20	0.07	-0.10	0.14
District 12	-0.25	0.09	-0.27	0.14	-0.30	0.08	-0.17	0.07	-0.26	0.07	-0.33	0.07
District 13	-0.12	0.07	-0.39	0.16	-0.03	0.08	-0.41	0.09	-0.20	0.07	-0.24	0.09
Question fixed effects												
US President	2.07	0.41	-	-	1.21	0.55	-	-	0.16	0.37	-	-
US Senate	1.12	0.41	2.28	1.19	-	-	0.85	0.71	0.05	0.37	-	-
US House												
District 01	1.00	0.41	2.53	1.20	-0.07	0.56	0.84	0.66	-0.30	0.37	1.70	0.55
District 02	0.92	0.40	2.47	1.22	-0.03	0.55	1.98	0.72	0.41	0.38	0.19	0.55
District 03	1.55	0.41	1.90	1.16	0.85	0.57	1.73	0.73	0.67	0.36	-0.02	0.56
District 04	1.49	0.40	2.80	1.23	0.35	0.57	1.31	0.72	0.57	0.36	-0.29	0.54
District 05	1.95	0.42	3.39	1.21	1.06	0.55	1.97	0.73	0.78	0.37	2.18	0.58
District 06	1.62	0.44	3.15	1.19	0.80	0.56	1.64	0.72	0.26	0.37	1.67	0.59
District 07	1.52	0.42	3.20	1.25	1.02	0.54	0.85	0.72	0.32	0.39	0.73	0.54
District 08	1.62	0.45	1.88	1.21	0.32	0.59	1.32	0.74	0.33	0.37	2.10	0.64
District 09	1.26	0.43	2.83	1.19	0.28	0.55	0.55	0.71	0.15	0.38	1.05	0.53
District 10	1.66	0.42	2.66	1.19	0.90	0.56	1.88	0.71	0.55	0.37	1.87	0.57
District 11	1.41	0.41	3.71	1.27	0.95	0.56	1.74	0.70	0.59	0.36	0.74	0.55
District 12	1.18	0.38	2.11	1.22	0.50	0.56	0.98	0.73	0.40	0.36	1.72	0.57
District 13	1.22	0.39	3.15	1.33	-0.01	0.56	1.26	0.71	0.30	0.37	0.35	0.60
NC Governor	1.18	0.40	-	-	0.66	0.55	-	-	0.50	0.37	-	-
NC Supreme Court Associate Justice	-	-	-	-	-	-	-	-	-	-	0.73	0.53
Avg. of NC Attorney Gen. and NC Sec. of State	0.99	0.41	-	-	0.40	0.56	-	-	0.21	0.37	-	-
Avg. of other NC state-level contests	0.76	0.41	-	-	0.32	0.56	-	-	-0.22	0.37	0.07	0.56
Indicator for a survey response	-0.65	0.03	-1.74	0.16	-1.00	0.06	-1.41	0.09	-0.89	0.05	-2.05	0.12

Notes: The table presents the λ coefficients from the model. Standard errors are clustered by county.

