Polarization and State Legislative Elections*

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Abstract

U.S. state legislatures are critical policymaking bodies and the major pipeline of candidates to national office. Polarization in state legislatures has increased substantially in recent decades, yet we understand little about the role of elections in this process. We offer the first systematic study of state legislative candidate ideology across all election stages using a new dataset on primary- and general-election results for over 84,000 candidates, 1992-2020. We find that the pool of candidates has polarized substantially in recent decades amidst consistently low electoral competition. More-extreme candidates have enjoyed a modest advantage in contested primaries that has doubled in the past decade. More-moderate candidates previously enjoyed an advantage in contested general elections, but this has shrunk to nearly zero in the last decade. The results indicate a shifting equilibrium in which more-extreme candidates increasingly seek office, win primaries more often, lose general elections less often, and face limited competition.

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1 Introduction

American elected officials at the state and national level are extraordinarily polarized along ideological and partisan lines (e.g., McCarty, Poole, and Rosenthal 2006; Shor and McCarty 2011). Political observers and researchers worry that this polarization might render the policy process less efficient, less responsive to citizens' needs, and less able to mount effective responses to crises. As a result, a large body of research seeks to understand the causes of legislative polarization, including its possible roots in the electoral system. While the research on candidate ideology and electoral outcomes focuses mainly on the national level (e.g., Ansolabehere, Snyder, and Stewart 2001; Canes-Wrone, Brady, and Cogan 2002; Canes-Wrone and Kistner 2021; Hall 2015), understanding whether state legislative elections favor more-moderate or more-extreme candidates is important because state legislatures are themselves highly consequential and increasingly polarized policymaking bodies (Grumbach 2018; Shor and McCarty 2011), and because they are the main source of future House and Senate candidates (e.g., Thomsen 2014) and could therefore be driving national polarization.[1] To determine how the state legislative electoral system favors more-moderate or more-extreme candidates, we must analyze all three stages of the process: how ideologically polarized are the people who choose to run for office? How much are more-extreme candidates favored in primary elections? How much are more-moderate candidates favored in general elections?

Two key empirical obstacles have prevented the comprehensive analysis of all three stages and their potential roles in the growth of legislative polarization: we lack a measure of state legislative candidate ideology that applies to both incumbents and non-incumbents and corresponds closely to legislative polarization, and we lack data on state legislative primary election returns.

In this study, we address these two obstacles and offer the first systematic assessment of candidate ideology and electoral selection in state legislative elections. First, we develop

[1]For arguments for why a more-extreme state legislative candidate pool could cause an important part of the rising polarization of Congress, see Thomsen (2017) and Hall (2019).

a new measure of state legislative candidate ideology that applies to incumbents and non-incumbents alike and addresses potential concerns about the low within-party correlation between Bonica (2014)'s CFScores and roll-call voting discussed in Barber (N.d.), Hill and Huber (2015), and Tausanovitch and Warshaw (2017). Building off of the ideas in Bonica (2018) and Bonica and Li (2021), we use a machine-learning based approach that uses campaign donation records to predict incumbent NP-Scores, a widely used measure of state legislator's roll-call-based ideology from Shor and McCarty (2011). We train the model using only contributions received in a candidate's first winning primary election campaign, addressing concerns that campaign finance based scalings could partially be a function of having won office previously. We then apply this predictive model to all candidates. The resulting measure correlates highly with NP-Scores, even within party.

Second, in collaboration with Fouirnaies and Hall (2020) and Rogers (2021), we construct a new dataset on state legislative primary elections, collected and digitized from each state's official records, and extensively cleaned and standardized. We merge this with data on general elections from 1992 through 2020, and then we merge all of this data with our machine-learning based candidate ideology scores to form a dataset containing the estimated ideological positions and primary- and general-election performances of over 84,000 candidates for state legislative office.

With this new data, we document three key empirical patterns about state legislative elections and polarization. First, after reviewing the low levels of electoral competition (e.g., Rogers 2021)—which makes who chooses to seek office particularly important for polarization—we show that the polarization of the whole pool of candidates seeking state legislative office has risen dramatically over the past several decades. The growing polarization of state legislators tracks the polarization of the pool of candidates running for office quite tightly. We argue that who runs for state legislature may therefore be very important for understanding state legislative polarization, despite the focus of existing research on incumbent positioning, and may therefore be important for explaining polarization at the federal level, too. If the entire pipeline of candidates seeking state legislative office is polarizing, this will increase the polarization of congressional candidates, too.

Next, we show that contested primary elections favor more-extreme candidates, on average. This advantage has more than doubled in magnitude over the past decade. Primaries are a key stage of the candidate selection process, but to date there are no systematic empirical studies of candidate ideology and electoral performance in primaries (though see Rogers (2021) for a valuable analysis of *incumbent* accountability in primary elections, which concludes that more-liberal state legislator incumbents perform somewhat better in Democratic primaries). The growth in the advantage of more-extreme candidates in primaries suggests the need for deeper studies of the nomination process, as well as the ways that this advantage might deter more-moderate candidates from running for state legislative office in the future. While much of the state legislative elections literature is currently focused on the important process of nationalization and partisanship, these concepts cannot explain the changing dynamics of primary elections since these elections concern intraparty competition and do not provide voters with party labels to help them with their voting decision.

Finally, using a panel design that compares over-time changes in the ideological midpoint between candidates within a given district, we show that contested general elections have weakly favored more-moderate candidates, on average, consistent with the findings in Caughey and Warshaw (2020). However, this advantage has fallen to almost zero in elections since 2010, consistent with the growing literature on the nationalization of state legislative elections (Abramowitz and Webster 2016; Hopkins 2018; Rogers 2016, 2021). These findings are also consistent with a small literature that finds relatively weak correlations between more-moderate roll-call voting and electoral success (Birkhead 2015; Hogan 2008; Rogers 2017). On the other hand, despite these patterns of nationalization, meaningful amounts of split-ticket voting still occur in state legislative races (Kuriwaki 2020),[2] and it remains a puzzle why there has been a more substantial advantage to more-moderate candidates

[2]Moreover, where information is higher, split-ticket voting occurs at higher rates (Moskowitz 2021).

in the 1990s and 2000s, when partisanship was still important and voter information was presumably still low in state legislative elections.

Having established these key findings, we use the rich variation among the U.S. states to try to learn more about them. We show that the advantage to more-moderate candidates is significantly larger in off-cycle elections, where turnout is lower without a presidential race at the top of the ticket and voter information is therefore likely to be higher. This is consistent with the idea from the nationalization literature that low rates of voter information, and increasing rates of partisan voting, have played a role in eroding the advantage of more-moderate candidates. However, the advantage to more-extreme primary candidates is just as large in off-cycle elections, pointing to the need for new theorizing about candidate entry and primary elections in low-information environments.

The remainder of the paper is organized as follows. In Section 2, we describe the new scaling method we use to measure candidate ideology in state legislative elections. Section 3 describes the new election data we have assembled in collaboration with other researchers. Section 4 describes the low rates of competition in state legislative elections and shows how the candidate pool has polarized in recent decades. Sections 5, 6, and 7 measure the relative advantages of more-extreme and more-moderate candidates in contested primaries, contested general elections, and in the overall election system, respectively. Section 8 shows how these effects have varied over time, and across key institutional variables in the states, and Section 9 shows how effects vary by party. Finally, Section 10 concludes.

2 A Machine-Learning Based Measure of Candidate Ideology

In this section, we motivate and explain the new machine-learning based measure of candidate ideology that we created to study state legislative elections and polarization.

2.1 Existing Measures Not Optimized for Studying Legislative Polarization

Since our goal is to assess the electoral roots of roll-call based polarization, we need a measure that closely captures how candidates would cast roll-call votes in state legislatures. However, no existing measures of ideology that extend to candidates for state office are optimized explicitly for capturing roll-call voting behavior in state legislatures. Bonica (2014)'s CF-Scores, which use an unsupervised approach to extract a dimension of ideology from donations to candidates, have relatively low within-party correlations with roll-call based measures for incumbents (Barber N.d.; Hill and Huber 2015; Tausanovitch and Warshaw 2017).[3] While there may be many settings in which that low correlation is not in and of itself problematic, for cases where it is a problem, Bonica (2018) developed supervised scalings that predict incumbent DW-NOMINATE scores in Congress based on campaign contributions. These "DWDIME" scores are highly correlated with roll-call voting behavior within party, but they do not extend to most candidates for state office. Hence, our goal in this section is to build a supervised scaling similar to Bonica (2018) but for state legislative elections.

2.2 Predicting NP-Scores with Campaign Finance Records

We begin with the key target variable that we want to predict, the ideological mappings for state legislators from Shor and McCarty (2011), called NP-Scores. These mappings are the result of projecting a roll-call-based measure of ideology onto one based on legislator responses to the Project Vote Smart National Political Awareness Test (NPAT), so that all state legislators are measured on a common, national issue space. The bridging procedure across states amounts to a state-specific OLS regression of an NPAT-based scaling onto a

[3] To be clear, there may be many instances in which a high within-party correlation with DW-NOMINATE is not the right empirical goal. Different applied settings require different types of scalings.

roll-call based scaling using legislators who have both scores available. The most recent version provides NP-Scores for 24,716 state legislators between 1993 and 2018.[4]

Since these NP-Scores are only available for legislators who won election, we need another set of information to help us predict scores for people who have not, and may not ever, serve in office. While there are many potential data sources one might use for this purpose—such as the text of candidate speeches or behavior on social media—we follow the supervised learning approach of Bonica (2018) to estimate scores for the full set of candidates running for state office using campaign donations. Campaign contributions are ideal for our purpose because state legislators raise money from many donors, giving the data wide coverage, and because a meaningful number of sophisticated donors possess substantial on-the-ground knowledge about candidates and donate in substantial part based on ideological motivations (e.g., Barber, Canes-Wrone, and Thrower 2017). These are useful a priori reasons for using campaign-finance scalings, though we should point out that we do not need to assume any particular behavior by donors; whether the campaign finance data can predict NP-Scores or not is a simple empirical matter that we confirm below.

We obtain campaign donations for state legislative candidates from the National Institute on Money in Politics, which digitizes and standardizes information from campaign finance reports for all state-office candidates.[5] The data are quite comprehensive, consisting of nearly 44 million transactions between 1989 and 2020. We merge this donation information at the legislator-election-year level to the NP-Scores to obtain a unified set of predictors and outcomes for 19,292 state legislators in at least one election.

Design Choices in Supervised Scaling Procedure

To construct our supervised scalings, we learn a party-specific function $\hat{f}_p(\cdot)$ that captures the predictive relationship between primary donations before a legislator ever serves in office,

[4]The July 2020 release of the data was downloaded via `https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/GZJOT3`.

[5]See `https://www.followthemoney.org/our-data/about-our-data` for more information. For an overview of the diverse campaign finance regulatory landscape in state legislatures, see Powell (2012).

and NP-Score after winning office for the first time:

$$y_{i,t+1} = \hat{f}_p(\boldsymbol{x}_{it}) + \epsilon_{i,t+1} \tag{1}$$

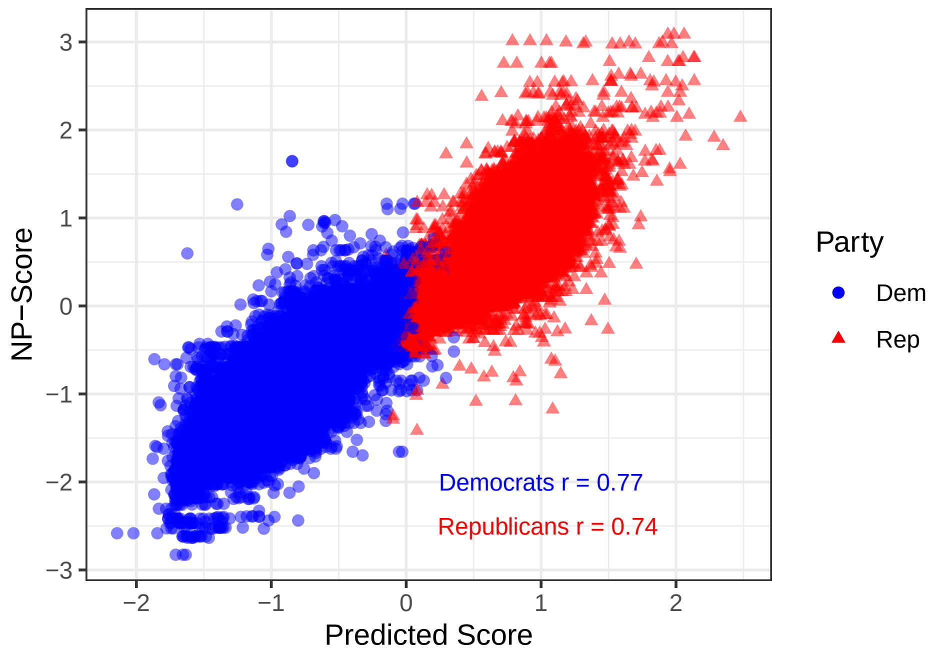
where $y_{i,t+1}$ is the NP-Score for legislator i in party p that captures votes beginning in year $t+1$, the year they first took office, and $\boldsymbol{x}_{it}$ is a vector of predictors for legislator i as of the primary for party p in year t, the year the legislator ran for election and won for the first time. As in Bonica (2018), our donation-based predictors include both standalone donations received from larger donors and summaries of donations received across all donors, large and small, in the dataset.[6] To avoid measurement error bias in our downstream regressions, we must assume that $\hat{f}_p(\cdot)$ is equally accurate on average for both winners and losers of primary elections, an assumption made more plausible by our design choice to use only primary donations before a candidate has ever taken office. This avoids biasing the predictive models with information following primary victories when studying performance in primary elections (Hall and Snyder 2015), and improves the generalizability of the models to losers of elections by mimicking the information set that donors have about candidates whom they have not yet observed in office. Learning two separate functions for Republicans and Democrats improves accuracy within party and hence our ability to measure extremism within partisan primaries. These design choices limit our training data to 10,858 candidates with at least one donation in their first winning primary from among 991,123 primary donors.

We use a single ten-fold cross-validation loop to choose the best machine learning method for our prediction problem, the type of donations included, and the granularity of the donor summary features.[7] The final set of models was chosen based on which combination of

[6]We transform the raw positive dollar amounts from each donor that gave to at least 10 candidates in the training data into 2020 dollars and normalize them to lie between 0 and 1, representing the proportion of money received by a legislator in a given primary cycle. Appendix A.2 describes in more detail how we constructed the donor summary features. We also include state dummies as predictors.

[7]Given our large number of possible predictors (e.g., amounts from each donor in an election cycle), we test the performance of three types of machine learning methods that are well suited to handle large predictor sets with possibly many irrelevant variables: elastic net regression (Zou and Hastie 2005), random forests (Breiman 2001), and gradient-boosted regression trees (Friedman 2001). Appendix A.1 describes how these methods work in more detail.

