The Democratic and the Republican Way to Clean the Street: Estimating Partisan Voting in Nonpartisan Offices Using Cast Vote Records

Mason Reece

Massachusetts Institute of Technology

Most Recent Draft: May 17, 2024

Abstract

Partisanship is an enduring aspect of voters' behavior in American elections, yet nearly 70% of local governments in the United States use nonpartisan elections. One strand of research emphasizes the nonpartisan duties of local governments while another focuses on the convergence of national, state, and local preferences, policies, and politics. I use an original, ballot-level, data set to estimate an ideal point model on 7,500 voters in Adams County, Colorado, then use the model to estimate the degree of partisan voting in nonpartisan elections. I show that although partisanship is more present in partisan elections, voters still use partisanship in nonpartisan elections to choose among candidates. There is also important hetereogeneity based on the contest, which my method demonstrates more clearly than previous research.

I am indebted to feedback from Charles Stewart III, Devin Caughey, Teppei Yamamoto, Fotini Christia and participants of the MIT Second-Year Paper Workshop. Additionally, I acknowledge the MIT SuperCloud and Lincoln Laboratory Supercomputing Center for providing HPC resources that have made the research results reported within this paper possible.

The title is inspired by a quote from the former mayor of New York City, Fiorella La Guardia: *"There is no Democratic or Republican way of cleaning the streets."*

Corresponding author: Mason Reece, Ph.D. Student, MIT. mpreece@mit.edu

Introduction

Partisan identification is a central vehicle through which American voters see themselves, process political information, and make political decisions (Campbell et al. 1960; Fiorina 1981; Green, Palmquist, and Schickler 2002). When Americans head to the polls, they must become informed and decide which candidates to support (Downs 1957). Due to the centrality of partisan identification, political parties are incented to cultivate "party brands" (Aldrich 2011) that make the party affiliation of candidates a useful "heuristic" (Mondak 1993; Lau and Redlawsk 2001; Kam 2005) of what candidates stand for and are likely to do once in office. Given the regularity with which partisan control of state and local governments predicts policy outcomes (Hertel-Fernandez 2019; Grumbach 2022), party labels are an increasingly useful heuristic for voters up and down the ballot.

Yet, across the U.S., 70% of local governments use *nonpartisan* election systems (DeSantis and Renner 1991; Svara 2003), in which candidates are elected without a partisan primary process and, crucially, no party labels are present on the ballot (Adrian 1952, 1959; Bledsoe and Welch 1987). Do patterns in vote choice also fall along a partisan divide in the absence of party labels on the ballot? Recent research on the nationalization of subnational politics (Hopkins 2018), the increasing correlation between local policy and elite preferences (Tausanovitch and Warshaw 2013), and the convergence of voting behavior at the local level to the national level (Sievert and McKee 2019; Weinschenk 2022; Kuriwaki 2023) would suggest that partisanship continues to be a dominating influence on American political behavior, even when elections are nonpartisan.

This research primarily relies on survey data and aggregated data to draw correlations between groups. Survey research is limited by interviewers' inability to ask voters who they voted for in every single contest on the ballot, and by voters' unreliable reports about who they cast their ballots for (Ansolabehere and Hersh 2012). Aggregated data overcomes these two issues by using real election results and examining up- and down-ballot races. However, aggregated data sets cannot track the same voter in different races and must rely on strong ecological inference assumptions to make valid claims. To avoid these problems, I use an original data set of ballot-level data, commonly called ”cast vote records” (CVRs), that reveals anonymous, individual voter choices in each race in the 2020 election. CVRs contain the true votes on all races a voter could have cast a ballot for in the election, which helps them avoid some of the issues of survey and aggregated data. The downside of using CVRs is that they reveal very little information beyond vote choice. CVRs do not have any names, voter IDs, demographic information, or any other identifying information.[1] Despite their limitations, CVRs allow me to explore down-ballot heterogeneity and set the stage for future research using ballot-level data.