Table A6: Δ_t^X and Δ_q coefficients

	2008		2010		2012		2014		2016		2018	
	Coef.	Std. err.	Coef.	Std. err.	Coef.	Std. err.	Coef.	Std. err.	Coef.	Std. err.	Coef.	Std. err.
Demographics and party												
Race: black	-4.00	0.21	-7.72	1.54	-5.72	0.50	-8.78	0.73	-6.52	0.29	-16.06	1.63
Race: other non-white	-1.21	0.19	-2.07	0.86	-2.70	0.42	-2.15	0.48	-2.58	0.51	-5.06	0.85
Registered Democrat	-1.38	0.26	-4.59	1.25	-1.78	0.38	-5.31	1.15	-3.03	0.29	-7.26	1.18
Registered Republican	1.81	0.25	6.26	2.26	4.06	0.60	10.30	1.48	3.41	0.37	21.03	6.98
Female	0.08	0.02	-0.52	0.12	0.07	0.05	-0.49	0.09	-0.10	0.08	-1.27	0.44
Age (years)	0.00	0.00	0.01	0.02	0.00	0.01	-0.02	0.02	-0.01	0.01	0.03	0.02
Age (years) times Democrat	0.02	0.00	0.05	0.02	0.03	0.01	0.10	0.02	0.06	0.01	0.11	0.03
Age (years) times Republican	-0.02	0.01	-0.06	0.03	-0.04	0.01	-0.06	0.02	-0.02	0.01	-0.18	0.11
White, Democrat, age 60 or over	0.10	0.09	0.13	0.23	0.10	0.13	0.57	0.35	-0.12	0.17	2.08	1.26
Parcel value per registrant (20 groups)	0.00	0.01	-0.04	0.02	-0.04	0.01	-0.13	0.03	-0.04	0.01	-0.23	0.05
Party changes												
Democrat in t and Unaffil. (1) or Republican (2) in t-4 to t+4	0.06	0.07	1.28	0.27	0.29	0.09	2.00	0.29	0.30	0.14	-10.96	1.52
Unaffil. in t and Democrat in t-4 to t+4	-0.92	0.16	-3.40	0.87	-1.98	0.38	-4.04	0.81	-1.76	0.26	-4.17	0.68
Unaffil. in t and Republican in t-4 to t+4	0.70	0.16	3.12	0.64	1.61	0.39	5.47	0.73	1.41	0.25	7.71	1.20
Republican in t and Unaffil. (1) or Democrat (2) in t-4 to t+4	-0.43	0.10	-1.08	0.39	-0.81	0.20	-2.19	0.45	-0.28	0.22	5.57	3.51
Block and block group characteristics												
Ln: population density in block (pop. / sq. km)	-0.10	0.01	-0.15	0.05	-0.13	0.02	-0.32	0.05	-0.24	0.02	-0.67	0.10
Ln: household median income in block group (2010 $)	0.53	0.05	1.43	0.33	0.88	0.13	1.66	0.25	0.86	0.11	2.76	0.44
Share college graduates in block group	-1.10	0.13	-3.84	0.87	-2.04	0.32	-4.57	0.51	-3.13	0.36	-9.36	1.23
Predicted turnout utility												
Predicted turnout utility times non-white	0.18	0.06	0.19	0.24	0.38	0.09	0.82	0.24	0.44	0.09	1.13	0.43
Predicted turnout utility times white	0.09	0.03	0.13	0.16	0.20	0.04	0.62	0.17	0.10	0.04	0.32	0.26
Predicted turnout utility times lean Democratic	-0.21	0.04	-0.22	0.19	-0.38	0.06	-0.76	0.22	-0.37	0.06	-0.48	0.34
Predicted turnout utility times lean Republican	-0.05	0.04	-0.45	0.26	-0.14	0.07	-1.04	0.20	-0.07	0.05	-0.84	0.36
Interactions between registrant and precinct characteristics												
High-education precinct	-0.41	0.19	-0.93	0.55	-0.88	0.33	-2.57	1.01	-0.81	0.37	-2.31	1.21
Non-white registrant times high-education precinct	1.07	0.19	1.99	0.52	1.61	0.24	3.48	0.49	1.48	0.32	5.31	0.62
Democrat times high-education precinct	-0.17	0.20	0.19	0.46	-0.43	0.29	-1.02	0.67	-0.75	0.31	-4.32	1.44
Republican times high-education precinct	1.09	0.37	4.80	1.35	1.08	0.54	3.98	0.68	1.15	0.45	1.85	2.71
Age (years) times high-education precinct	0.00	0.00	-0.01	0.01	0.01	0.00	0.03	0.01	0.01	0.01	0.04	0.02
Closeness of NC House and NC Senate races	-0.01	0.02	0.04	0.07	0.06	0.02	0.09	0.05	-0.03	0.03	-0.12	0.12
US House district fixed effects												
District 02	-0.19	0.05	-0.83	0.18	0.21	0.17	0.13	0.35	0.10	0.21	0.10	0.64
District 03	-0.01	0.05	-0.07	0.16	0.32	0.15	0.21	0.32	0.47	0.20	0.69	0.66
District 04	-0.45	0.07	-1.52	0.24	-0.39	0.20	-0.95	0.36	-0.22	0.26	-0.54	0.81
District 05	-0.28	0.06	-1.19	0.29	-0.04	0.14	-0.60	0.30	-0.03	0.21	-0.80	0.68
District 06	-0.07	0.05	-0.69	0.20	0.13	0.13	-0.15	0.31	0.15	0.21	-0.23	0.66
District 07	-0.16	0.08	-0.30	0.25	0.15	0.14	-0.07	0.30	0.28	0.21	0.26	0.64
District 08	-0.05	0.05	-0.74	0.24	0.22	0.14	-0.03	0.37	0.39	0.22	0.32	0.70
District 09	0.00	0.07	-0.98	0.24	0.31	0.16	-0.27	0.32	0.50	0.24	0.88	0.72
District 10	-0.13	0.08	-1.32	0.32	-0.04	0.22	-0.57	0.38	0.18	0.27	-0.44	0.80
District 11	-0.51	0.07	-1.61	0.32	-0.36	0.14	-1.09	0.31	-0.22	0.20	-1.49	0.60
District 12	-0.22	0.06	-1.11	0.22	-0.15	0.16	-1.13	0.30	-0.04	0.22	-0.68	0.73
District 13	-0.24	0.06	-0.87	0.26	0.20	0.18	0.30	0.37	0.15	0.22	-0.11	0.70
Question fixed effects												
US President	0.88	0.20	-	-	0.82	0.36	-	-	1.68	0.42	-	-
US Senate	0.55	0.18	3.00	0.75	-	-	1.29	1.01	1.81	0.40	-	-
US House												
District 01	0.47	0.19	2.96	0.75	0.29	0.34	0.88	0.99	1.37	0.35	-0.17	1.86
District 02	-0.20	0.19	2.83	0.75	0.83	0.35	1.59	1.04	1.87	0.40	0.17	1.86
District 03	1.48	0.18	4.31	0.83	1.41	0.36	3.25	1.01	2.43	0.41	0.16	1.84
District 04	0.56	0.19	2.71	0.74	0.35	0.36	1.07	1.02	1.68	0.39	-1.16	2.03
District 05	0.73	0.18	2.68	0.72	0.54	0.34	1.54	1.02	1.67	0.39	0.48	1.87
District 06	1.16	0.20	3.98	0.81	1.14	0.33	1.61	1.01	1.97	0.41	0.74	1.84
District 07	-0.49	0.23	0.80	0.81	-0.07	0.39	2.02	1.03	2.00	0.40	-0.03	1.87
District 08	0.68	0.20	1.67	0.80	0.37	0.35	2.68	1.05	1.88	0.40	0.32	1.86
District 09	1.21	0.20	4.21	0.86	0.08	0.35	1.17	1.01	1.86	0.40	-1.41	1.72
District 10	0.48	0.21	3.59	0.80	0.65	0.34	2.10	1.05	1.90	0.41	0.57	1.88
District 11	-0.12	0.19	1.21	0.75	0.47	0.34	1.88	1.02	1.82	0.40	0.54	1.85
District 12	0.59	0.19	2.65	0.74	0.34	0.35	2.22	1.08	1.90	0.40	-0.71	1.92
District 13	0.26	0.19	2.31	0.73	0.91	0.34	1.88	1.00	1.89	0.40	-0.08	1.88
NC Governor	0.75	0.20	-	-	1.38	0.33	-	-	1.43	0.40	-	-
NC Supreme Court Associate Justice	-	-	-	-	-	-	-	-	-	-	0.49	1.83
Avg. of NC Attorney Gen. and NC Sec. of State	0.21	0.19	-	-	0.25	0.34	-	-	1.29	0.38	-	-
Avg. of other NC state-level contests	0.73	0.18	-	-	0.56	0.33	-	-	1.77	0.39	0.28	1.85

Notes: The table presents the Δ coefficients from the model. Standard errors are clustered by county.