Figure 1 – Predicted Scalings Correlate Well With NP-Score Scalings, Even Within Party.



choices had the lowest cross-validated mean squared prediction error (MSPE). Appendix A.3 provides the details of the cross-validation results for all model and data choices. The final model chosen through cross-validation was a random forest using all types of contributors for both Republicans and Democrats.

2.3 Strong Correlation with NP-Scores, Within Party

Figure 1 presents a validation of our measure using the correlation between the predicted NP-Scores and the true NP-scores for candidate-year observations involving incumbents in our election dataset.[8] All scores are out-of-sample in the sense that they are generated by a model that has not seen the candidate-year's data in training.[9] The correlations are

[8]See Appendix A.9 for additional information on the correlation between our predicted NP-scores and existing measures of candidate ideology.

[9]Because we cross-validate our input data choices as well as the machine learning methods, we accomplish this in two ways. For candidate-years in the training data, we produce out-of-sample scores by leaving each cross-validation fold entirely out of the model training, re-running the cross-validation procedure with the 9 remaining folds, and making predictions on the held-out fold with the model that was optimized without access to its data. For all other candidate-years not in the training data, we produce out-of-sample scores by using the final model cross-validated using all ten folds to make predictions.

Table 1 – Predicted NP-Score More Correlated With True NP-Score Than Existing Measures. Correlations with true NP-Scores for the predicted NP-Scores, dynamic CFScores, and static CFScores. By construction, the predicted NP-Score is more highly cor ¿ related with the true NP-Score, especially within party.

Party	Predicted NP Score	Dynamic CF	Static CF
Republicans	0.74	0.50	0.40
Democrats	0.77	0.39	0.29
Combined	0.95	0.84	0.85
N	58,370	48,791	48,993

high within party ($r = 0.77$ and $r = 0.74$ for Democrats and Republicans respectively). Table 1 compares the correlations between our measure and the true NP-Scores with the analogous correlations between CFScores and the true NP-Scores. By construction, our predicted NP-scores correlate more highly within party with the true NP-Scores than do the CFScores, which are not optimized to describe roll-call based ideology in state legislatures. Our predicted NP-Scores are therefore better positioned to predict roll-call based ideology in state legislatures for non-incumbents than existing measures.

Having shown that our predicted NP-Scores correlate strongly with the true NP-Scores, we consider how a potential breakdown in the efficacy of the NPAT bridging procedure in Shor and McCarty (2011) could affect our measure and downstream regression results. Because response rates to the NPAT have declined over time and are uneven across states,[10] there may be concerns about whether the bridging procedure still can recover meaningful ideological orderings between states. A breakdown in the bridging procedure would adversely impact our prediction error by limiting our ability to pool donation information across states to predict the NP-Scores. In support of this idea, Appendix A.4 shows that states with higher average NP-Score estimation error have higher average model prediction error. However,

[10] "Candidates Running in 2011 Lack Courage." Oct. 17, 2011. Darren McDivitt, *Project Vote Smart* blog. `https://votesmart.org/blog-archive/2011/oct/17/2011-candidates-lack-courage/`. Since the 2010 election, Project Vote Smart has tried to circumvent non-response by using candidates' public records to fill in the missing information on their positions, see `https://justfacts.votesmart.org/about/political-courage-test/`.

the fact that the model still successfully makes use of pooled donation information across states suggests that the bridging procedure does provide useful between-state ideological information, even if it is limited. The between-state disparity in predictive accuracy should not confound our within-state regressions, but we caution that our measure is not optimized for between-state analyses.

To further support the claim that a model trained on winners can predict losing candidates' ideology effectively, Appendix A.4 also shows that the models maintain high within-party accuracy even for losing elections before candidates go on to win for the first time. Appendix A.5 shows that losing candidates share many large donors in common with winners, and that the percentage overlap in donor base between winners and losers does not correlate with predicted extremism. Appendix A.6 reports the larger donors that contributed most to the predictive performance for each party, according to a permutation-based measure of feature importance. The most predictive large donors tend to reflect state-specific, party-specific sources of campaign funding, with some reflecting ideological fault lines within the Republican Party in particular. This suggests that, as desired, the predicted scalings contain information about the ideological battles within partisan primaries.

To summarize, we use random forest models selected through cross-validation to predict incumbent ideology scores based on campaign finance records. Our measure is built to avoid being trained on "post-treatment" data on contributions that come in after a candidate wins election, and strongly predicts NP-Scores. Because it is set up to predict roll-call-based measures of ideology as strongly as possible, it has strong within-party correlations with NP-Scores, ensuring both that it is a tractable measure for studying how state legislative elections favor candidates who will contribute more or less to legislative polarization, and that it is detecting ideological rather than only partisan differences among candidates. Armed with this measure, we now turn to describing the election data that we pair the measure with in order to study state legislative elections.

3 New Data on State Legislative Elections

In order to provide a comprehensive analysis of candidate ideology and electoral performance in both primary and general elections, we assemble a new dataset of state legislative election results. We begin with the State Legislative Election Returns (SLERs) dataset from Klarner (2021) which covers all general elections in state legislatures, including full coverage of the years of our study, 1992–2020.

Next, we construct a comprehensive record of primary election outcomes for 1992-2020 in all relevant states. To do this, we started from partial data on 40 states for the period 1992-2014 from Rogers (2021). We added data on primaries in runoff states collected in Fouirnaies and Hall (2020). We then collected the remainder of the data—filling in gaps in the other datasets, adding the remaining states, and extending the data through 2020—from state websites, and cleaned and standardized the resulting combined dataset extensively. Overall, almost exactly 50% of the data we use was collected anew for our study, with the other half coming roughly equally from the two sources referenced above. When applicable, our primary data includes both first-round and runoff primary-election results. The complete primary dataset includes full coverage of all primary elections corresponding to general elections in our sample.

We merge the primary and general election data together into a master dataset along with the new candidate ideology scores outlined above. The resulting dataset features 156,009 candidate-election observations, including 120,529 observations for 55,359 distinct general election candidates and 86,734 primary election observations. A total of 51,254 candidate-elections appear in both the primary and general election dataset.

Finally, to facilitate meaningful comparisons between candidates, we restrict our analysis data along three margins. First, we focus on Democratic and Republican candidates. Second, we subset our data to include state-chamber-years for which a majority of all available seats are in single-member districts. Finally, we exclude state-chamber-years with non-conventional primary election systems (i.e. top-two and blanket primaries), all special elections, and require each election to send its winner to office for a full term.[11] In total, our data span 45 states between 1992 and 2020. See Table A.10 for a state-by-year breakdown of our primary and general election data coverage.

4 Polarization and Electoral Competition in State Legislatures: Initial Descriptives

To understand the links between candidate ideology, the electoral system, and polarization in state legislatures, we start by using our data to describe rates of electoral contestation, competition, and candidate polarization. As already established in Rogers (2021), rates of contestation are middling, and roughly 80% of state legislative elections are decided by 20 percentage points or more. With relatively little electoral competition, who runs for office becomes very important in determining how polarized the legislature will be. As we show, the pool of people running for state legislative office has polarized dramatically over time, just as the legislatures themselves have polarized.

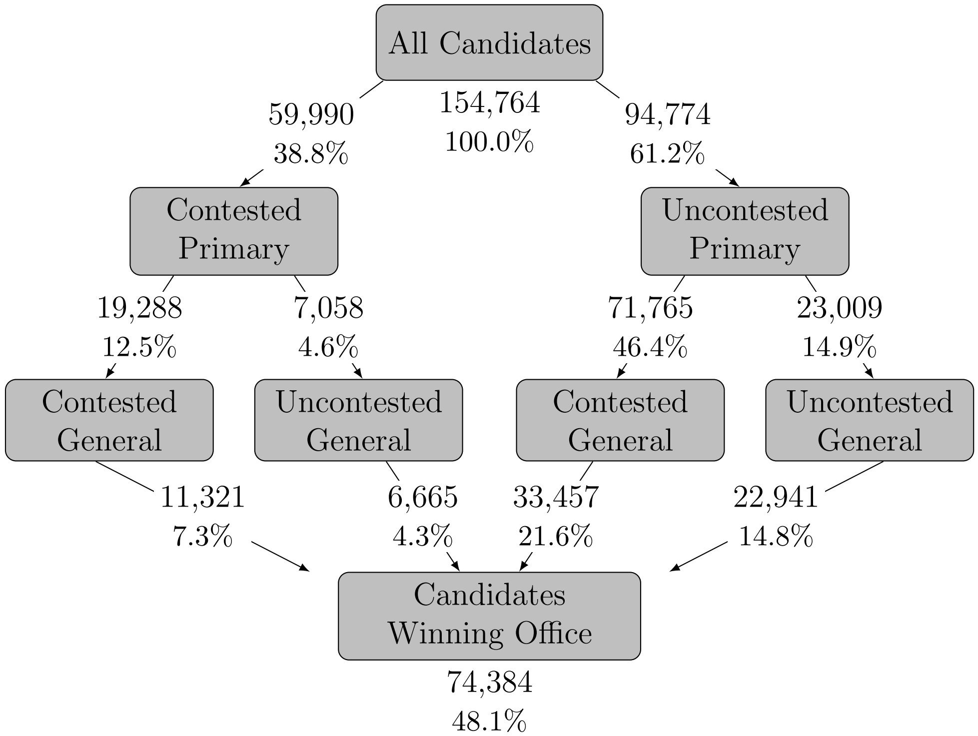
4.1 Contestation and Competition in State Legislative Elections

One of the striking features of state legislative elections relative to national elections is the lower degree of competition and contestation. Figure 2 breaks down the process by which candidates flow through primary and general elections and into the legislature. The unit of analysis is a candidate-year, and the flowchart shows the number of instances in which candidates in any given year face contested primary or general elections.

As the figure shows, in roughly 61% of cases, a candidate faces no primary opponent. Approximately 20% of candidates face no general-election opponent; 4.6% of whom faced at least one primary opponent, and 14.8% of whom faced no opponent in the primary, either.

[11]The latter two restrictions affect few legislators, reducing our sample by approximately .08%.

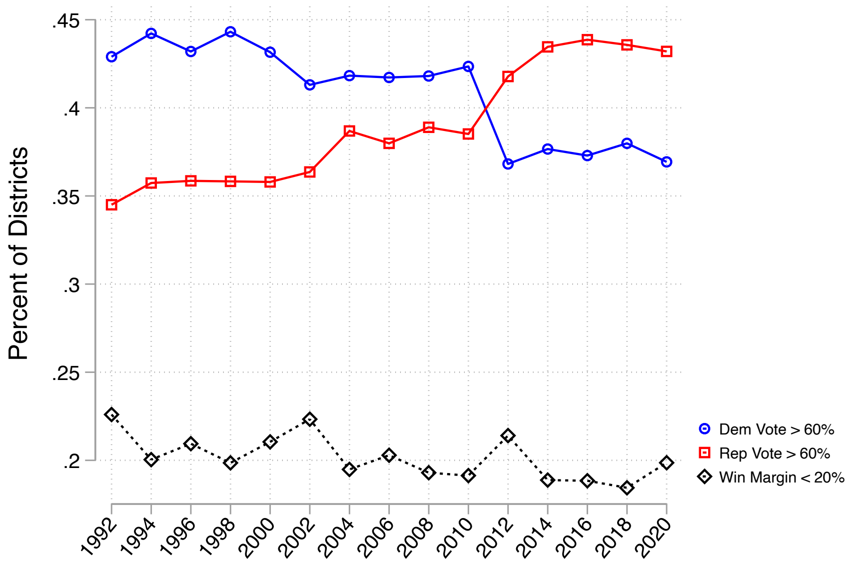
Figure 2 – The Candidate Funnel in State Legislatures



These figures are even more dramatic if we focus on incumbents: Rogers (2021) reports, for example, that 98% of incumbents win their primaries.

The flowchart only captures contestation. By looking at resulting vote shares, we find that there is less competition than the flowchart might suggest, because many of the contested races are quite lopsided. As Figure 3 shows, approximately 20% of state legislative general elections are decided by fewer than 20 percentage points (i.e., the winner received less than 60% of the two-party vote). This rate of competitiveness is fairly constant over time. The remaining 80% of races are won relatively easily by one party or the other, with a notable inversion occurring after the 2010 election and redistricting cycle, after which there is a much higher rate of comfortable Republican-won districts and a much lower rate of comfortable Democratic-won districts, compared to the previous two decades.

Figure 3 – Electoral Competitiveness in State Legislatures Over Time. Plots the rate at which districts see two-party competition or are safe for one party or the other, by year.



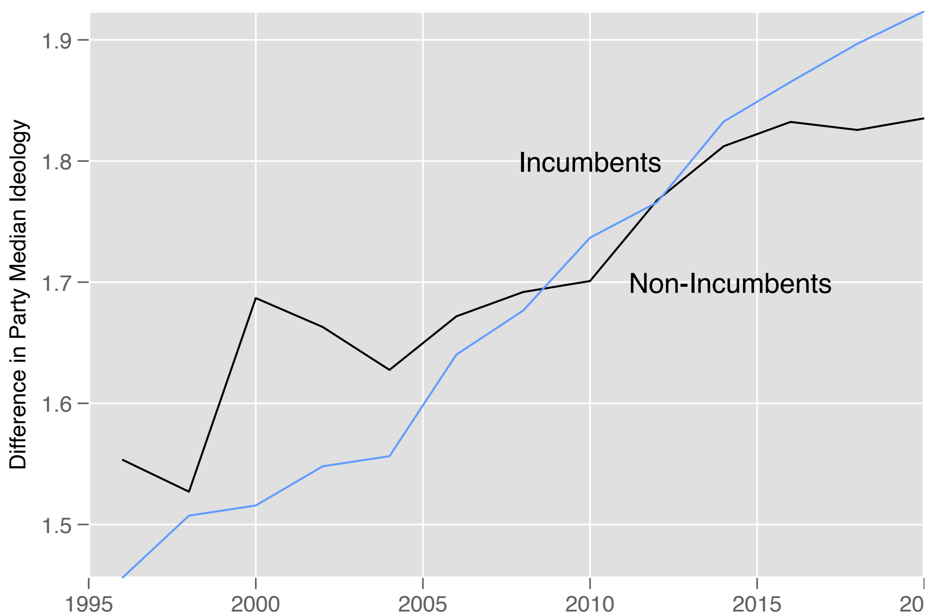
4.2 The Polarizing Candidate Pool in State Legislative Elections

With relatively low rates of electoral competition, who runs for office becomes especially important in determining the polarization of state legislatures. To investigate the ideological polarization of the candidate pool, Figure 4 plots the difference in the median candidate's ideology for each party, using our new measure of candidate ideology, over time. The plot shows separate lines for the entire set of new candidates in each cycle (i.e., all non-incumbent candidates), and for sitting legislators (i.e., incumbents). To keep the plot easily readable, we omit odd year elections from it. We also omit data from before 1996 because we have few observations for NP-Score until 1996.