I estimate ideal points for voters with cast vote records, continuing a rich tradition of using dimension reduction techniques to better understand political actors using large, public data. I use the item-response theory method developed in Lewis (2001) and Clinton, Jackman, and Rivers (2004), but modify it in two ways. First, I slightly adapt the model to allow for categorical choices, which better represents the choices voters face on their ballots. Second, I leverage what are typically nuisance parameters in the estimation as quantities of interest to better answer the question at hand. In the methodology section, I expound more on these choices and what they mean for the estimation of the model and interpretation of its results. My research additionally contributes to the ideal point literature by focusing on an understudied group, voters themselves. Policymakers regularly produce large amounts of public data (e.g., roll call votes, social media posts, and campaign contribution records) that have been used to estimate ideal points (Poole and Rosenthal 1985; Barberá 2015; Bonica 2014), while voters do not regularly produce big data that is shared publicly. CVRs are an exception to this, since they are both publicly available and represent the choices of all voters in a

1. See Kuriwaki, Lewis, and Morse (2024) for a review of the privacy of CVRs. Their basic conclusion is that CVRs reveal no more about the secret ballot than aggregated, precinct-level results do.

jurisdiction.

In this paper, I demonstrate a proof-of-concept method to estimate voters' general political orientation using anonymous ballot-level data on voter choices in Colorado's 2020 presidential election. I use these measures to assess the degree of partisan voting in nonpartisan elections. I show that partisan voting exists in nonpartisan elections, although it is not nearly as prevalent as in partisan elections. I find important heterogeneity among the offices on the ballot, although I defer to future research to discover why this pattern exists. I proceed as follows. I first review the literature and develop competing theories for why voters will (not) vote like partisans in nonpartisan elections. Second, I introduce my method for estimating voter ideal points and validate it with other, similar methods. Third, I use those measures to adjudicate between my competing theories. Finally, I conclude with steps for future research.

Partisanship in Nonpartisan Elections

Two separate but related investigative threads provide the basis for the answers this study might deliver. On the one hand, the distinctiveness of the work subnational governments do – often nonpartisan and nonideological in nature with a focus on economic growth and development (Peterson 1981; Oliver, Ha, and Callen 2012; Anzia 2021) – would cast doubt on the expectation that vote choice in nonpartisan elections would fall along any sort of partisan dimension. On the other hand, the nationalization of subnational politics (Hopkins 2018), increasing correlation between local policy and elite preferences (Tausanovitch and Warshaw 2013), and convergence of voting behavior at the local level to that of national politics (Sievert and McKee 2019; Weinschenk 2022; Kuriwaki 2023) would suggest that partisanship continues to be a dominating influence on American political behavior, even when not made readily accessible by the ballot itself.

Around the turn of the 20th century, progressive reformers called for changes to America's political system that would insulate government from the pressures of parties and political machines. One way they advocated for this to happen was to make local elections nonpartisan. In their view, those elected to judges should be seen as ”neutral arbiters” rather than ”political officers” (Bonneau and Hall 2009) and those elected to local government should act as ”business-like administrators” (Adrian 1952). Put another way, reformers believed that ”there being no Republican way to pave a street and no Democratic way to lay a sewer” (766), candidates should be elected based on merit rather than party connections. Consequently, by 1956, 61% of municipalities used nonpartisan elections (Adrian 1959), increasing to over 70% in recent years (DeSantis and Renner 1991; Svara 2003). Broadly, the American public seems to have supported this change, and is generally in favor of using nonpartisan elections to fill key roles (Alvarez, Hall, and Llewellyn 2008; Crawford 2022). Have the efforts of reformers been successful in removing partisanship from local elections?