Table A7: c_t^Z coefficients

	2008		2010		2012		2014		2016		2018	
	Coef.	Std. err.	Coef.	Std. err.	Coef.	Std. err.	Coef.	Std. err.	Coef.	Std. err.	Coef.	Std. err.
Demographics and party												
Race: black	0.13	0.04	0.04	0.04	0.13	0.03	0.17	0.03	-0.13	0.03	-0.02	0.03
Race: other non-white	0.03	0.07	-0.04	0.07	0.09	0.05	0.01	0.06	0.13	0.03	0.19	0.02
Registered Democrat	0.00	0.12	0.06	0.17	0.05	0.08	0.13	0.04	-0.10	0.08	0.19	0.04
Registered Republican	-0.23	0.14	0.03	0.09	-0.02	0.13	0.19	0.04	0.03	0.11	0.00	0.03
Female	0.12	0.01	-0.14	0.02	0.08	0.02	-0.09	0.00	0.10	0.02	-0.07	0.01
Age (years)	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Age (years) times Democrat	0.00	0.00	-0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Age (years) times Republican	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
White, Democrat, age 60 or over	-0.27	0.12	0.03	0.07	-0.07	0.08	0.02	0.02	-0.24	0.05	-0.12	0.02
Parcel value per registrant (20 groups)	0.02	0.00	0.01	0.00	0.01	0.00	0.01	0.00	0.01	0.00	0.01	0.00
Party changes												
Democrat in t and Unaffil. (1) or Republican (2) in t-4 to t+4	-0.18	0.06	0.02	0.02	-0.10	0.03	-0.09	0.01	0.08	0.03	0.00	0.05
Unaffil. in t and Democrat in t-4 to t+4	0.09	0.03	-0.21	0.05	-0.02	0.02	-0.05	0.02	-0.05	0.04	0.07	0.02
Unaffil. in t and Republican in t-4 to t+4	0.03	0.05	0.18	0.03	-0.04	0.03	-0.07	0.01	0.10	0.03	-0.08	0.02
Republican in t and Unaffil. (1) or Democrat (2) in t-4 to t+4	-0.43	0.15	-0.06	0.03	-0.34	0.15	-0.10	0.02	0.12	0.08	0.12	0.01
Block and block group characteristics												
Ln: population density in block (pop. / sq. km)	0.02	0.01	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Ln: household median income in block group (2010 $)	0.02	0.02	-0.01	0.03	0.04	0.02	-0.03	0.03	0.06	0.02	0.00	0.02
Share college graduates in block group	-0.05	0.04	-0.25	0.08	-0.09	0.04	-0.03	0.08	-0.33	0.05	-0.06	0.05
Predicted turnout utility												
Predicted turnout utility times non-white	1.09	0.02	1.08	0.02	1.09	0.01	1.09	0.01	1.09	0.01	1.12	0.01
Predicted turnout utility times white	1.10	0.01	1.01	0.01	1.08	0.01	1.07	0.01	1.11	0.01	1.11	0.01
Predicted turnout utility times lean Democratic	-0.06	0.01	0.02	0.02	-0.03	0.01	-0.01	0.01	-0.05	0.01	-0.02	0.01
Predicted turnout utility times lean Republican	0.00	0.01	0.06	0.02	0.00	0.01	-0.04	0.01	-0.04	0.01	-0.05	0.01
Interactions between registrant and precinct characteristics												
High-education precinct	0.25	0.05	-0.01	0.05	0.12	0.04	-0.06	0.03	-0.04	0.04	0.17	0.04
Non-white registrant times high-education precinct	-0.08	0.04	0.20	0.04	-0.04	0.04	-0.03	0.03	-0.01	0.03	-0.11	0.02
Democrat times high-education precinct	-0.04	0.05	-0.01	0.04	-0.14	0.04	0.00	0.02	-0.08	0.04	0.01	0.02
Republican times high-education precinct	-0.18	0.08	0.18	0.06	-0.19	0.06	0.01	0.02	-0.11	0.03	-0.20	0.02
Age (years) times high-education precinct	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Closeness of NC House and NC Senate races	0.00	0.01	-0.05	0.02	0.01	0.01	-0.01	0.01	0.00	0.01	-0.03	0.01
US House district fixed effects												
District 01	1.08	0.09	-0.98	0.12	1.20	0.06	-0.84	0.06	1.47	0.05	-0.18	0.06
District 02	0.98	0.10	-0.92	0.12	1.22	0.06	-0.74	0.04	1.42	0.06	-0.08	0.04
District 03	1.09	0.09	-0.98	0.11	1.18	0.07	-0.75	0.07	1.39	0.06	-0.18	0.05
District 04	1.05	0.09	-0.98	0.11	1.21	0.07	-0.70	0.04	1.47	0.05	-0.08	0.03
District 05	1.06	0.09	-1.10	0.11	1.25	0.08	-0.92	0.08	1.49	0.06	-0.05	0.04
District 06	1.03	0.09	-1.22	0.13	1.25	0.06	-0.71	0.05	1.50	0.06	-0.04	0.04
District 07	0.98	0.10	-0.91	0.13	1.16	0.07	-0.85	0.05	1.43	0.05	-0.13	0.05
District 08	1.03	0.09	-1.11	0.12	1.18	0.07	-0.96	0.07	1.44	0.06	-0.10	0.05
District 09	1.03	0.09	-1.17	0.10	1.34	0.07	-0.76	0.05	1.37	0.06	-0.03	0.07
District 10	1.04	0.09	-1.22	0.11	1.23	0.07	-0.81	0.04	1.49	0.06	-0.09	0.04
District 11	0.86	0.09	-0.90	0.13	1.06	0.07	-0.86	0.06	1.37	0.06	-0.03	0.04
District 12	1.10	0.08	-1.12	0.10	1.29	0.07	-0.80	0.06	1.51	0.05	-0.04	0.04
District 13	1.06	0.09	-1.10	0.10	1.23	0.07	-0.71	0.06	1.49	0.05	0.00	0.04
Cost instruments												
Ln: distance to nearest early-voting location / block length	-0.02	0.01	-0.04	0.02	-0.03	0.01	-0.02	0.01	-0.02	0.01	-0.02	0.01
Intensity of election-day rainfall (3 groups)	-0.04	0.02	-	-	-	-	-	-	-	-	0.00	0.02