As the figure shows, we see a steep increase in the polarization of the overall candidate pool over time; as legislative polarization has increased, so, too, has the polarization of the set of people running for office in the first place.[12] The figure also suggests that, in the

[12] Appendix A.5 shows that predicted extremism for non-incumbents is not correlated with how many donors they share with incumbents, allaying concerns that non-incumbents appear more polarized because only donors to incumbents, who may be more extreme, factor into the model predictions.

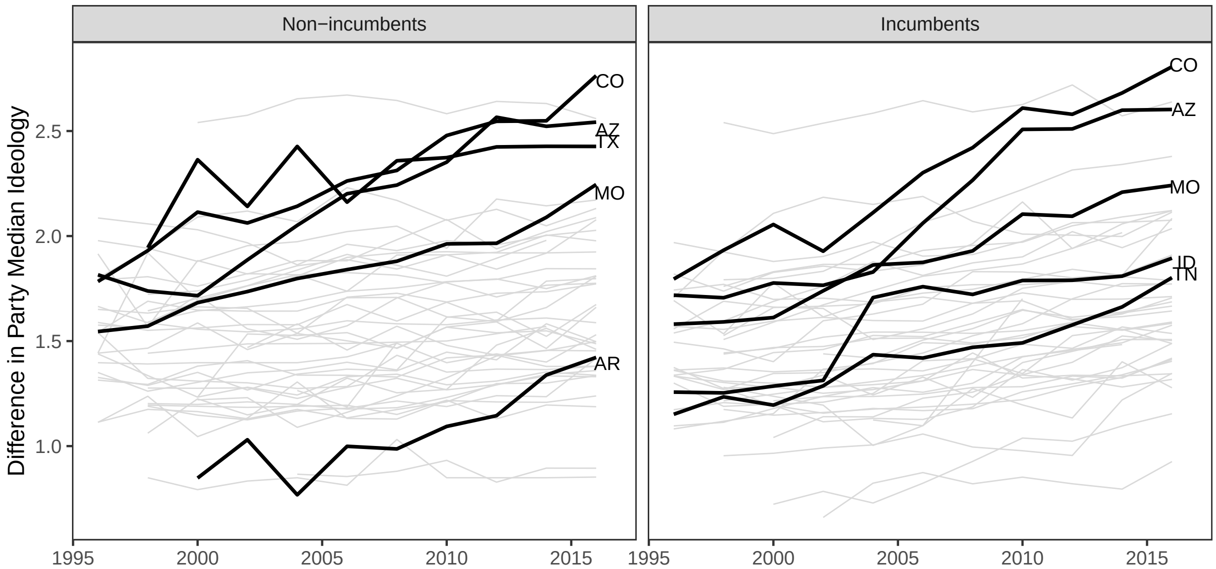
Figure 4 – Polarization of the Candidate Pool in State Legislatures Over Time, 1996-2020. Plots the absolute difference between each party's median incumbent legislator (blue line) and between each party's median non-incumbent candidate (black line), across all states, by year. Non-incumbent includes both challengers and open-seat candidates.



period from the 1990s through 2010, incumbents were systematically less polarized than non-incumbents (although the difference was not huge in substantive terms). Since 2010, this pattern has inverted, with incumbents now a bit more polarized than the rest of the candidate pool. This suggests that, in addition to a steady polarization in who runs for office over the past several decades, there has also been a shift in electoral selection, from a system that weakly favored more-moderate candidates from among the pool, to a system that weakly favors more-extreme candidates from among the pool. We will formally document this pattern in the analyses below.

Figure 5 explores how this pattern varies across states. The right panel shows over-time trends in the polarization of incumbents, while the left panel shows the over-time trends in the polarization of non-incumbents. Again, we see a broad upward trend in both types of polarization over time.

Figure 5 – Polarization of the Candidate Pool in State Legislatures Over Time, Across States. Plots the absolute difference between each party's median incumbent (right panel) and non-incumbent (left panel), by year and by state. The five states with the most growth are labeled and bolded.



These patterns do not necessarily imply that the polarization of state legislatures is caused by the polarization of the candidate pool directly. People may choose to seek office in anticipation of how the primary and general elections will treat them; as such, rates of competition and contestation, the polarization of the candidate pool, and the advantage or disadvantage of more-moderate or more-extreme candidates in primary and general elections are all part of some type of equilibrium. The goal of our study is to characterize this equilibrium and how it has changed over time. Hence, we turn now to exploring the links between candidate ideology and electoral outcomes directly.

5 Primary Elections and the Advantage of More-Extreme Candidates

Next, we turn to estimating the advantage for more-extreme candidates in contested primary elections. Following Canes-Wrone, Brady, and Cogan (2002) and many others, we compute the "extremism" of each candidate as the absolute value of their ideological score. Districts are likely to vary in their ideological preferences, which means that a candidate in one district that has a greater absolute value of her score could be more "moderate" for that district than a candidate in another district with a lower absolute value score. To address this issue, we include primary district fixed effects, so that we are making comparisons of candidates within a district. We estimate equations of the form

$$Y_{jpct} = \beta_1 Extremism_{jpct} + X_{jpct} + \gamma_p + \delta_t + \epsilon_{jpct}, \tag{2}$$

where Y_{jpct} reflects the vote share or victory indicator for candidate j in primary p in chamber c at time t. The vector X again stands in for an optional vector of covariates, and γ_p and δ_t stand in for primary-district and time fixed effects.

A secondary issue to address is that primaries vary in the number of candidates that run. As the number of candidates increases, average vote share mechanically decreases, and there may be a correlation between a larger number of candidates in a primary and the average level, and heterogeneity, of candidate extremism. Accordingly, in all specifications, we must directly account for the number of candidates in the race.

We do this in two different ways. First, we include district-by-party fixed effects, party-by-year fixed effects, and fixed effects for the number of candidates in the race. In this specification, we are performing a difference-in-differences in which we compare within-primary-district variation in candidate extremism over time, conditional on the number of candidates in the primary.

Table 2 – Advantage of More-Extreme Candidates in Contested Primary Elections, 1992-2020.

	Primary Vote Share		Win Primary	
	(1)	(2)	(3)	(4)
Cand Extremism	0.07	0.10	0.14	0.18
	(0.02)	(0.02)	(0.06)	(0.06)
Log Contributions	0.08	0.10	0.18	0.23
	(0.00)	(0.00)	(0.00)	(0.00)
# Observations	36,008	35,718	36,640	36,168
District-by-Party FE	Y	N	Y	N
Party-by-Year FE	Y	N	Y	N
Number of Candidate FE	Y	N	Y	N
Race FE	N	Y	N	Y

Robust standard errors clustered by state in parentheses. Cand Extremism scaled to run from 0 to 1. Sample is restricted to contested primary elections.

Second, we instead include fixed effects for the specific election (that is, for each state-district-party-year), making comparisons only amongst candidates in a given race. In this latter specification we do not need to include fixed effects for the number of candidates, since it is fixed within each race. This is arguably the strongest specification, since it does not require making any cross-district comparisons (relative to the specification above which draws on cross-district information to estimate counterfactual trends), but it may be statistically noisier.[13]

Table 2 presents the results. In the first two columns, we see that, on average, more-extreme candidates receive higher vote share in primary elections, regardless of specification. The extremism variable is scaled to run from 0 to 1, and we estimate that shifting from the most-moderate to the most-extreme candidate predicts a 7 or 10 percentage-point increase in vote share. In the final two columns we re-estimate this for probability of victory, finding that

[13]Both specifications may present a further issue of statistical inference, because we include all candidates within each election in the sample. For an election with k candidates, the kth candidate's vote share is mechanically determined by the vote shares of the other $k-1$ candidates. While we could attempt to directly address this issue, either by omitting one candidate from the regression or applying a correction to the standard errors, the clustered standard errors that we employ should address the induced auto-correlation within elections.

this same shift predicts a 14 or 18 percentage-point increase in the probability of winning the nomination. For a one standard deviation increase in extremism (roughly 0.13 points on the extremism scale), these estimates imply a .9 or 1.3 percentage-point increase in vote share and a 1.8 or 2.3 percentage-point increase in win probability. Interestingly, these results are in the same direction, but larger in magnitude, than the estimated relationship between Democratic liberalism and primary win probability for incumbents in Rogers (2021).[14]

6 General Elections and the Advantage of More-Moderate Candidates

We now turn to assessing the advantage of more-moderate candidates in contested general elections. Similar to the primary election analysis, the key empirical challenge for this analysis is that we only have a measure of ideology for candidates, not for voters. If we want to understand if "more-moderate" candidates do better, we need to compare them to their electorates in order to define who is "more moderate" and who is "more extreme." To do this, we follow the method of Ansolabehere, Snyder, and Stewart (2001). For each contested election, we compute the distance in ideology between the Democrat and Republican candidates, and we compute the midpoint between their estimated platforms. As this midpoint increases (shifts to the right), holding the distance between the candidates constant, the left-wing candidate becomes more-moderate relative to the right-wing candidate.

While the midpoint method is not feasible in primary elections (it relies on having only two candidates in each race being analyzed), it offers a nice advantage over the absolute-value method for general elections, because it further relaxes the assumption that more-extreme candidates necessarily have higher absolute-value scores even within district. As the Appendix to Ansolabehere, Snyder, and Stewart (2001) establishes, the midpoint method

[14] Rogers (2021) estimates that a one standard deviation in roll-call liberalism for Democratic incumbents leads to a 1.3 percentage-point increase in primary win probability, on average.

estimates the association between moderation and election outcomes even in cases where both candidates are to the left or to the right of the median voter, an edge case in which the absolute value method fails.

To implement the midpoint method, we estimate regressions of the form

$$Y_{ict} = \beta_1 Midpoint_{ict} + \beta_2 Distance_{ict} + X_{ict} + \gamma_i + \delta_t + \epsilon_{ict}, \tag{3}$$

where Y_{ict} represents either the Democratic vote share or victory indicator in district i in chamber c at time t. The vector X_{ict} stands in for an optional vector of control variables, and γ_i and δ_t stand in for district and time fixed effects.

The quantity of interest is β_1 which captures the association between how moderate the Democratic candidate is (when the midpoint between the two candidates shifts right while holding the distance between them equal) and Democratic electoral outcomes.

In the original Ansolabehere, Snyder, and Stewart (2001) approach, the unobserved district median voter's preferences are held constant by controlling for presidential vote share in the district. Because presidential vote share is not widely available by state legislative district, we instead use district fixed effects. We generate these fixed effects separately for each redistricting period. Finally, we also include year fixed effects.

The estimates that result from this approach do not intend to capture the "causal effect" of a candidate changing her platform; rather, it is a "selection effect" that asks whether candidates who offer more-moderate platforms, and who may vary from more-extreme candidates across many other attributes, do better electorally or not.

Table 3 presents the results. In the first two columns, we estimate the association between how moderate the Democratic candidate is, relatively speaking, and vote share, with or without controls for the amount of money raised by each candidate. As the first row shows, we find a positive relationship. The midpoint variable is standardized to run from 0 to 1,

Table 3 – Advantage of More-Moderate Candidates in Contested General Elections, 1992-2020.

	Dem Vote Share		Dem Win	
	(1)	(2)	(3)	(4)
Midpoint (Dem Moderation)	0.02	0.05	-0.00	0.07
	(0.01)	(0.01)	(0.05)	(0.05)
Distance Between Candidates	0.08	0.03	0.32	0.18
	(0.01)	(0.01)	(0.05)	(0.05)
Log Dem Total Contributions		0.25		0.63
		(0.01)		(0.03)
Log Rep Total Contributions		-0.22		-0.60
		(0.01)		(0.03)
# Observations	23,012	23,012	23,012	23,012
District-by-Regime FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y

Robust standard errors clustered by district in parentheses. Midpoint and Distance Between Candidates are scaled to run from 0 to 1. Sample is restricted to contested general elections.

hence these estimates indicate that moving from the most-extreme to most-moderate case, Democratic vote share increases by 2 or 5 percentage points.

The final two columns re-estimate this for win probability, finding mixed effects. Moving from the most-extreme to the most-moderate case, Democratic win probability either remains constant or increases by 7 percentage points. The standard deviation in the midpoint variable is roughly 0.14; hence, for a one standard deviation shift in the midpoint, we would estimate a 1 percentage-point increase in win probability using the larger estimate in the final column, or a 2.4 percentage-point increase at the upper bound of the 95% confidence interval for this estimate. Hence, the overall average advantage seems small in magnitude.

Robustness to Measurement Error

As mentioned in Section 2.2, we must assume that measurement error in our predicted scores is the same in expectation between winning and losing candidates in order for our regression estimates involving predicted NP-Scores to be unbiased. If this were not the case, then the measurement error would be correlated with our outcome of winning elections, confounding the true relationship between winning and regressors derived from the NP-Score. Our decision to avoid using post-victory information in model training is one safeguard against this possibility, but the error estimates presented in Appendix A.4 for losing elections suggest that measurement error is weakly correlated with incumbency. In Appendix A.7, we present results from the following robustness checks to address concerns about differences in measurement error between incumbents and non-incumbents. The main concern is that, because donors gain more information on candidate ideology after observing them in office, we might expect a measure of ideology based on donor behavior to be more precise for incumbents than for non-incumbents. To investigate the sensitivity of our results to this possibility, we first subset our regressions to elections involving training data legislators and their challengers. For the training data legislators, we use a static predicted score that carries over their out-of-sample, first winning election score to all subsequent elections they participated in. The comparison between the static score and non-incumbent challenger score replicates the donors' information about two first-time potential winners even for subsequent elections after the training data legislator has become an incumbent. Second, we re-estimate our regressions using open seat elections only. The results are directionally similar for all but the open seat general election races, where we cannot reject the null that the midpoint coefficient is zero.

For comparison, in Appendix A.8 we also re-estimate our regressions using Bonica (2014)'s static CF-Scores instead of our predicted NP-Scores. The CF-Score regressions find a strong relationship between moderation and victory for both primary and general elections. However, since the CF-Scores incorporate information post-victory for incumbent candidates, estimates using the CF-Scores are vulnerable to the same source of bias we describe above.[15]

[15] Consistent with this possibility, the estimates based on CF-Scores generally suggest a larger advantage to more "moderate" candidates.

Table 4 – Overall Candidate Selection in State Legislative Elections, 1992-2020.

	Candidate Extremism			
	(1)	(2)	(3)	(4)
Win Election	0.007	0.014	0.015	0.015
	(0.001)	(0.001)	(0.001)	(0.001)
Intercept	0.330	–	–	–
# Observations	110,086	110,086	110,086	110,083
State FE	N	Y	Y	N
Year FE	N	N	Y	N
State-by-Year FE	N	N	N	Y

Robust standard errors clustered by state in parentheses. Cand Extremism scaled to run from 0 to 1.

7 Overall Advantage for More-Extreme Candidates

On average since 1992, contested state legislative general elections have very modestly favored more-moderate candidates, while contested primary elections have favored more-extreme candidates. How do these effects net out? Comparing the consequences of the two effects is complicated, because it depends not only on the coefficient estimates but on the rates of contestation in primaries and generals and the degree of variation in candidate positions.