Anzia (2021) suggests that there is little evidence to show that voter preferences on local issues mirrors preferences on national issues, initial evidence in favor of nonpartisan elections. Indeed, previous work focusing on specific local offices has found mixed evidence of partisan voting behavior in local executive (Schaffner, Streb, and Wright 2001; Taylor and Schreckhise 2003; Alvarez, Hall, and Levin 2018), state legislator (Schaffner, Streb, and Wright 2001; Ansolabehere et al. 2006; Garlick 2015), judge (Squire and Smith 1988; Klein and Baum 2001; Rock and Baum 2010; Burnett and Tiede 2014; Bonneau and Cann 2015; Lim and Snyder 2015; Kritzer 2021; Weinschenk et al. 2021), and school board (Weinschenk 2022) offices. The initial goals of nonpartisan elections combined with mixed evidence to the contrary indicate that nonpartisan elections might be nonpartisan.

Although some research suggests that nonpartisan elections are truly nonpartisan, researchers have repeatedly, and increasingly, emphasized the role of partisanship in voters' choices in all types of elections. When choosing candidates in elections, especially in down-ballot, low information elections, voters rely on "heuristics" to help make sense of political information without needing to carefully scrutinize it for themselves (Downs 1957; Mondak 1993; Lau and Redlawsk 2001). One such heuristic is the party affiliation of candidates on the ballot before them (Kam 2005). The utility of party labels has been enhanced by the nationalization of state and local politics (Hopkins 2018). As Democrats and Republicans across levels of government have increasingly enacted policies concordant with the platforms of their national parties (Grumbach 2022) – the result of concerted efforts to implement cohesive ideological agendas in subnational governments (Hertel-Fernandez 2019) – American voters can reliably foresee the sort of policy outcomes that will arise from voting Democrat or Republican candidates to office. Indeed, recent evidence suggests a correlation between local public opinion, elite preferences, and policy outcomes in subnational governments (Tausanovitch and Warshaw 2013; Einstein and Kogan 2016; de Benedictis-Kessner and Warshaw 2016; Einstein and Glick 2018; de Benedictis-Kessner, Jones, and Warshaw 2023; Sievert and McKee 2019; Weinschenk 2022; Kuriwaki 2023). In parallel to the regularity with which partisan control of government structures the ideological agendas subnational governments pursue, among the mass public, issue orientations increasingly structure the partisanship of voters (Highton and Kam 2011). Together, trends at mass-, elite-, and policy-levels suggest that ideology increasingly structures political outcomes.

Although in this research I cannot address it, I acknowledge that voters' ability to take advantage of partisan cues may be dependent on other factors. Voters with high levels of base political knowledge may be more capable of identifying the partisanship of a candidate based on other heuristics (Delli Carpini and Keeter 1996; Schaffner and Streb 2002). As a complement to baseline political knowledge, the information environment in which a voter resides will also affect their ability to make this connection. Local news coverage can help inform voters on a candidate's partisanship or otherwise help them identify how well the candidate represents them (Schaffner and Streb 2002; Rock and Baum 2010; Peterson 2017; Moskowitz 2021).

The initial goals of progressive reformers and some research suggests nonpartisan elections remain nonpartisan, while other work highlights the presence of partisan cues and voting behavior in nonpartisan elections. In the next section I outline the method I use to help adjudicate between these competing explanations. The results I show contribute to this literature because they rely on the full cast ballots of voters, rather than work using aggregated data (e.g., Hopkins 2018) or survey work (e.g., Jensen et al. 2021). In the next section, I detail the method I use to estimate the degree of partisanship in nonpartisan elections.

Methodology

Dimension reduction techniques are regularly used to uncover common latent dimensions among policymakers. These methods have been applied to roll call votes (Poole and Rosenthal 1985; Lewis et al. 2024), social media posts (Barberá 2015), campaign contribution records (Bonica 2014, 2018), executive branch members (Bertelli and Grose 2011), judicial decisions (Bailey and Maltzman 2011; Lauderdale and Clark 2012; Martin and Quinn 2002), bureaucrats (Clinton et al. 2012), interest groups (Crosson, Furnas, and Lorenz 2020; Abi-Hassan et al. 2023), international political parties (Herrmann and Döring 2023), and online platforms like YouTube (Lai et al. 2024). Typically, this research takes a large corpus of public data produced by policymakers and transforms it into a single (or, sometimes, multiple) measure that describes the actors in that space. I follow previous work in assuming that the first dimension is a measure of ”ideology”, but there is nothing inherent about the methods used that guarantees the first common dimension is ideological in nature (Poole and Rosenthal 1985).