Notes: The table presents the c coefficients from the model. Standard errors are clustered by county.

Table A8: Out-of-sample prediction quality for vote data using OLS

	2008	**2010**	**2012**	**2014**	**2016**	**2018**
A. Precinct vote shares, conditional on turnout						
R-squared	0.944	0.961	0.969	0.968	0.972	0.978
Mean absolute error	0.032	0.029	0.025	0.025	0.025	0.023
B. Precinct vote shares, unconditional on turnout						
R-squared	0.941	0.953	0.967	0.959	0.969	0.970
Mean absolute error	0.033	0.032	0.026	0.029	0.026	0.027

Notes: The table summarizes measures of out-of-sample prediction quality for vote data based on a regression of precinct vote shares on precinct characteristics. The values are calculated in a two-step process. First, the regression is run on a random sample of two-thirds of the precincts. Second, predictions are created for the excluded precincts and compared with observed outcomes. In Panel A, vote share predictions use information on the voter sample in the excluded precincts. To generate these predictions, the regressions use the mean covariates of a precinct's voters. In Panel B, vote share predictions do not use information on the voter sample in the excluded precincts. To generate these predictions, the regressions use the mean covariates of a precinct's registrants. All predictions that are less than 0 or larger than 1 are set to 0 or 1, respectively. Results are weighted by the number of registrants in the precinct.

Table A9: Prediction quality for preference choices in survey data using OLS

All respondents	**Voters**	**Non-voters**
0.76	0.78	0.70

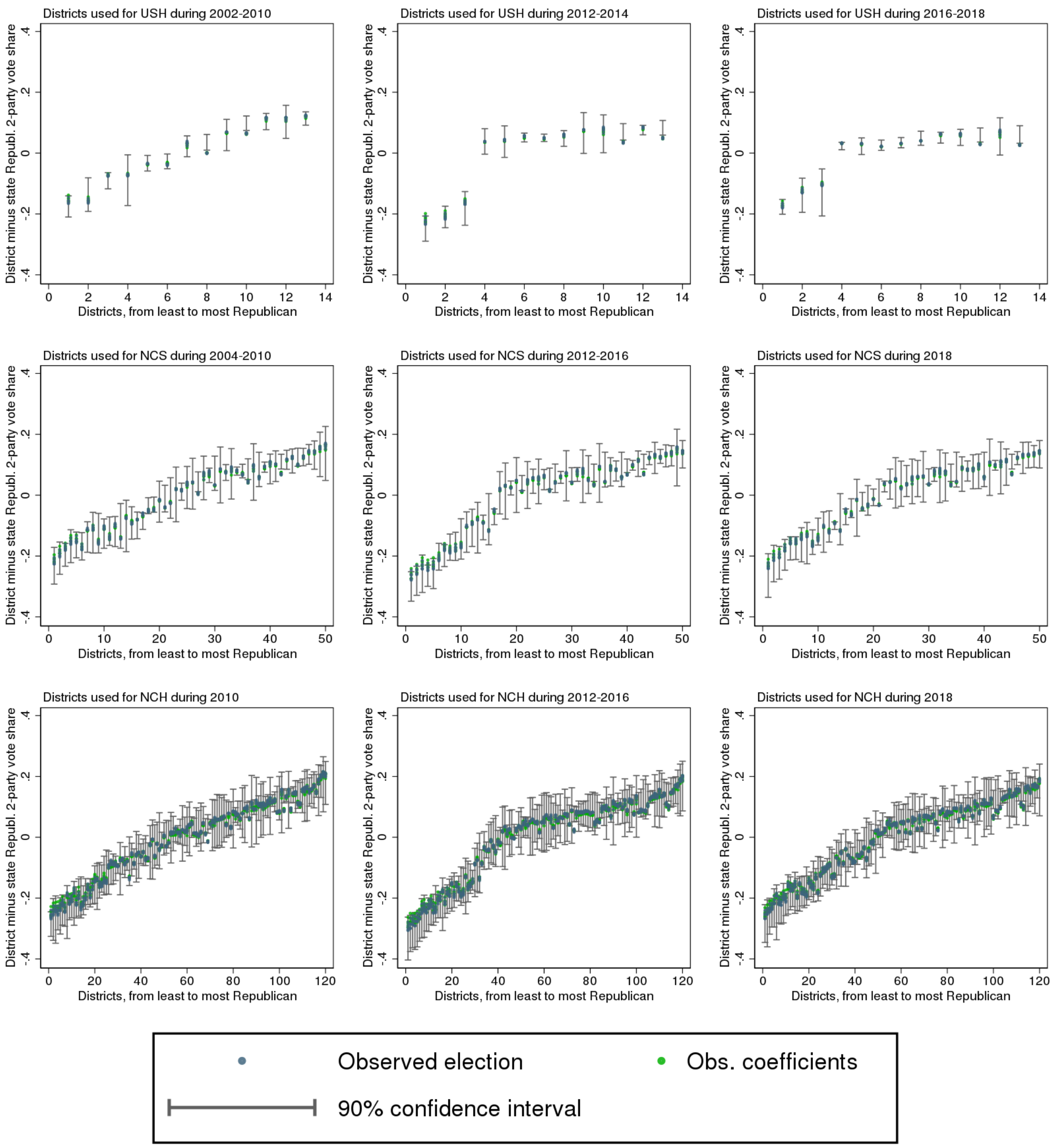
Notes: The table shows classification rates for preference choices in survey data. The predictions are based on a regression of precinct vote shares on precinct characteristics, as described in Table A8. In running the regressions, I use the mean covariates of a precinct's voters. I generate predictions for survey preference choices in two additional steps. First, I multiply the regression coefficients by the mean covariates for a survey respondent's registrant matches. Second, I round these values to 0 or 1. The results presented in the table are for survey respondents in all years. "Voters" are respondents who turned out to vote in the given election, and "non-voters" are respondents who did not.