To examine how the effects offset in a systematic way, we run very simple regressions in which we compare the average extremism of winning and losing candidates, defined as the simple absolute value of the ideological measure. If the advantage for more-extreme candidates in primaries outweighs the advantage for more-moderate candidates in general elections, then we would expect the average ideology of winners to be more extreme than losers; and vice-versa if the general-election effect outweighs the primary-election effect.

Table 4 presents the results. In the first column, we show the simplest possible pooled regression, where we regress candidate ideology on a simple indicator for winning office. As the coefficient shows, winning candidates are only 0.007 points more extreme than losing candidates, on average.

States and years vary in how many seats are up for election and the degree of electoral competition, and this could be correlated with the ideological positions of candidates. In the subsequent columns, we add state fixed effects, year fixed effects, and finally state-by-year fixed effects to investigate whether there are stronger overall selection effects once we account for these differences. As the coefficient estimates show, we find that winning candidates are a little bit more extreme in these subsequent specifications, but the difference is never substantively large. As a result, we conclude that the advantage of more-extreme candidates in primaries and the advantage of more-moderate candidates in general elections roughly cancel out.

8 Heterogeneity Across States and Time

Thus far, we have mainly focused on diagnosing the overall links between elections and polarization in state legislatures. However, one of the things that makes studying state legislatures so valuable is the variation in context across states and over time. In this section, we investigate some of these key sources of variation in order to gain a deeper understanding of state legislative elections.

First, pursuant to our discussion in the introduction, we examine how the overall effects we estimated above have changed over time, to assess the possibility that the increasing polarization and nationalization of state legislative elections, as well as other factors, have attenuated the advantage of more-moderate candidates. Second, to get at the informational mechanism, we examine whether this advantage is smaller in on-cycle elections; and third, similarly, we look at whether the advantage is larger in more-professionalized state legislatures.

Table 5 presents the results. Because the general-election midpoint analysis relies on district fixed effects, it is not feasible to estimate year-specific effects—we need sufficient within-district over-time variation to get reliable effects. While we experimented with many specifications, all coming to similar conclusions, we focus on the very simplest version, in which we simply add an interaction of the midpoint variable and the distance variable from equation 3 with an indicator for the year being after 2010—capturing the most recent previous redistricting cycle.

As the first column in the table shows, the association between fielding a more-moderate Democratic candidate (a shift to the right in the midpoint between the two candidates) and Democratic vote share has declined dramatically in the post-2010 period. While shifting from the most-extreme to the most-moderate Democratic position was associated with a 9 percentage-point increase in vote share between 1990 and 2010, it is only associated with a 1 percentage-point increase after 2010. This is a substantively minuscule effect; the standard deviation in the midpoint variable in the post-2010 period is 0.14, so this estimate reflects a 0.14 percentage-point increase in vote share for a one standard deviation increase in how relatively moderate the Democratic candidate is. The advantage to more-moderate candidates in contested general elections has fallen nearly to zero, on average, in the last decade. Appendix A.8 shows similar results using CF-Scores.

The second column studies another dimension of state legislative elections. Here we interact the midpoint variable (and the distance variable) with indicators for whether the election was held off cycle—that is, in a midterm election year for national elections—or in an odd year, as is done in Mississippi, New Jersey, and Virginia. In column 2, therefore, the main effect on midpoint reflects on-cycle elections where voters' ballots have the president at the top of the ticket. In the most extreme version of the "nationalization hypothesis," we might expect there to be no difference across these three contexts. If voters are mainly evaluating their state legislative candidates on the basis of national issues and partisanship, then which voters turn out to vote should matter relatively little. On the other hand, if nationalization is a conditional phenomenon which is amplified when a larger share of voters have turned out for the presidential election and know less about state legislatures, then we might expect to find large interaction terms.[16]

As it turns out, the estimated coefficients on the interaction terms show that the positive association between more-moderate candidates and vote share is significantly larger when the president is not at the top of the ticket. The estimated interaction is especially large for odd-year elections, where there is no presidential race and, barring special elections, no House or Senate candidates either, though the small number of states in this category makes the estimate imprecise.

Finally, in the third column we investigate whether the association between more-moderate candidates and vote share is stronger in states with more professionalized state legislatures, where voters are arguably more likely to know more about their state legislative candidates. We find tentative evidence in favor of this possibility, with the estimated association roughly twice as large in the most professionalized state legislature vs. the least. However, we cannot reject the null of no difference, and it is also worth noting that this interaction term attenuates to almost zero if we estimate this regression for only the post-2010 period.

The final three columns repeat this exercise for primary elections, replacing the interactions with midpoint with interactions with the extremism variable from equation 2.

As column 4 shows, we find that the advantage to being more extreme in primary elections was approximately zero prior to the 2012 period, in terms of its association with vote share, while it has become large in magnitude in the period from 2012 to 2020. At the same time that general elections advantage more-moderate candidates less than they used to, primary elections are favoring more-extreme candidates more strongly than in the past.

Interestingly, as column 5 shows, in contrast to general elections, the advantage to more-extreme primary candidates is not appreciably different in elections that are not held concurrently with presidential elections. On the other hand, as column 6 shows, the advantage to more-extreme candidates is substantially lower, and close to zero on average, in more-

[16]Consistent with this idea, Anzia (2011) shows that election timing is important for interest-group influence.

Table 5 – Variation in Ideological Effects.

	Dem Vote (General)			Primary Vote		
	(1)	(2)	(3)	(4)	(5)	(6)
Midpoint (Dem Moderation)	0.09	0.03	0.02			
	(0.01)	(0.01)	(0.02)			
Midpoint · Year $\geq$ 2012	-0.08					
	(0.02)					
Midpoint · Off Cycle		0.03				
		(0.01)				
Midpoint · Odd Year		0.01				
		(0.07)				
Midpoint · Professionalization			0.05			
			(0.03)			
Extremism				0.00	0.08	0.16
				(0.03)	(0.02)	(0.03)
Extremism · Year $\geq$ 2012				0.13		
				(0.04)		
Extremism · Off Cycle					-0.01	
					(0.02)	
Extremism · Odd Year					-0.19	
					(0.16)	
Extremism · Professionalization						-0.19
						(0.06)
District FEs	Yes	Yes	Yes	No	No	No
Year FEs	Yes	Yes	Yes	No	No	No
District-by-Party FEs	No	No	No	Yes	Yes	Yes
Party-by-Year FEs	No	No	No	Yes	Yes	Yes
# Cand FEs	No	No	No	Yes	Yes	Yes
# Observations	23,012	23,012	23,012	36,008	36,008	36,008

Robust standard errors in parentheses. Professionalization scaled to run from 0 (least professionalized state) to 1 (most professionalized state).

professionalized state legislatures. This latter result suggests that primaries might especially favor more-extreme candidates in settings where reelection incentives, interest in seeking office, and voter information are lower—conditions under which, it seems possible, parties and interest groups might play an especially strong role in selecting, encouraging, and supporting those who choose to seek office.

9 Differences Across Parties

Although it is not the focus of our study, there is widespread interest in studying differences in polarization across the parties. In this section, we evaluate whether the electoral selection effects we documented above vary by party.

The midpoint method from Ansolabehere, Snyder, and Stewart (2001) does not allow for estimating separate effects by party; accordingly, for this analysis, we switch to measuring Democratic and Republican extremism in contested general elections using the absolute value of each candidate's estimated ideological position as in Canes-Wrone, Brady, and Cogan (2002). Column 1 of Table 6 presents the results, which show that Republicans are punished more for extremism in general elections, though the magnitude of the effect is small in substantive terms. We estimate that moving from the most-moderate Democratic candidate to the most extreme predicts a statistically non-significant 1 percentage-point decrease in Democratic vote share in the general election, while moving from the most-moderate Republican candidate to the most extreme predicts a statistically significant 6 percentage point decrease in Republican vote share (note that the coefficient is negative for Democrats and positive for Republicans because the outcome variable is Democratic vote share).

In column 2, we investigate primary elections by simply interacting the Extremism variable from equation 2 with a dummy for the candidate being in the Democratic party. As the point estimate on the interaction term shows, we estimate that the advantage to more-

Table 6 – Effects Across Party, 1992-2020.

	Dem Vote (General) (1)	Primary Vote (2)	Extremism (3)
Dem Extremism	-0.01		
	(0.01)		
Rep Extremism	0.06		
	(0.02)		
Extremism		0.00	
		(0.02)	
Extremism · Dem		0.14	
		(0.04)	
Win General			-0.00
			(0.00)
Win General · Dem			0.03
			(0.00)
District FEs	Y	N	N
Year FEs	Y	N	N
District-by-Party FEs	N	Y	N
Party-by-Year FEs	N	Y	N
# Cand FEs	N	Y	N
# Observations	23,012	36,008	110,086

Robust standard errors in parentheses. Extremism scaled to run from 0 to 1.

extreme candidates is meaningful in Democratic but not Republican primaries.[17] This is again consistent with results for incumbents presented in Rogers (2021), where roll-call liberalism correlates with primary victory for Democratic incumbents but not for Republican incumbents.

Finally, in column 3, we assess whether each party's winners are systematically more extreme or more moderate than the pool of candidates. While both differences are small, we find that there is no difference for Republicans while there is a very small but positive difference for Democrats: that is, Democratic winners are slightly more extreme than losing Democratic candidates, on average.

[17] If we re-estimate this equation on win probability, we again find a greater coefficient for Democrats, but we cannot reject the null of no difference.

In sum, we find that extreme Republicans tend to fare worse in general elections, and we find that Democratic primaries favor more-extreme candidates more strongly than Republican primaries—contrary to some expectations based on asymmetric polarization at the federal level. However, what these results mean for asymmetric polarization is not clear. The above estimates show the conditional association between candidate ideology and electoral outcomes only for (a) contested primaries and (b) contested general elections, while polarization is a function not only of these two quantities but of who runs for office and how much competition there is in each stage of the election process. As we documented in Figure 3, there are now significantly more safe Republican districts than safe Democratic districts, and this might have complex effects on the polarization of both parties. Nevertheless, these results do suggest that Democratic primary elections are a particularly important electoral setting to study with respect to polarization.

10 Conclusion

Understanding how state legislatures have polarized is important both because the state legislatures are themselves highly important policymaking bodies, and because they are the main pathway for candidates to Congress. In this paper, we have offered the first systematic analyses of the links between candidate ideology, electoral competition, and legislative polarization in state legislatures that cover all three stages of the process: candidate entry, primary elections, and general elections. After creating a new measure of candidate ideology that predicts roll-call voting with strong accuracy, we have combined this measure with new data on primary and general elections covering roughly the past three decades of state legislative elections.

Using this new data, we have established three empirical findings that are relevant for future work on elections and polarization.

First, because rates of competition in state legislatures are low, who runs for office is especially important in determining the degree of polarization in the legislature. As we have shown, the set of people running for state legislative office has polarized dramatically over the past several decades. Although research does suggest that structural factors affecting the desire to seek office are important for understanding polarization at the federal level (Thomsen 2017; Hall 2019), there is a lack of research exploring this pattern at the local and state level. This represents an important opportunity for future research, not only to understand polarization in the states directly, but also to understand polarization in Congress. A majority of members of Congress come from state legislatures, and recent work suggests that it is the overall polarization of state legislators, more than the differential selection of more-extreme state legislators to seek federal office, that is driving Congressional polarization (Phillips, Snyder, and Hall N.d.).

Second, there is an important advantage for more-extreme candidates in contested primary elections, and this advantage has newly manifested in the period from 2012 to present. This pattern is important, because it suggests at least two possible ways in which primary elections may be contributing to polarization in state legislatures: directly, by sending more-extreme candidates to low-competition general elections that they are relatively likely to win, and indirectly, by potentially deterring more-moderate candidates from seeking office in the first place.

While the dominant thrust in research on ideology and elections at the state level focuses on nationalization and partisanship, party labels play no role in primary elections. With low levels of information and low rates of entry, it seems likely that parties and interest groups have large effects on influencing who chooses to seek office, whether they face opponents in the primary, and whether they win nomination. Deeper study of these mechanisms in state legislative primaries is an important next step for research in this area.

Third, and finally, we show that there is, at most, a very modest advantage for more-moderate candidates in the general election, and this advantage has fallen dramatically in the past decade. Moreover, the penalty to more-extreme candidates is larger in general elections that occur in non-presidential elections, suggesting that more-extreme candidates are benefitting, at least indirectly, from straight-ticket voting among voters who turn out primarily to vote in national elections. While it is not dispositive, this pattern is certainly consistent with work that documents the ways in which state legislative elections have become nationalized, with relatively uninformed voters voting on the basis of national partisan issues (Abramowitz and Webster 2016; Hopkins 2018; Rogers 2016, 2021).

More generally, our study is meant to be only the first key step in what must be a broader effort to understand why state legislative elections work the way that they do. Why are the people running for state legislature themselves so much more polarized than they used to be? Why has their advantage in primaries increased, and why has their disadvantage in general elections decreased? How could state legislative elections sustain a meaningful advantage for more-moderate candidates in previous decades, at a time when voter information in state legislative elections was presumably still very low? These are key questions for future research, and should be aided by the new measures and data that we have assembled to understand state legislative elections.

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Online Appendix

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Contents

A.1 Description of Machine Learning Methods

In this section, we describe in detail the machine learning methods that we tested for predictive performance in developing our roll-call based scalings. First, we consider elastic net regression (Zou and Hastie 2005), which is a method of restricting ordinary least squares regression to accommodate the case of many irrelevant or redundant predictors. Elastic net regression coefficients are found by solving

$$\hat{\beta} = \text{argmin}_{\beta}\Big\{\sum_{i=1}^{N}(y_i - \beta_0 - \sum_{j=1}^{p} x_{ij}\beta_j)^2 + \lambda \sum_{j=1}^{p}(\alpha\beta_j^2 + (1-\alpha)|\beta_j|)\Big\}$$

where the penalty term, controlled by the tuning parameters λ and $\alpha \in [0, 1]$, determines the degree to which the magnitude of the coefficients are shrunk towards zero. When $\alpha = 1$, the penalty is equivalent to ridge regression, which does not produce a parsimonious model but performs well in certain scenarios when predictors are highly correlated, and when $\alpha = 0$, the penalty is equivalent to LASSO regression, which achieves a parsimonious model by setting a large number of coefficients to zero but is dominated by ridge regression in certain settings (Zou and Hastie 2005).