The method for estimating voter ideal points using ballot-level data was originally pioneered by Lewis (2001). Lewis uses an item-response theory method, similar to Poole and Rosenthal (1985) and formally described in Clinton, Jackman, and Rivers (2004). I extend this method to use all contests on the ballot, rather than limiting the data to only contests that can be represented by a binary variables, as Lewis does.[2] I apply this method to ballot level data, which I describe more formally in the next section.

Data

I use ballot-level data, commonly called ”cast vote records” (CVRs), from the 2020 general election. CVRs are anonymized records of all the choices made by each voter on their ballot. The data is fully anonymous and I am unable to identify anything about the voters except where they voted. The data has been standardized into a common format across the nation to facilitate analysis.[3]

CVRs from the 2020 election were released by some local election administrators in response to increasing calls from election activists to be able to independently verify the results of the 2020 election.[4] I do not know why each county in my data released their data so I treat my data as a non-random sample of CVRs. Nevertheless, it contains over 1 billion choices in elections at all levels of government and in localities of all kinds from all over the country, representing the choices of roughly 40 million voters. I remove all uncontested races[5], and all races where a voter could select more than one candidate.[6] For this paper, to demonstrate my method and to make estimation compu-

2. In Appendix A, I formally describe the binary variable method and show how it could be applied to my data.

3. More details on this process can be found in Kuriwaki et al. (2024)

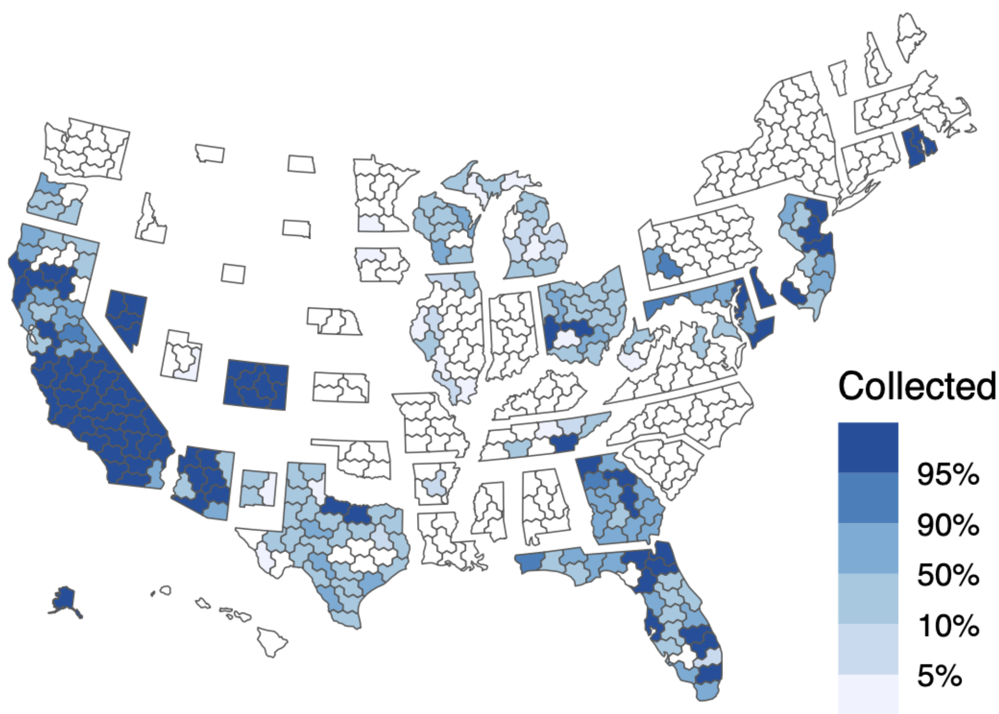
4. Some states prohibit releasing CVRs in any form, and for other states the ability to do so depended on whether a group requested them from a certain county, whether the county used technology enabling this data to be easily compiled, and whether the county election office had the capacity to even complete the request.