Table A10: Simulation parameters

Variable	$\tilde{\lambda}_t^{X_0}$		$\tilde{\Delta}_t^{X_0}$		$c_t^{Z_0}$	
	Mean	*Std. dev.*	*Mean*	*Std. dev.*	*Mean*	*Std. dev.*
Intercept	1.04	0.44	-0.25	0.32	0.68	1.14
Demographics and party						
Race: black	-0.20	0.24	-2.75	0.45	0.05	0.24
Race: other non-white	0.10	0.32	0.77	0.34	-0.11	0.20
Female	0.02	0.14	-0.14	0.19	0.02	0.12
Age (years)	-0.07	0.00	-0.06	0.00	-0.02	0.01
Parcel value per registrant (20 groups)	0.00	0.01	-0.03	0.02	0.03	0.01
Block and block group characteristics						
Ln: population density in block (pop. / sq. km)	0.00	0.02	-0.13	0.06	-0.02	0.04
Ln: household median income in block group (2010 $)	0.19	0.09	0.66	0.21	0.09	0.13
Share college graduates in block group	0.14	0.58	-1.85	0.73	-0.16	0.31
Interactions between registrant and precinct characteristics						
High-education precinct	-0.06	0.46	-0.09	0.44	0.04	0.13
Non-white registrant times high-education precinct	0.20	0.07	0.44	0.24	0.00	0.09
Age (years) times high-education precinct	0.00	0.01	0.00	0.01	0.00	0.00
Closeness of NC House and NC Senate races	0.01	0.01	-0.01	0.03	-0.01	0.02
Region fixed effects						
Region 02	0.06	0.06	0.09	0.02	0.06	0.10
Region 03	0.08	0.14	0.26	0.09	-0.01	0.22
Region 04	0.11	0.16	0.32	0.07	0.02	0.20
Region 05	0.10	0.10	0.26	0.08	0.00	0.23
Region 06	0.14	0.17	0.42	0.13	-0.04	0.14
Region 07	0.13	0.13	0.28	0.15	0.01	0.19
Region 08	0.05	0.16	0.47	0.14	0.00	0.11
Region 09	0.12	0.14	0.53	0.15	-0.08	0.12
Region 10	0.11	0.17	0.57	0.18	-0.03	0.17
Cost instruments						
Ln: distance to nearest early-voting location / block length	-	-	-	-	-0.04	0.02
Intensity of election-day rainfall (3 groups)	-	-	-	-	0.01	0.02