The other two methods, random forest and gradient-boosted trees, use ensembles of decision trees, which are robust to many irrelevant or noisy predictors but tend to produce high-variance predictions. To reduce the prediction variance, the random forest method (Breiman 2001) grows a decision tree on each of B bootstrapped samples from the training data, further decreasing the correlation between each tree by randomly selecting a subset of the predictor variables to consider for splits at each terminal node. The number of variables to randomly choose at each split acts as a tuning parameter. The final prediction is the average of the predictions over the entire ensemble of trees:

$$F_B(\boldsymbol{x}) = \frac{1}{B}\sum_{b=1}^{B} F_b(\boldsymbol{x})$$

where $F_b(\boldsymbol{x})$ is the prediction of the decision tree grown on bootstrapped sample b. Gradient-boosted regression trees (Friedman 2001) reduce the variance by sequentially growing trees to predict the generalized residuals from the previous tree in the sequence. As in random forest, to reduce variance, a random subset of the predictors is considered for splitting at each terminal node. The final prediction is a weighted sum of the predictions using the terminal regions and coefficients of each tree. For instance, at iteration m, the prediction

$F_m(\boldsymbol{x})$ given predictor vector $\boldsymbol{x}$ is

$$F_m(\boldsymbol{x}) = F_{m-1}(\boldsymbol{x}) + \rho_m \sum_{j=1}^{J} b_{jm} I(\boldsymbol{x} \in R_{jm})$$

where b_{jm} and R_{jm} are region j's least squares coefficient and boundaries found by growing tree m to predict the generalized residuals from tree $m-1$, and ρ_m is a scaling factor found by a line search to minimize Huber loss against the original target.

A.2 Donor Summary Features

In this section, we describe how we engineered donor summary features to incorporate information from smaller donors into our machine learning models. The summary features were calculated in accordance with the ten-fold cross-validation scheme as follows. Given candidate i' in election cycle t' not part of the test fold $\mathcal{F}$, we calculate the dollar-weighted average scaling for each donor j to candidate i' as:

$$w_j = \sum_{i \neq i';\ i \notin \mathcal{F}} y_i \cdot \frac{\sum_{t'-4 \leq t \leq t'} d_{ijt}}{\sum_{k \neq i';\ k \notin \mathcal{F}} \sum_{t'-4 \leq t \leq t'} d_{kjt}}$$

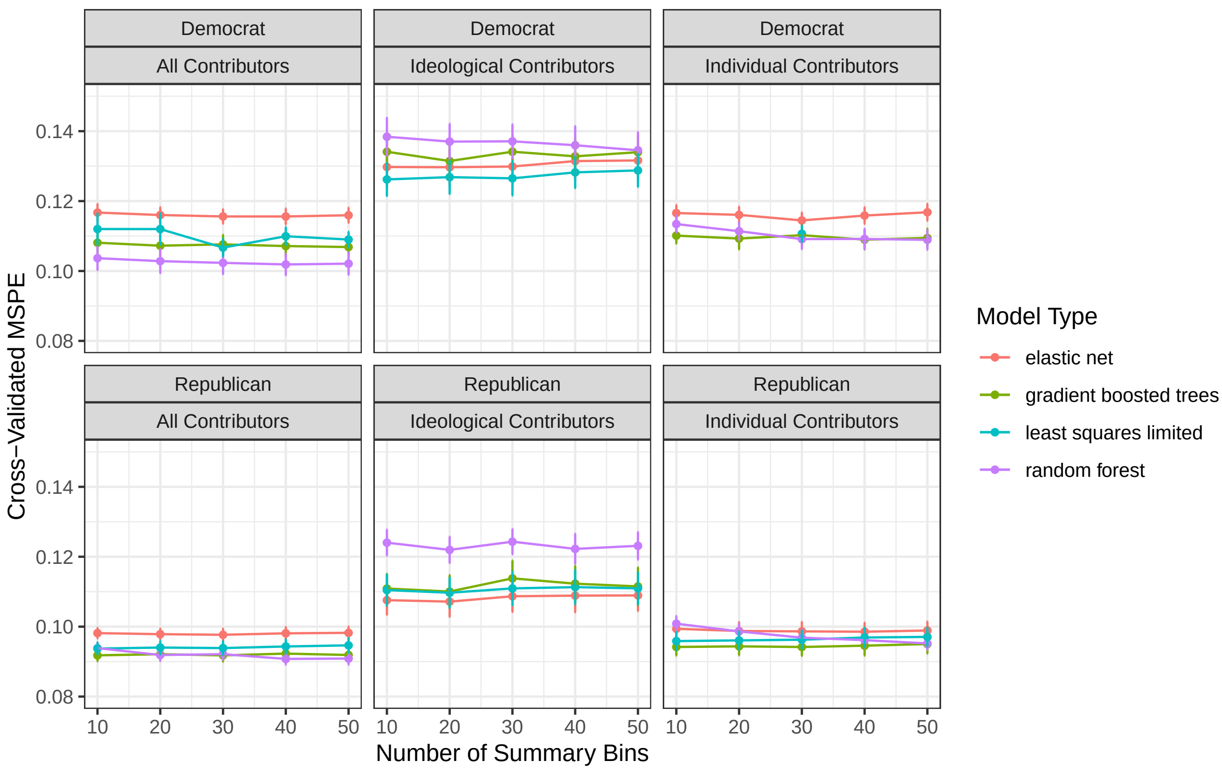
where y_i is the static scaling for candidate i after they take office, and d_{ijt} is the total positive amount given to candidate i by donor j in election cycle t. In this framework, which precludes using information from the future to predict the present, we can also make use of donations to incumbents from the donors of interest. With these weighted averages in hand, we can calculate two types of summary features for candidate i' that include no forbidden information from the candidate itself, candidates in the test set, or future election cycles. First, we calculate the dollar-weighted average scaling for candidate i' in election cycle t' using the donor scalings w_j, where the weights are the proportion of donations candidate i' received in election cycle t' from donor j. Second, we bin the w_j's into M evenly spaced bins, and calculate the proportion of donations to candidate i' in election cycle t' that fall into each bin. This produces a total of $M + 1$ summary features. M is selected via a grid search using ten-fold cross-validation.

A.3 Model Cross-Validation Results

In this section, we report the cross-validation results for method type, donor type, and number of bins in the donor summary predictors using all training observations. Figure A.1 shows the cross-validated mean-squared prediction error (MSPE) for each set of choices. As a baseline model, we fit an OLS regression using only state dummies and the summary predictors to gauge the extent to which more sophisticated machine learning methods that can handle the full donation matrix give us leverage over the prediction problem (labeled "least squares limited" in the plot).

Including all types of contributors (e.g., individuals as well as PACs) outperforms restricting the donor pool to only individual contributors, as in Bonica (2018), or to only contributors that the National Institute on Money in Politics categorized as "ideological" contributors. When restricting the donor pool in these ways, the baseline least squares model, which does not use any of the individual donor features, sometimes outperforms the more complex machine learning methods. Only when the models have access to the full set of contributors are the machine learning methods able to make meaningful accuracy gains over the simpler baseline model. Increasing the number of bins for the summary features did not typically produce meaningful changes in MSPE. Among the machine learning methods, the tree-based methods tended to outperform the elastic net when given access to all contributors, though the difference between the two tree-based methods did not typically exceed one standard error.

Figure A.1 – Cross-validated MSPE For Primary Donation Scalings across Machine Learning Methods, Contributor Types, and Number of Summary Feature Bins.



A.4 Measurement Error

In this section, we report how error in the NP-Score estimation procedure correlates with prediction error for candidate-years in our election dataset. We obtained the most recent estimates of NP-Score estimation error from Shor and McCarty's July 2020 aggregate data release.[18] The error estimates are arrived at by simulating state-specific OLS bridging coefficients using draws from the posterior distribution of the Bayesian IRT model underlying the roll-call based ideal points. Since these estimates are reported only at the state-year level, we also aggregate our prediction error estimates up to the state-year level for comparison, and then average the two types of error over years by state. Figure A.2 shows that states with higher average NP-Score estimation error tend to also have higher average prediction error, which suggests that breakdown in the NPAT bridging procedure would adversely impact our ability to predict NP-Scores by impeding the model's ability to pool ideology information between states.

Figure A.2 – Model Prediction Error vs NP-Score Estimation Error.

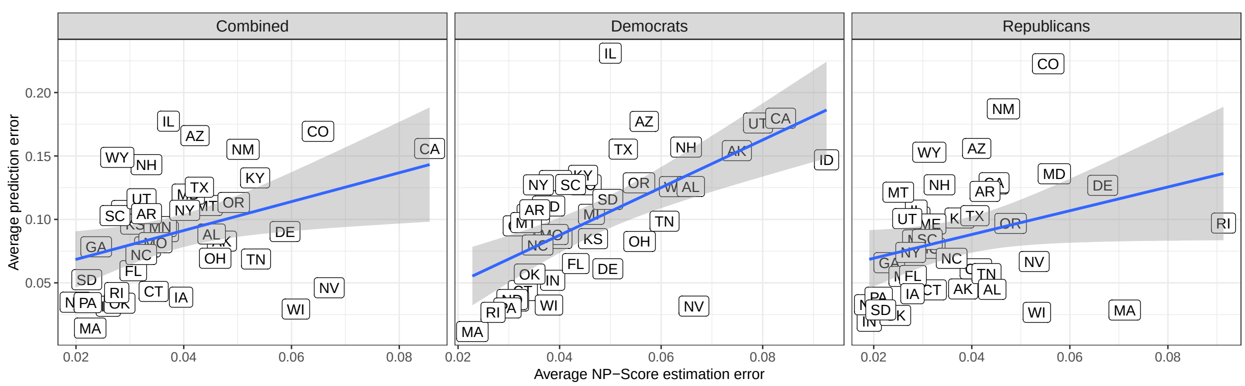


Table A.1 reports MSPE and correlation between the predicted and actual NP-Scores for three groups of candidate-year observations in our election dataset: those in the training data, those not in the training data but that involve training data legislators, and those that did not involve training data legislators. Because the donors have more information about incumbents once they are in office, and because candidate-years involving training legislators are more similar to the training data, candidate-years involving training data legislators have slightly lower MSPE than other out-of-sample predictions. The training data observations have the highest MSPE likely because the predictors are from donors that had never before observed the candidate in office, though these out-of-sample scores may also have higher prediction error because they use slightly less training data (9 folds instead of 10).

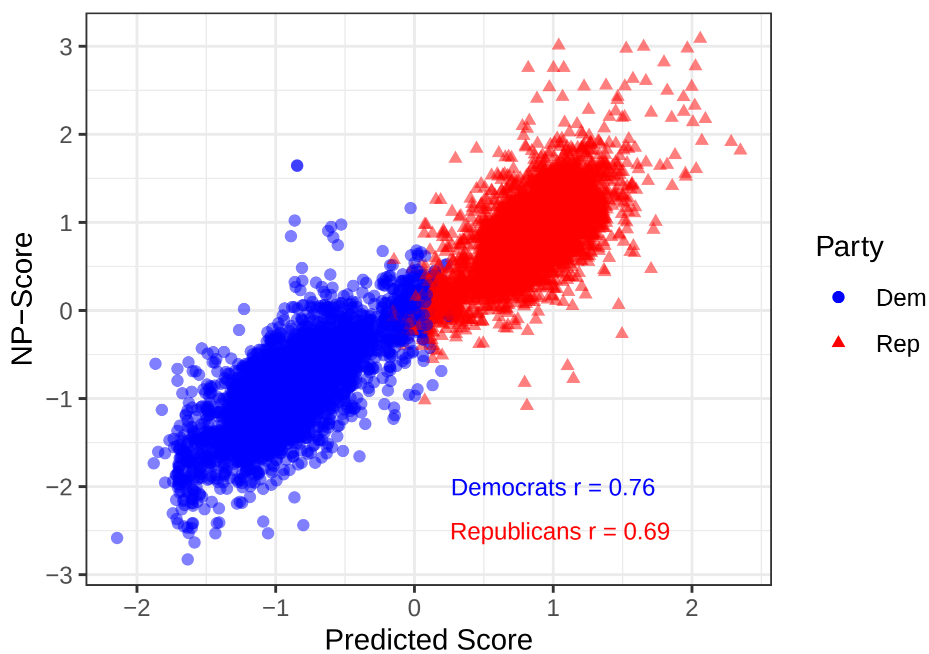
[18] https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/AP54NE

Table A.1 – MSPE highest for first winning primary elections. Predicted NP scores have slightly higher MSPE in the first winning primary elections in the training data, in which donors are uncertain of how the candidate will behave once in office.

	Democrats			Republicans		
Election type	MSPE	Corr.	N	MSPE	Corr.	N
Candidate-years in training data	0.10	0.78	3827	0.09	0.70	4999
Other candidate-years involving training data legislators	0.09	0.77	11942	0.08	0.73	14229
Candidate-years not involving training data legislators	0.10	0.75	12594	0.08	0.74	10779

To further probe the accuracy of the model for losers of elections, Figure A.3 re-produces the scatterplot of predicted vs. actual scores for losing candidates who later go on to win for the first time in the observation window. The within-party correlations are still high, though slightly lower for Republicans compared to the elections involving incumbents ($r = 0.69$ when excluding incumbents vs $r = 0.74$ including incumbents).

Figure A.3 – Predicted vs. Future NP-Scores for Losing Candidates.



Because this suggests that measurement error could be weakly correlated with winning elections, Appendix A.7 explores the robustness of the regression results using sets of elections where the measurement error is most comparable between incumbents and non-incumbents. Appendix A.8 reports results using static CFscores.

A.5 Overlap in Donors Between Winners and Losers

In this section, we report the overlap in donors between winners and losters of elections as a check for whether losing candidates look systematically more extreme or more moderate than winning candidates because they disproportionately raise money from donors who do not donate to incumbents and therefore are not properly incorporated into the model. We find that the median losing candidate receives 45% of their money from donors that also donated to winning candidates, and these "winning donors" represent 27% of the median losing candidate's unique donor base. Figure A.4 shows that the degree of predicted extremism for losing candidates, as measured by the absolute value of their predicting scalings, does not meaningfully vary based on the degree of overlap in donors with winners.