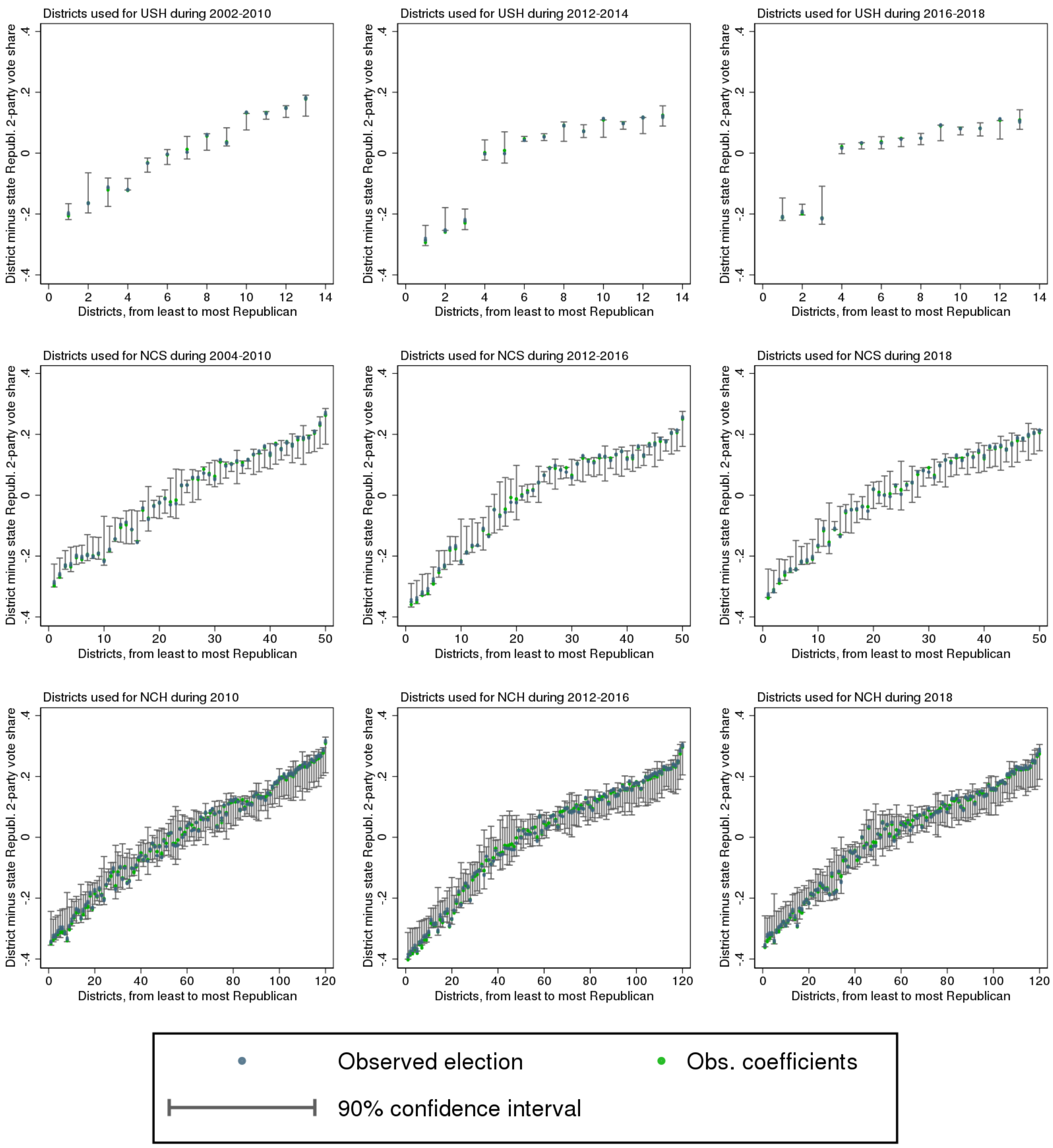
Notes: The table presents means and standard deviations of preference and cost shocks used in the simulation. These are calculated as the across-election mean and standard deviations of the coefficients in regressions 10 and 11. $X_{it,0}$ and $Z_{it,0}$ exclude covariates that depend on political conditions, such as party registration and the utility from turning out. In addition, covariate values differ across elections for (i) the closeness of NC House and NC Senate races, (ii) distance to early-voting locations, and (iii) election-day rainfall. I account for this uncertainty by drawing values of these covariates in the simulation. See Section 5 for a discussion of the simulation.

Figure A1: Predicting district-minus-state vote shares in 2008



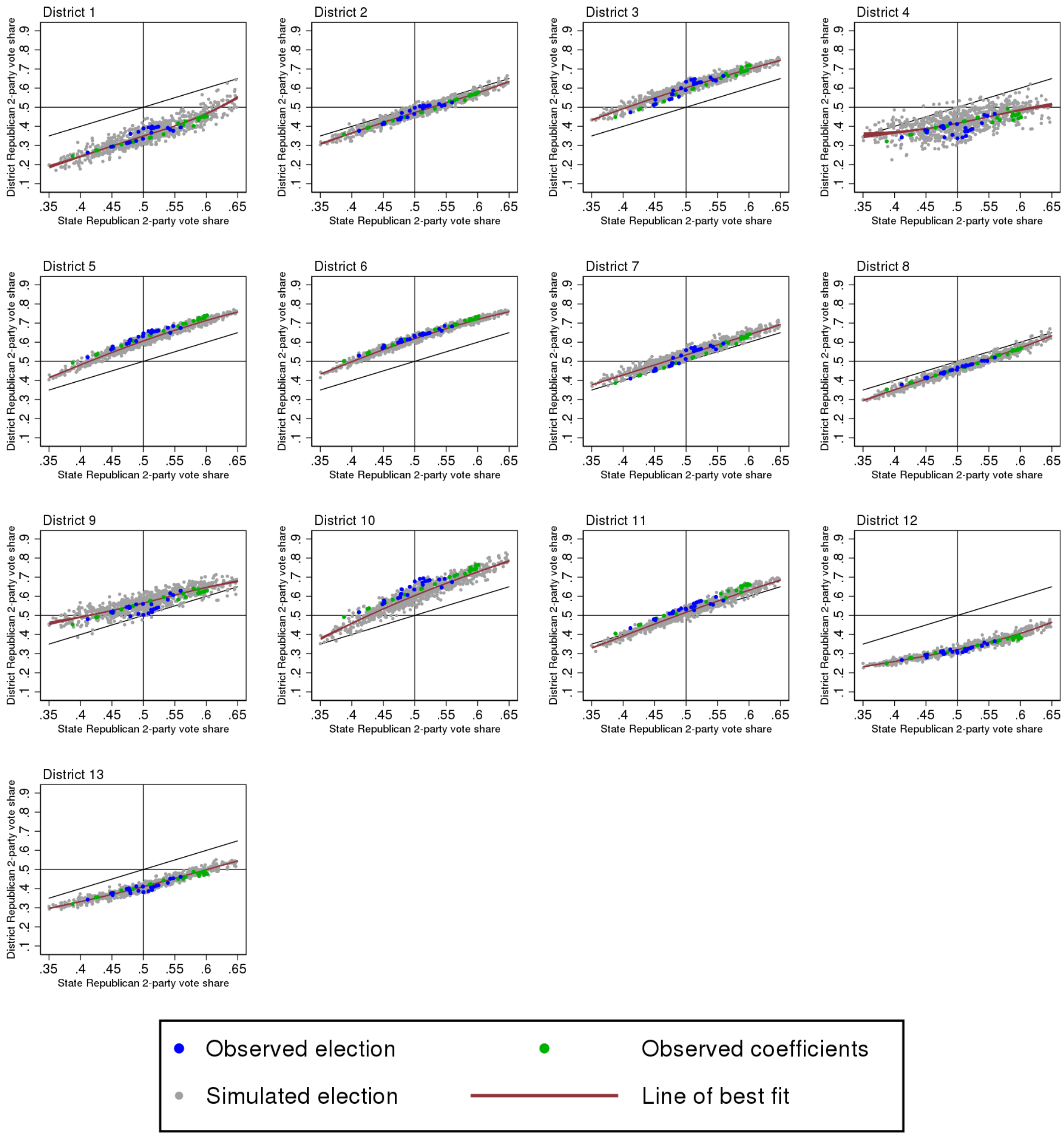
Notes: The figure plots confidence intervals and observed values for the difference between district and state two-party vote shares in 2008. The confidence intervals are calculated by fitting the model and running the simulations using the 2010-2018 elections. They represent the 90% range of differenced two-party vote shares predicted for the given district by the simulations. The green and blue dots represent observed values. The green dots are for pseudo 2008 district minus state vote shares that are calculated by combining the 2008 model coefficients with the 2010 electorate. The blue dots are for actual 2008 district minus state vote shares (i.e., those that use the 2008 model coefficients and the 2008 electorate). Green and blue dots are presented for all 2008 contests. They are calculated by aggregating votes in the contests according to the given districts and then subtracting the contests' statewide vote shares. The simulations correspond to those described in Table 12.