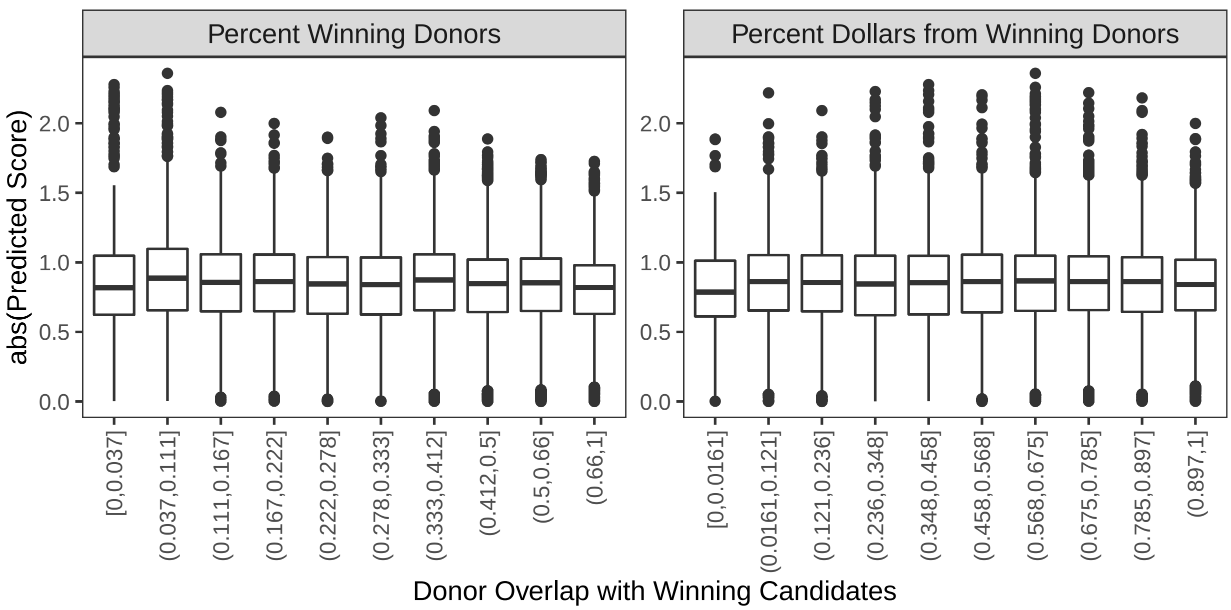


Figure A.4 – Predicted Extremism For Losing Candidates Does Not Depend on Degree of Donor Overlap With Winners. The left panel shows the distribution of predicted extremism for losing candidates by the percent of donors shared with winning candidates. The right panel shows the distribution of predicted extremism for losing candidates by the percent of dollars from donors who also donated to winning candidates. Neither measure of overlap correlates with predicted extremism.

A.6 Feature Importance

To better understand which larger donors drive the predicted scalings, we employ a permutation-based feature importance procedure based on the one suggested for classification problems by Breiman (2001). For a given train-test split in the ten-fold cross-validation scheme, we train the model on the training folds and predict on the test fold to obtain a baseline accuracy. Then, for each feature separately, we randomly permute the values in the test fold, predict new scalings, and measure the percent change in accuracy relative to the baseline. After cycling through all the train-test splits, we average the change in test fold accuracy for each feature.

Table A.2 reports these permuted accuracy changes for the top 10 most predictive standalone donors in each party's primary-donation scalings.[19] Public financing, an aggregated entity representing campaign funding from public sources, shows up as a predictive feature in both models. This source of donations mainly affects candidates in states with well-established public financing programs for state-office candidates, such as Maine, Minnesota, Connecticut, and Arizona. Other donors reflect state-specific, within-party ideological battles over primary candidates. For instance, the most predictive single donor for Republicans was Empower Texans, a conservative advocacy group that is well-known for supporting primary challenges from the right in Texas Republican primaries.[20] Other far-right groups such as Rocky Mountain Gun Owners, a Colorado-based gun activism group recently deemed "Colorado's Taliban" by the former head of the El Paso County Republican Party, also factor into the Republican model.[21] The top Democratic donors are a mix of unions, trade associations, and influential party leaders that give exclusively to Democrats, such as former Illinois House speaker Michael J. Madigan.

[19] The standalone donor features tended to be less predictive than the most predictive donor summary features, which transmit information from many donors.

[20] See `https://public-accountability.org/report/the-money-behind-empower-texans/`

[21] Joshua Hosler. "As a former leader in Colorado's GOP, I'm here to tell you Rocky Mountain Gun Owners is this state's Taliban." *The Denver Post*. July 7, 2019. `https://www.denverpost.com/2019/07/07/joshua-hosler-rocky-mountain-gun-owners/`

Table A.2 – Most Important Donors for Predictive Performance of Primary Donation Scalings.

Donor Name	# Candidates	Pct. First Time Winners	Avg. NP Score	Std. NP Score	Amount Donated (1000s)	Pct. Accuracy Change
Republicans						
EMPOWER TEXANS	160	0.20	1.85	0.50	5244.48	0.31
AGGREGATED INDIVIDUAL CONTRIBUTION	13782	0.09	0.68	0.45	49107.63	0.27
PUBLIC FUND	1730	0.12	0.65	0.42	32524.85	0.26
KANSAS NATIONAL EDUCATION ASSOCIATION	371	0.14	0.20	0.25	259.43	0.24
PLUM CREEK TIMBER CO	639	0.08	0.92	0.32	256.41	0.19
IDAHO CHOOSES LIFE PAC	260	0.08	1.20	0.40	132.45	0.18
ROCKY MOUNTAIN GUN OWNERS	52	0.31	1.88	0.60	60.55	0.16
STAND UP FOR KANSAS	199	0.13	0.84	0.33	41.73	0.14
KANSAS HOSPITAL ASSOCIATION	560	0.06	0.56	0.40	313.37	0.13
EXCELLENCE IN VOTING	43	0.26	1.37	0.24	8.11	0.11
Democrats						
PUBLIC FUND	2669	0.10	-1.10	0.33	45393.84	1.02
ARKANSAS HEALTH CARE ASSOCIATION / ARKANSAS ASSISTED LIVING ASSOCIATION	435	0.11	0.02	0.28	736.39	0.31
ARKANSAS MEDICAL SOCIETY	363	0.13	0.04	0.24	246.78	0.22
NORTH CAROLINA ASSOCIATION OF EDUCATORS	263	0.06	-0.69	0.33	417.81	0.21
ARKANSAS OIL MARKETERS ASSOCIATION	279	0.16	0.05	0.24	83.96	0.21
UNITED MINE WORKERS OF AMERICA / UMWA	1226	0.05	-0.47	0.29	986.92	0.17
ILLINOIS TRIAL LAWYERS ASSOCIATION	892	0.03	-0.87	0.51	2760.95	0.15
MICHAEL J MADIGAN CAMPAIGN CMTE	303	0.06	-0.85	0.58	3211.12	0.11
ASSOCIATED GENERAL CONTRACTORS OF ARKANSAS	324	0.10	0.06	0.27	139.73	0.10
CALIFORNIA CABLE & TELECOMMUNICATIONS ASSOCIATION	528	0.11	-1.53	0.46	1616.20	0.10

Note: Contributors without an entity label in the donation data have been removed.

A.7 Specification Robustness Checks

Table A.3 – Extremism and Midpoint Specification Robustness

	Estimated Ideology		Estimated Ideology (Static)		Estimated Ideology	
	(1)	(2)	(3)	(4)	(5)	(6)
Cand Extremism	0.07		0.04		0.12	
	(0.02)		(0.02)		(0.03)	
Log Contributions	0.08		0.09		0.08	
	(0.00)		(0.00)		(0.00)	
Midpoint (Dem Moderation)		0.05		0.09		-0.02
		(0.01)		(0.02)		(0.03)
Distance Between Cands		0.03		0.01		0.01
		(0.01)		(0.01)		(0.03)
Log Rep Contributions		-0.22		-0.20		-0.22
		(0.01)		(0.01)		(0.02)
Log Dem Contributions		0.25		0.23		0.23
		(0.01)		(0.01)		(0.02)
Specification	All Elections		Races Containing A Training Legislator		Open Seat Races	
# Observations	36,008	23,012	23,173	14,072	18,452	2,198
District-by-Party FE	Yes	No	Yes	No	Yes	No
District-by-Year FE	Yes	No	Yes	No	Yes	No
Number of Candidates FE	Yes	No	Yes	No	Yes	No
District-by Regime FE	No	Yes	No	Yes	No	Yes
Year FE	No	Yes	No	Yes	No	Yes

A.8 Static CF Score Results

Table A.4 – Advantage of More-Extreme Candidates in Contested Primary Elections, 1992-2020.

	Primary Vote Share		Win Primary	
	(1)	(2)	(3)	(4)
Cand Extremism	-0.15	-0.12	-0.51	-0.50
	(0.02)	(0.02)	(0.06)	(0.07)
Log Contributions	0.09	0.10	0.19	0.24
	(0.00)	(0.00)	(0.00)	(0.00)
# Observations	23,234	21,989	23,583	22,258
District-by-Party FE	Y	N	Y	N
Party-by-Year FE	Y	N	Y	N
Number of Candidate FE	Y	N	Y	N
Race FE	N	Y	N	Y

Robust standard errors clustered by state in parentheses. Cand Extremism scaled to run from 0 to 1. Sample is restricted to contested primary elections.

Table A.5 – Advantage of More-Moderate Candidates in Contested General Elections, 1992-2020.

	Dem Vote Share		Dem Win	
	(1)	(2)	(3)	(4)
Midpoint (Dem Moderation)	0.17	0.12	0.68	0.57
	(0.02)	(0.01)	(0.07)	(0.07)
Distance Between Candidates	0.17	-0.07	-0.45	-0.36
	(0.02)	(0.01)	(0.06)	(0.06)
Log Dem Total Contributions		0.23		0.52
		(0.01)		(0.04)
Log Rep Total Contributions		-0.24		-0.55
		(0.01)		(0.04)
# Observations	13,199	13,199	13,199	13,199
District-by-Regime FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y

Robust standard errors clustered by district in parentheses. Midpoint and Distance Between Candidates are scaled to run from 0 to 1. Sample is restricted to contested general elections.

Table A.6 – Overall Candidate Selection in State Legislative Elections, 1992-2020.

	Candidate Extremism			
	(1)	(2)	(3)	(4)
Win Election	-0.022	-0.020	-0.021	-0.021
	(0.000)	(0.000)	(0.000)	(0.000)
Intercept	0.168	–	–	–
# Observations	88,152	88,152	88,152	88,147
State FE	N	Y	Y	N
Year FE	N	N	Y	N
State-by-Year FE	N	N	N	Y

Robust standard errors clustered by state in parentheses. Cand Extremism scaled to run from 0 to 1.

Table A.7 – Variation in Ideological Effects.

	Dem Vote (General)			Primary Vote		
	(1)	(2)	(3)	(4)	(5)	(6)
Midpoint (Dem Moderation)	0.13	0.09	0.14			
	(0.01)	(0.01)	(0.02)			
Midpoint · Year $\geq$ 2012	-0.07					
	(0.03)					
Midpoint · Off Cycle		0.04				
		(0.01)				
Midpoint · Odd Year		0.07				
		(0.09)				
Midpoint · Professionalization			-0.06			
			(0.05)			
Extremism				-0.19	-0.13	-0.13
				(0.03)	(0.03)	(0.04)
Extremism · Year $\geq$ 2012				0.15		
				(0.05)		
Extremism · Off Cycle					-0.04	
					(0.04)	
Extremism · Odd Year					-0.27	
					(0.13)	
Extremism · Professionalization						-0.05
						(0.07)
District FEs	Yes	Yes	Yes	No	No	No
Year FEs	Yes	Yes	Yes	No	No	No
District-by-Party FEs	No	No	No	Yes	Yes	Yes
Party-by-Year FEs	No	No	No	Yes	Yes	Yes
# Cand FEs	No	No	No	Yes	Yes	Yes
# Observations	13,199	13,199	13,199	23,234	23,234	23,234

Robust standard errors in parentheses. Professionalization scaled to run from 0 (least professionalized state) to 1 (most professionalized state).

Table A.8 – Effects Across Party, 1992-2020.

	Dem Vote (General) (1)	Primary Vote (2)	Extremism (3)
Dem Extremism	-0.15		
	(0.02)		
Rep Extremism	0.02		
	(0.01)		
Extremism		0.15	
		(0.03)	
Extremism · Dem		-0.59	
		(0.05)	
Win General			0.00
			(0.00)
Win General · Dem			-0.05
			(0.00)
District FEs	Y	N	N
Year FEs	Y	N	N
District-by-Party FEs	N	Y	N
Party-by-Year FEs	N	Y	N
# Cand FEs	N	Y	N
# Observations	13,199	23,234	88,152

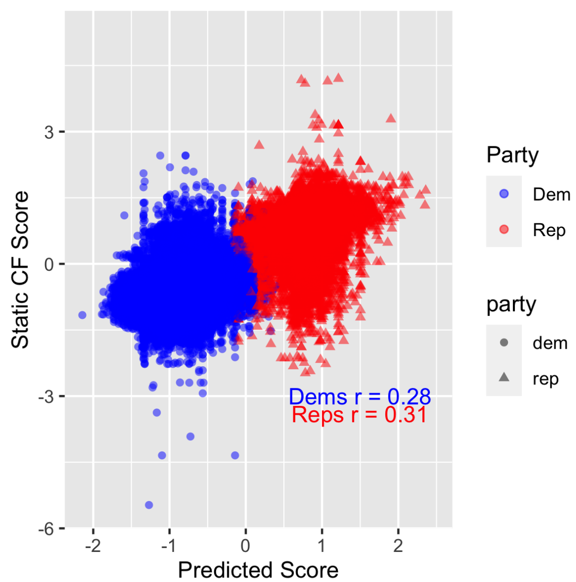
Robust standard errors in parentheses. Extremism scaled to run from 0 to 1.

Table A.9 – Comparing Effects Across Time, 1992-2020.

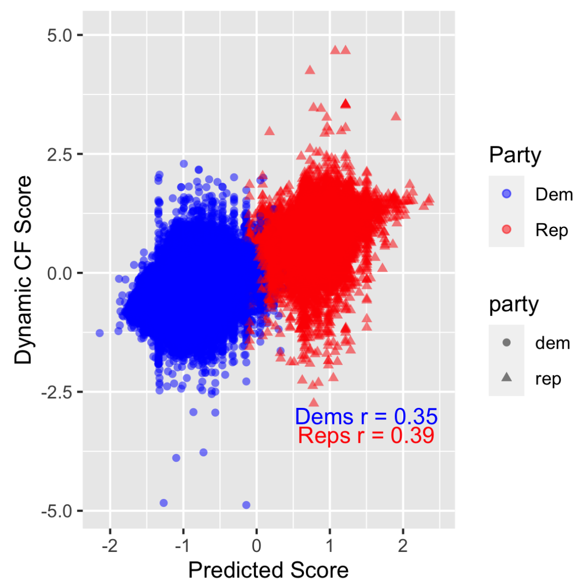
	Dem Vote (1)	Primary Vote (2)	Extremism (3)
Midpoint (Dem Moderation)	0.13 (0.01)		
Midpoint $\cdot$ Year $\geq$ 2012	-0.07 (0.03)		
Extremism		-0.19 (0.03)	
Extremism $\cdot$ Year $\geq$ 2012		0.15 (0.05)	
Win General			-0.02 (0.00)
Win General $\cdot$ Year $\geq$ 2012			0.01 (0.00)
District FEs	Y	N	N
Year FEs	Y	N	N
District-by-Party FEs	N	Y	N
Party-by-Year FEs	N	Y	N
# Cand FEs	N	Y	N
# Observations	13,199	23,234	88,152

Robust standard errors in parentheses. Extremism scaled to run from 0 to 1. Column 1 also includes control for ideological distance between candidates, and the interaction of this variable with the year $\geq$ 2012 indicator.

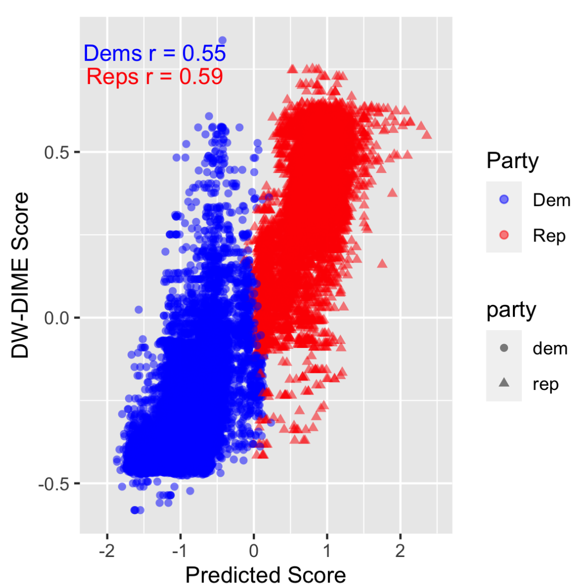
A.9 Predicted Score Correlations



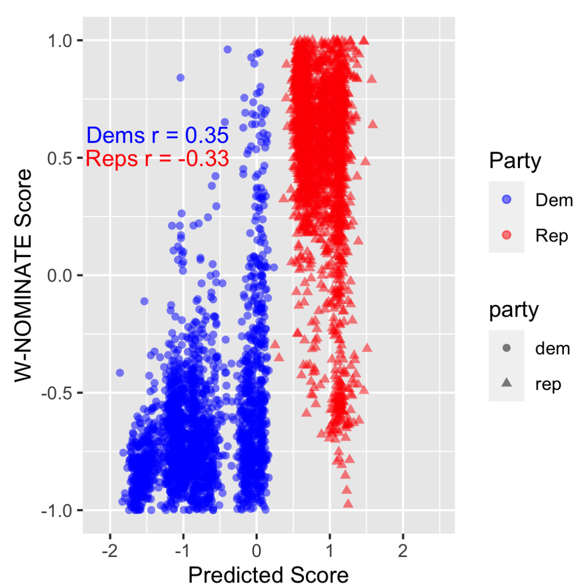
(a) Static CF Score



(b) Dynamic CF Score

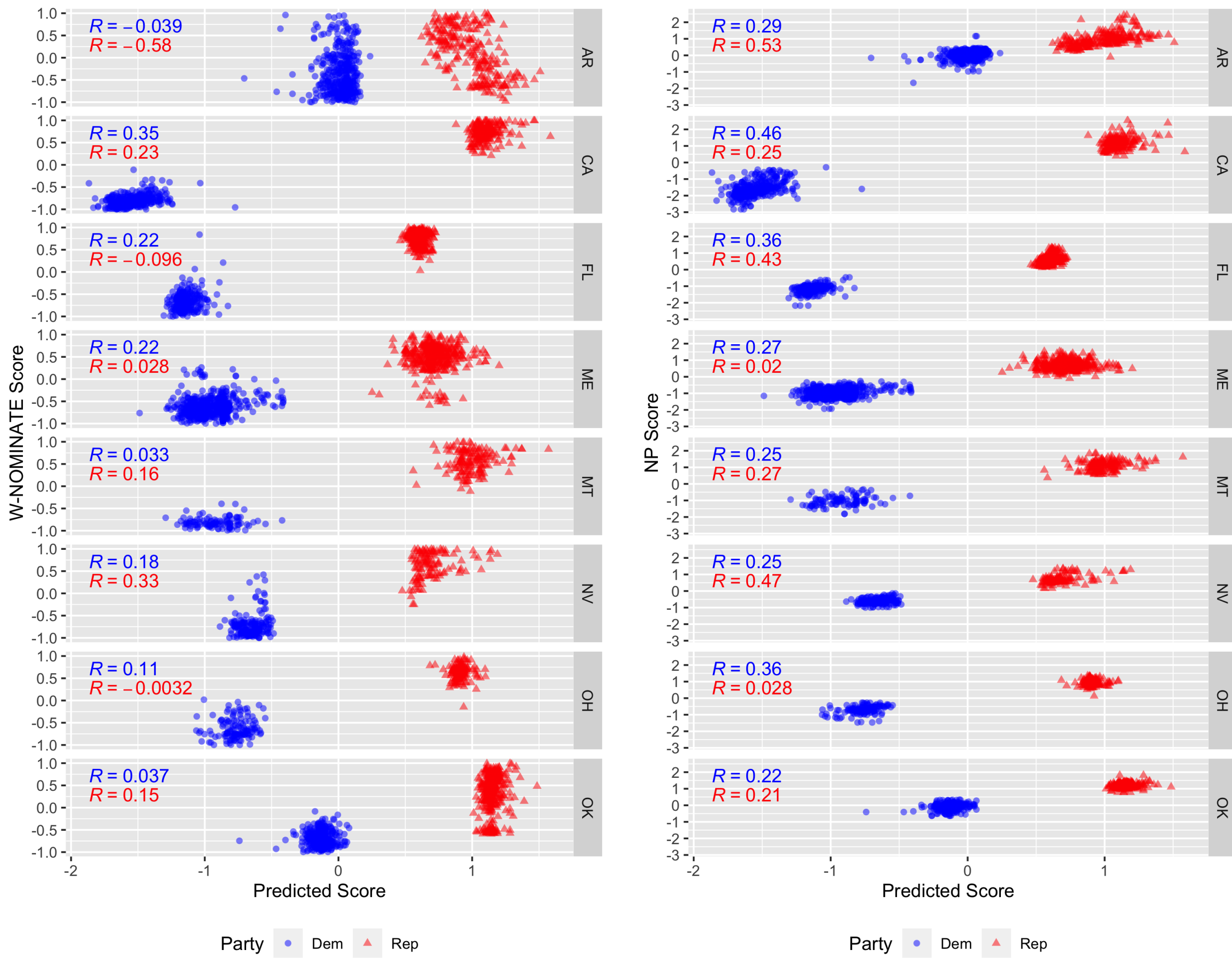


(c) DW-DIME Score



(d) W-NOMINATE Score

Figure A.5 – Correlations between Predicted Score and existing measures of candidate ideology. Results are presented in their original scales.



(a) W-NOMINATE Score

(b) NP Score

Figure A.6 – Correlations between Predicted Score and existing measures of candidate ideology.