Figure A2: Predicting district-minus-state vote shares in 2018



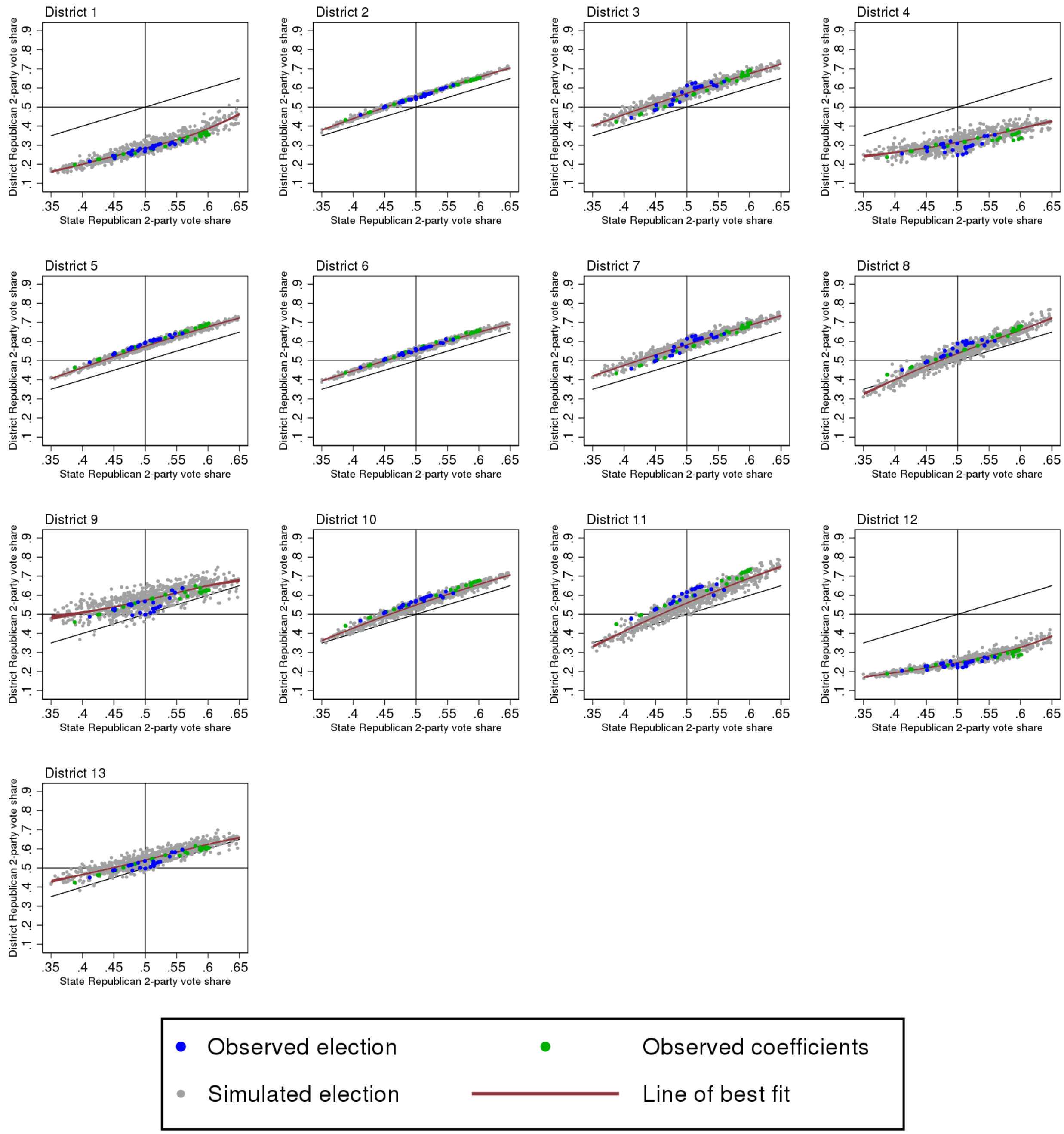
Notes: The figure plots confidence intervals and observed values for the difference between district and state two-party vote shares in 2018. The confidence intervals are calculated by fitting the model and running the simulations using the 2008-2016 elections. They represent the 90% range of differenced two-party vote shares predicted for the given district by the simulations. The green and blue dots represent observed values. The green dots are for pseudo 2018 district minus state vote shares that are calculated by combining the 2018 model coefficients with the 2016 electorate. The blue dots are for actual 2018 district minus state vote shares (i.e., those that use the 2018 model coefficients and the 2018 electorate). Green and blue dots are presented for all 2018 contests. They are calculated by aggregating votes in the contests according to the given districts and then subtracting the contests' statewide vote shares. The simulations correspond to those described in Table 12.