A.10 Data Descriptives

<table>
<tr><th>State</th><th>1992</th><th>1993</th><th>1994</th><th>1995</th><th>1996</th><th>1997</th><th>1998</th><th>1999</th><th>2000</th><th>2001</th><th>2002</th><th>2003</th><th>2004</th><th>2005</th><th>2006</th><th>2007</th><th>2008</th><th>2009</th><th>2010</th><th>2011</th><th>2012</th><th>2013</th><th>2014</th><th>2015</th><th>2016</th><th>2017</th><th>2018</th><th>2019</th><th>2020</th><th>Total</th></tr>
<tr><td>AK</td><td>123|102</td><td></td><td>37|86</td><td></td><td>129|90</td><td></td><td>55|80</td><td></td><td>62|82</td><td></td><td>49|88</td><td></td><td>52|88</td><td></td><td>47|84</td><td></td><td>40|87</td><td></td><td>24|78</td><td></td><td>133|100</td><td></td><td>106|90</td><td></td><td>105|76</td><td></td><td>125|88</td><td></td><td>111|77</td><td>1198|1296</td></tr>
<tr><td>AL</td><td></td><td></td><td>238|206</td><td></td><td></td><td></td><td>177|222</td><td></td><td></td><td></td><td>188|212</td><td></td><td></td><td></td><td>168|207</td><td></td><td></td><td></td><td>173|203</td><td></td><td></td><td></td><td>152|195</td><td></td><td></td><td></td><td>172|204</td><td></td><td></td><td>1268|1449</td></tr>
<tr><td>AR</td><td>82|165</td><td></td><td>96|160</td><td></td><td>73|155</td><td></td><td>106|170</td><td></td><td>92|156</td><td></td><td>106|180</td><td></td><td>71|149</td><td></td><td>81|149</td><td></td><td>60|140</td><td></td><td>103|155</td><td></td><td>73|199</td><td></td><td>57|155</td><td></td><td>45|145</td><td></td><td>46|165</td><td></td><td>48|164</td><td>1139|2407</td></tr>
<tr><td>AZ</td><td>25|44</td><td></td><td>12|39</td><td></td><td>23|47</td><td></td><td>14|41</td><td></td><td>28|47</td><td></td><td>58|42</td><td></td><td>52|44</td><td></td><td>59|52</td><td></td><td>54|50</td><td></td><td>70|50</td><td></td><td>57|47</td><td></td><td>66|51</td><td></td><td>55|46</td><td></td><td>75|53</td><td></td><td>56|50</td><td>704|703</td></tr>
<tr><td>CA</td><td>291|192</td><td></td><td>205|196</td><td></td><td>218|193</td><td></td><td>185|191</td><td></td><td>182|197</td><td></td><td>164|186</td><td></td><td>149|192</td><td></td><td>201|188</td><td></td><td>157|191</td><td></td><td>295|192</td><td></td><td>270|194</td><td></td><td>262|193</td><td></td><td>258|193</td><td></td><td>140|187</td><td></td><td>160|189</td><td>3137|2874</td></tr>
<tr><td>CO</td><td>25|149</td><td></td><td>35|146</td><td></td><td>32|143</td><td></td><td>51|145</td><td></td><td>42|144</td><td></td><td>158|139</td><td></td><td>154|146</td><td></td><td>169|149</td><td></td><td>177|157</td><td></td><td>171|155</td><td></td><td>176|158</td><td></td><td>160|147</td><td></td><td>175|151</td><td></td><td>179|155</td><td></td><td>172|155</td><td>1876|2239</td></tr>
<tr><td>CT</td><td>100|365</td><td></td><td>54|347</td><td></td><td>14|327</td><td></td><td>33|323</td><td></td><td>17|302</td><td></td><td>22|316</td><td></td><td>24|299</td><td></td><td>26|304</td><td></td><td>37|302</td><td></td><td>41|327</td><td></td><td>32|334</td><td></td><td>39|321</td><td></td><td>24|325</td><td></td><td>48|349</td><td></td><td>20|338</td><td>531|4879</td></tr>
<tr><td>DE</td><td>28|101</td><td></td><td>29|77</td><td></td><td>26|84</td><td></td><td>17|72</td><td></td><td>17|81</td><td></td><td>35|95</td><td></td><td>21|77</td><td></td><td>30|81</td><td></td><td>11|85</td><td></td><td>26|86</td><td></td><td>46|93</td><td></td><td>24|80</td><td></td><td>19|76</td><td></td><td>44|85</td><td></td><td>28|78</td><td>401|1251</td></tr>
<tr><td>FL</td><td>267|250</td><td></td><td>149|211</td><td></td><td>111|211</td><td></td><td>139|192</td><td></td><td>230|219</td><td></td><td>169|217</td><td></td><td>97|183</td><td></td><td>134|195</td><td></td><td>122|208</td><td></td><td>165|212</td><td></td><td>179|232</td><td></td><td>98|193</td><td></td><td>211|233</td><td></td><td>156|237</td><td></td><td>180|254</td><td>2407|3247</td></tr>
<tr><td>GA</td><td>288|318</td><td></td><td>176|312</td><td></td><td>439|339</td><td></td><td>443|336</td><td></td><td>407|318</td><td></td><td>119|83</td><td></td><td>493|340</td><td></td><td>384|308</td><td></td><td>370|291</td><td></td><td>416|314</td><td></td><td>398|288</td><td></td><td>364|283</td><td></td><td>305|280</td><td></td><td>435|325</td><td></td><td>467|349</td><td>5504|4484</td></tr>
<tr><td>HI</td><td>115|108</td><td></td><td>129|109</td><td></td><td>104|112</td><td></td><td>105|124</td><td></td><td>95|113</td><td></td><td>98|136</td><td></td><td>43|119</td><td></td><td>60|116</td><td></td><td>57|96</td><td></td><td>104|126</td><td></td><td>93|123</td><td></td><td>128|108</td><td></td><td>139|96</td><td></td><td>140|85</td><td></td><td>136|99</td><td>1546|1670</td></tr>
<tr><td>IA</td><td>131|229</td><td></td><td>77|197</td><td></td><td>57|224</td><td></td><td>42|201</td><td></td><td>33|211</td><td></td><td>101|222</td><td></td><td>57|205</td><td></td><td>26|199</td><td></td><td>56|221</td><td></td><td>61|209</td><td></td><td>100|217</td><td></td><td>211|188</td><td></td><td>231|210</td><td></td><td>255|214</td><td></td><td>253|215</td><td>1691|3162</td></tr>
<tr><td>ID</td><td>27|52</td><td></td><td>20|51</td><td></td><td>31|57</td><td></td><td>25|48</td><td></td><td>27|47</td><td></td><td>46|62</td><td></td><td>27|54</td><td></td><td>19|57</td><td></td><td>23|54</td><td></td><td>31|53</td><td></td><td>78|58</td><td></td><td>62|51</td><td></td><td>59|55</td><td></td><td>76|55</td><td></td><td>65|50</td><td>616|804</td></tr>
<tr><td>IL</td><td>330|317</td><td></td><td>156|234</td><td></td><td>124|266</td><td></td><td>104|238</td><td></td><td>68|204</td><td></td><td>153|278</td><td></td><td>59|209</td><td></td><td>71|239</td><td></td><td>70|229</td><td></td><td>100|219</td><td></td><td>343|253</td><td></td><td>227|191</td><td></td><td>254|218</td><td></td><td>299|239</td><td></td><td>253|205</td><td>2611|3539</td></tr>
<tr><td>IN</td><td>122|217</td><td></td><td>100|210</td><td></td><td>77|209</td><td></td><td>55|195</td><td></td><td>33|192</td><td></td><td>85|186</td><td></td><td>71|192</td><td></td><td>95|207</td><td></td><td>115|208</td><td></td><td>100|215</td><td></td><td>268|208</td><td></td><td>215|189</td><td></td><td>238|205</td><td></td><td>264|211</td><td></td><td>252|209</td><td>2090|3053</td></tr>
<tr><td>KS</td><td>123|299</td><td></td><td>108|211</td><td></td><td>112|279</td><td></td><td>69|190</td><td></td><td>113|265</td><td></td><td>88|180</td><td></td><td>171|252</td><td></td><td>61|200</td><td></td><td>88|274</td><td></td><td>77|200</td><td></td><td>399|280</td><td></td><td>245|202</td><td></td><td>353|275</td><td></td><td>232|188</td><td></td><td>334|273</td><td>2573|3568</td></tr>
<tr><td>KY</td><td>90|165</td><td></td><td>112|165</td><td></td><td>135|190</td><td></td><td>118|185</td><td></td><td>58|165</td><td></td><td>70|164</td><td></td><td>88|181</td><td></td><td>58|172</td><td></td><td>58|156</td><td></td><td>77|185</td><td></td><td>84|172</td><td></td><td>60|178</td><td></td><td>92|189</td><td></td><td>122|220</td><td></td><td>89|187</td><td>1311|2674</td></tr>
<tr><td>LA</td><td></td><td></td><td></td><td>0|74</td><td></td><td></td><td></td><td>0|65</td><td></td><td></td><td></td><td>0|67</td><td></td><td></td><td></td><td>0|71</td><td></td><td></td><td></td><td>0|60</td><td></td><td></td><td></td><td>0|58</td><td></td><td></td><td></td><td>0|75</td><td></td><td>0|470</td></tr>
<tr><td>MA</td><td>62|312</td><td></td><td>141|286</td><td></td><td>76|262</td><td></td><td>129|258</td><td></td><td>64|258</td><td></td><td>122|263</td><td></td><td>77|310</td><td></td><td>80|254</td><td></td><td>75|236</td><td></td><td>124|294</td><td></td><td>23|266</td><td></td><td>26|277</td><td></td><td>33|247</td><td></td><td>342|260</td><td></td><td>281|242</td><td>1655|4025</td></tr>
<tr><td>MD</td><td></td><td></td><td>133|82</td><td></td><td></td><td></td><td>105|76</td><td></td><td></td><td></td><td>116|79</td><td></td><td></td><td></td><td>112|78</td><td></td><td></td><td></td><td>110|75</td><td></td><td></td><td></td><td>108|77</td><td></td><td></td><td></td><td>115|79</td><td></td><td></td><td>799|546</td></tr>
<tr><td>ME</td><td>143|334</td><td></td><td>139|336</td><td></td><td>93|354</td><td></td><td>38|327</td><td></td><td>349|323</td><td></td><td>374|341</td><td></td><td>402|362</td><td></td><td>391|363</td><td></td><td>379|350</td><td></td><td>398|361</td><td></td><td>397|355</td><td></td><td>369|347</td><td></td><td>378|344</td><td></td><td>370|343</td><td></td><td>320|328</td><td>4540|5168</td></tr>
<tr><td>MI</td><td>281|207</td><td></td><td>311|295</td><td></td><td>209|220</td><td></td><td>410|295</td><td></td><td>148|218</td><td></td><td>370|295</td><td></td><td>256|218</td><td></td><td>309|291</td><td></td><td>323|210</td><td></td><td>494|293</td><td></td><td>361|218</td><td></td><td>525|296</td><td></td><td>418|222</td><td></td><td>571|296</td><td></td><td>394|219</td><td>5380|3793</td></tr>
<tr><td>MN</td><td>131|390</td><td></td><td>91|256</td><td></td><td>74|390</td><td></td><td>38|260</td><td></td><td>43|384</td><td></td><td>192|390</td><td></td><td>37|266</td><td></td><td>41|395</td><td></td><td>59|272</td><td></td><td>54|396</td><td></td><td>56|394</td><td></td><td>42|259</td><td></td><td>81|393</td><td></td><td>75|267</td><td></td><td>123|395</td><td>1137|5107</td></tr>
<tr><td>MO</td><td>214|287</td><td></td><td>168|292</td><td></td><td>169|296</td><td></td><td>353|289</td><td></td><td>361|274</td><td></td><td>487|309</td><td></td><td>390|291</td><td></td><td>375|296</td><td></td><td>357|277</td><td></td><td>412|282</td><td></td><td>392|269</td><td></td><td>332|269</td><td></td><td>336|255</td><td></td><td>435|313</td><td></td><td>373|270</td><td>5154|4269</td></tr>
<tr><td>MS</td><td></td><td></td><td></td><td>150|246</td><td></td><td></td><td></td><td>189|223</td><td></td><td></td><td></td><td>368|250</td><td></td><td></td><td></td><td>274|238</td><td></td><td></td><td></td><td>272|240</td><td></td><td></td><td></td><td>261|231</td><td></td><td></td><td></td><td>322|213</td><td></td><td>1836|1641</td></tr>
<tr><td>MT</td><td>63|219</td><td></td><td>108|228</td><td></td><td>58|208</td><td></td><td>81|193</td><td></td><td>92|222</td><td></td><td>117|216</td><td></td><td>134|216</td><td></td><td>124|229</td><td></td><td>134|224</td><td></td><td>161|217</td><td></td><td>283|226</td><td></td><td>292|230</td><td></td><td>282|222</td><td></td><td>255|210</td><td></td><td>267|205</td><td>2451|3265</td></tr>
<tr><td>NC</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td>233|272</td><td></td><td>175|252</td><td></td><td>114|254</td><td></td><td>113|259</td><td></td><td>184|284</td><td></td><td>221|266</td><td></td><td>130|257</td><td></td><td>132|262</td><td></td><td>173|337</td><td></td><td>132|326</td><td>1607|2769</td></tr>
<tr><td>ND</td><td>4|48</td><td></td><td>4|45</td><td></td><td>0|46</td><td></td><td>2|48</td><td></td><td>2|49</td><td></td><td>2|49</td><td></td><td>43|43</td><td></td><td>2|45</td><td></td><td>2|45</td><td></td><td>40|40</td><td></td><td>48|47</td><td></td><td>40|40</td><td></td><td>43|42</td><td></td><td>45|44</td><td></td><td>42|39</td><td>319|670</td></tr>
<tr><td>NH</td><td>33|44</td><td></td><td>0|41</td><td></td><td>18|40</td><td></td><td>28|47</td><td></td><td>23|46</td><td></td><td>20|47</td><td></td><td>16|47</td><td></td><td>9|46</td><td></td><td>11|48</td><td></td><td>11|48</td><td></td><td>57|47</td><td></td><td>59|46</td><td></td><td>64|48</td><td></td><td>55|47</td><td></td><td>59|48</td><td>463|690</td></tr>
<tr><td>NJ</td><td></td><td>97|76</td><td></td><td>2|2</td><td></td><td>85|76</td><td></td><td>0|2</td><td></td><td>90|76</td><td></td><td>96|77</td><td></td><td></td><td></td><td>86|76</td><td></td><td>5|4</td><td></td><td>88|79</td><td></td><td>89|78</td><td></td><td>1|1</td><td></td><td>47|77</td><td></td><td>2|2</td><td></td><td>688|626</td></tr>
<tr><td>NM</td><td>26|161</td><td></td><td>53|105</td><td></td><td>89|178</td><td></td><td>54|101</td><td></td><td>82|172</td><td></td><td>47|100</td><td></td><td>62|156</td><td></td><td>35|97</td><td></td><td>77|155</td><td></td><td>50|103</td><td></td><td>228|166</td><td></td><td>125|102</td><td></td><td>188|154</td><td></td><td>118|102</td><td></td><td>239|191</td><td>1473|2043</td></tr>
<tr><td>NV</td><td>98|81</td><td></td><td>69|75</td><td></td><td>56|76</td><td></td><td>45|76</td><td></td><td>43|74</td><td></td><td>13|84</td><td></td><td>69|81</td><td></td><td>56|73</td><td></td><td>50|86</td><td></td><td>115|90</td><td></td><td>87|96</td><td></td><td>79|87</td><td></td><td>101|93</td><td></td><td>84|89</td><td></td><td>75|86</td><td>1040|1247</td></tr>
<tr><td>NY</td><td>53|388</td><td></td><td>22|372</td><td></td><td>15|377</td><td></td><td>13|369</td><td></td><td>6|354</td><td></td><td>27|358</td><td></td><td>17|347</td><td></td><td>22|357</td><td></td><td>27|356</td><td></td><td>26|375</td><td></td><td>41|345</td><td></td><td>124|337</td><td></td><td>128|336</td><td></td><td>102|342</td><td></td><td>154|350</td><td>777|5363</td></tr>
<tr><td>OH</td><td>118|223</td><td></td><td>91|221</td><td></td><td>72|219</td><td></td><td>108|219</td><td></td><td>310|212</td><td></td><td>149|214</td><td></td><td>104|202</td><td></td><td>156|220</td><td></td><td>117|208</td><td></td><td>162|215</td><td></td><td>262|216</td><td></td><td>272|210</td><td></td><td>266|200</td><td></td><td>325|223</td><td></td><td>264|207</td><td>2776|3209</td></tr>
<tr><td>OK</td><td>155|186</td><td></td><td>163|184</td><td></td><td>142|217</td><td></td><td>102|194</td><td></td><td>108|198</td><td></td><td>100|189</td><td></td><td>242|206</td><td></td><td>133|187</td><td></td><td>102|192</td><td></td><td>99|179</td><td></td><td>108|169</td><td></td><td>125|173</td><td></td><td>201|213</td><td></td><td>318|216</td><td></td><td>122|174</td><td>2220|2877</td></tr>
<tr><td>OR</td><td>94|134</td><td></td><td>88|137</td><td></td><td>99|135</td><td></td><td>88|129</td><td></td><td>65|131</td><td></td><td>67|133</td><td></td><td>75|131</td><td></td><td>34|138</td><td></td><td>42|120</td><td></td><td>43|146</td><td></td><td>59|135</td><td></td><td>151|124</td><td></td><td>136|125</td><td></td><td>102|130</td><td></td><td>179|141</td><td>1322|1989</td></tr>
<tr><td>PA</td><td>285|425</td><td></td><td>197|377</td><td></td><td>194|390</td><td></td><td>116|360</td><td></td><td>92|349</td><td></td><td>118|366</td><td></td><td>108|345</td><td></td><td>252|383</td><td></td><td>159|346</td><td></td><td>159|364</td><td></td><td>420|346</td><td></td><td>412|332</td><td></td><td>354|345</td><td></td><td>465|372</td><td></td><td>452|376</td><td>3783|5476</td></tr>
<tr><td>RI</td><td>155|238</td><td></td><td>95|230</td><td></td><td>45|227</td><td></td><td>53|197</td><td></td><td>46|202</td><td></td><td>68|169</td><td></td><td>64|184</td><td></td><td>47|168</td><td></td><td>67|172</td><td></td><td>112|184</td><td></td><td>196|161</td><td></td><td>171|143</td><td></td><td>153|146</td><td></td><td>192|157</td><td></td><td>173|149</td><td>1637|2727</td></tr>
<tr><td>SC</td><td>147|235</td><td></td><td>89|165</td><td></td><td>121|239</td><td></td><td>46|159</td><td></td><td>124|234</td><td></td><td>104|159</td><td></td><td>94|221</td><td></td><td>94|155</td><td></td><td>169|223</td><td></td><td>91|159</td><td></td><td>80|207</td><td></td><td>63|154</td><td></td><td>145|209</td><td></td><td>103|171</td><td></td><td>149|251</td><td>1619|2941</td></tr>
<tr><td>SD</td><td>27|65</td><td></td><td>10|61</td><td></td><td>23|63</td><td></td><td>2|57</td><td></td><td>8|55</td><td></td><td>17|53</td><td></td><td>28|58</td><td></td><td>34|63</td><td></td><td>23|68</td><td></td><td>10|57</td><td></td><td>24|56</td><td></td><td>54|52</td><td></td><td>22|55</td><td></td><td>23|65</td><td></td><td>20|52</td><td>325|880</td></tr>
<tr><td>TN</td><td>303|179</td><td></td><td>276|175</td><td></td><td>270|175</td><td></td><td>210|159</td><td></td><td>211|160</td><td></td><td>283|180</td><td></td><td>235|176</td><td></td><td>254|169</td><td></td><td>220|160</td><td></td><td>238|183</td><td></td><td>269|173</td><td></td><td>219|162</td><td></td><td>247|171</td><td></td><td>291|202</td><td></td><td>162|162</td><td>3688|2586</td></tr>
<tr><td>TX</td><td>375|253</td><td></td><td>333|248</td><td></td><td>314|229</td><td></td><td>283|225</td><td></td><td>265|212</td><td></td><td>381|260</td><td></td><td>294|229</td><td></td><td>346|243</td><td></td><td>302|242</td><td></td><td>307|231</td><td></td><td>380|247</td><td></td><td>308|220</td><td></td><td>330|222</td><td></td><td>408|272</td><td></td><td>384|273</td><td>5010|3606</td></tr>
<tr><td>UT</td><td>16|162</td><td></td><td>42|160</td><td></td><td>25|142</td><td></td><td>32|158</td><td></td><td>34|162</td><td></td><td>25|146</td><td></td><td>20|150</td><td></td><td>26|159</td><td></td><td>10|174</td><td></td><td>16|162</td><td></td><td>34|161</td><td></td><td>14|158</td><td></td><td>20|147</td><td></td><td>40|160</td><td></td><td>11|149</td><td>365|2350</td></tr>
<tr><td>VA</td><td></td><td>12|155</td><td></td><td>12|226</td><td></td><td>17|138</td><td></td><td>22|195</td><td></td><td>23|150</td><td></td><td>36|189</td><td></td><td>45|136</td><td></td><td>36|188</td><td></td><td>35|153</td><td></td><td>41|191</td><td></td><td>23|143</td><td></td><td>49|189</td><td></td><td>64|160</td><td></td><td>77|227</td><td></td><td>492|2440</td></tr>
<tr><td>WI</td><td>140|186</td><td></td><td>97|184</td><td></td><td>98|194</td><td></td><td>66|184</td><td></td><td>69|183</td><td></td><td>90|175</td><td></td><td>115|179</td><td></td><td>80|189</td><td></td><td>122|191</td><td></td><td>137|199</td><td></td><td>283|197</td><td></td><td>238|177</td><td></td><td>219|173</td><td></td><td>224|190</td><td></td><td>264|205</td><td>2242|2806</td></tr>
<tr><td>WY</td><td>177|155</td><td></td><td>38|114</td><td></td><td>37|114</td><td></td><td>33|109</td><td></td><td>28|112</td><td></td><td>49|108</td><td></td><td>59|108</td><td></td><td>50|101</td><td></td><td>37|105</td><td></td><td>77|101</td><td></td><td>138|95</td><td></td><td>143|100</td><td></td><td>177|130</td><td></td><td>137|103</td><td></td><td>153|96</td><td>1333|1651</td></tr>
<tr><td>Total</td><td>5267|7985</td><td>109|231</td><td>4491|7626</td><td>164|548</td><td>4002|7717</td><td>102|214</td><td>4173|7442</td><td>211|485</td><td>4077|7327</td><td>113|226</td><td>5280|7741</td><td>500|583</td><td>4745|7508</td><td>45|136</td><td>4865|7860</td><td>396|573</td><td>4472|7468</td><td>40|157</td><td>5664|8017</td><td>401|570</td><td>7176|7814</td><td>112|221</td><td>6897|7444</td><td>311|479</td><td>7017|7527</td><td>111|237</td><td>8176|8050</td><td>401|517</td><td>7416|7826</td><td>86734|120529</td></tr>
</table>

Note: Table presents counts of unique legislators in analysis dataset by state-year-election. Cell tuples denote number of observed primary candidates (first) and general candidates (second).

Table A.10 – Data Coverage Matrix