Figure A3: District and state two-party vote shares: 2002-2010 U.S. House districts



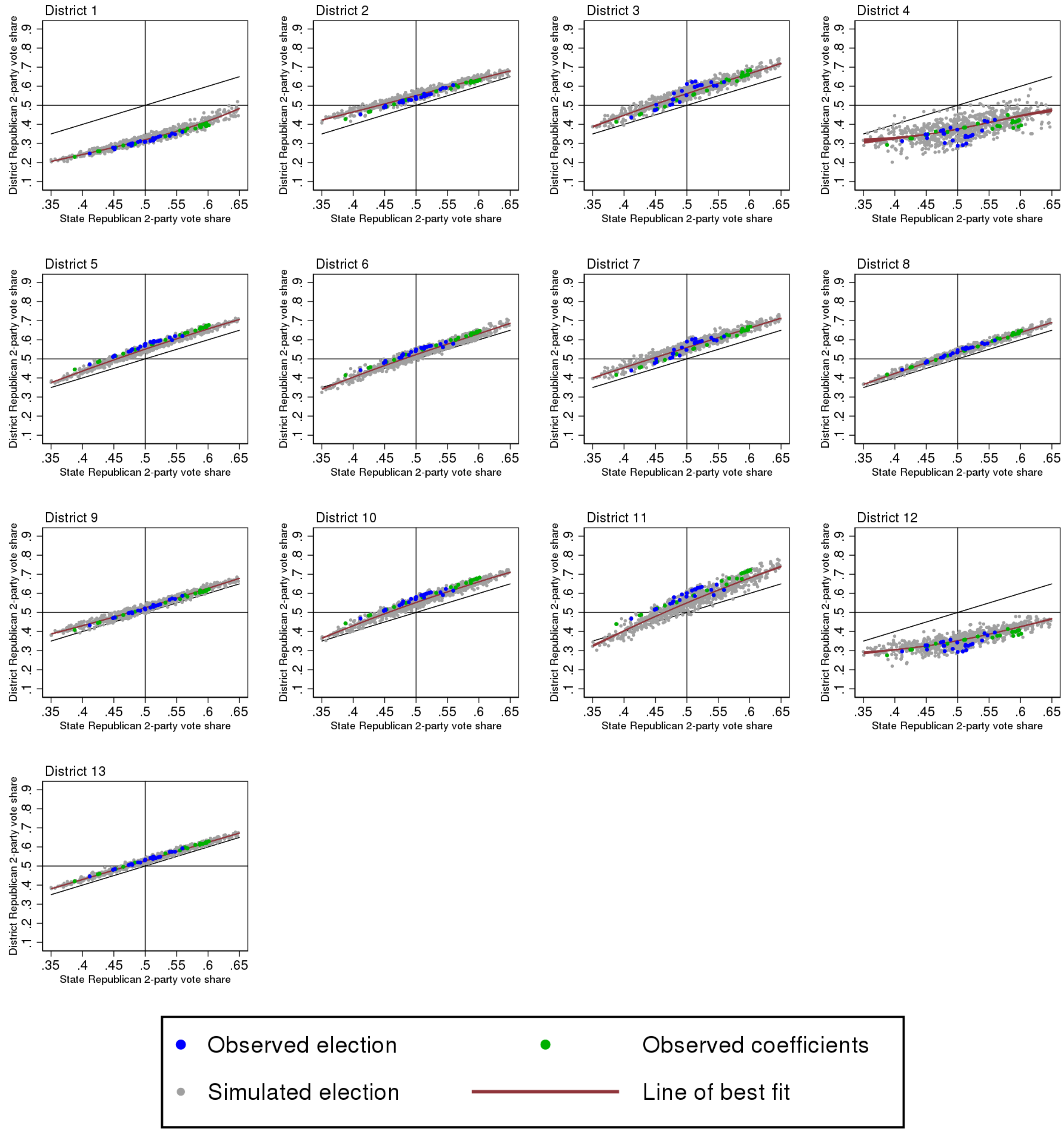
Notes: The figure plots district versus state two-party vote shares by U.S. House district. Blue dots represent contests from the 2008-2018 elections. Green dots represent contests in simulated elections that use the 2010 electorate and model coefficients from the 2008-2018 elections. Finally, gray dots are contests in simulated elections. The simulations correspond to those described in Figure 11. Districts are from the U.S. House map used during 2002-2010.

Figure A4: District and state two-party vote shares: 2012-2014 U.S. House districts



Notes: The figure plots district versus state two-party vote shares by U.S. House district. Blue dots represent contests from the 2008-2018 elections. Green dots represent contests in simulated elections that use the 2010 electorate and model coefficients from the 2008-2018 elections. Finally, gray dots are contests in simulated elections. The simulations correspond to those described in Figure 11. Districts are from the U.S. House map used during 2012-2014.

Figure A5: District and state two-party vote shares: 2016-2018 U.S. House districts



Notes: The figure plots district versus state two-party vote shares by U.S. House district. Blue dots represent contests from the 2008-2018 elections. Green dots represent contests in simulated elections that use the 2010 electorate and model coefficients from the 2008-2018 elections. Finally, gray dots are contests in simulated elections. The simulations correspond to those described in Figure 11. Districts are from the U.S. House map used during 2016-2018.