5. I first remove all candidates who received less than 20 votes in the data, then remove all races where only one candidate was contesting the election.

6. Future research should model these types of races since they represent about 10% of all elections in the data

tationally tractable, I focus only on the state of Colorado, and randomly select 83,729 voters to study, representing $\sim$ 2.7 million choices. For the most advanced model, which I describe below, I additionally subset this data to only voters in Adams County, Colorado. The Adams County data contains 7,535 voters, representing $\sim$ 250,000 choices. For a comparison of Adams County, Colorado at large, and the United States on a number of demographic and electorally relevant variables, see Table 1. The full data, which I defer to future research, covers 28 states, 470 counties, 40 million voters and 1 billion choices. See Figure 1 for the full distribution of the data. This data would allow me to simultaneously study local-level heterogeneity and make comparisons between different jurisdictions.

Figure 1: Cast Vote Record Distribution



Note: This is a map of the United States subdivided by state and congressional district. Since congressional districts are roughly equally weighted by population, this map shows more clearly how the data are distributed. The scale does not use even breaks since I do not equally value coverage. Districts with near-perfect coverage, like southern California and Colorado, are more useful for analysis than districts with below 50% coverage, like Michigan or New York.

Table 1: Comparison of Adams County, Colorado to Colorado and the United States At-Large

	Adams County	Colorado	United States
Demographics			
Age			
18+ years	74.3%	78.1%	77.9%
65+ years	11.1%	15%	16.8%
Race/Ethnicity			
White	55.8%	70.7%	61.6%
Black or African-American	3.4%	4.1%	12.4%
American Indian and Alaska Native	1.8%	1.3%	1.1%
Asian	4.5%	3.5%	6%
Native Hawaiian or Pacific Islander	0.2%	0.2%	0.2%
Other	16.8%	8%	8.4%
Hispanic or Latino	41.7%	21.9%	18.7%
Socioeconomic			
Median Household Income	$73,817	$75,231	$64,994
Elections			
Voters			
Citizen Voting Age Population	64.8%	73.1%	71.5%
Share Joseph R. Biden Vote	56.7%	55.4%	51.3%
Share Donald J. Trump Vote	40.4%	41.9%	46.8%
Ballot Contents			
(Average) Contests	52	32.9	37.6*
(Average) % Local Contests	71.1%	76.4%	75.2%*
(Average) % Nonpartisan Contests	61.2%	70%	44.8%*

Note: Data is gathered from the US 2020 Decennial Census (*Age*, *Race/Ethnicity*, *Citizen Voting Age Population*), the ACS 5-Year Estimates for 2020 (*Socioeconomic*), the New York Times (*Presidential election results*), and the author's CVR data (*Ballot Contents*).

* Average is based on the 28 states in the author's CVR data, and may be unrepresentative of the nation at large.

Model Estimation

I follow in the footsteps of other researchers and estimate an Item-Response Theory (IRT) model (Lewis 2001; Clinton, Jackman, and Rivers 2004; Martin and Quinn 2002). I choose this method as opposed to other methods because I am estimating a continuous, latent scale using only discrete information from each voter. A common specification of the IRT model, reformulated from Jackman (2009), is the 2-Parameter model. Equation 1 shows the model, where j indexes voters and k indexes the contest. There are three parameters of interest. First, $\alpha_j \in \mathbb{R}$ is the unobserved ideal point of voter j. Second, γ_k is an unknown vector of *item discrimination* or slope parameters for each candidate who could be chosen in contest k. γ_k describes the degree to which a vote for each candidate in contest k informs the model's placement of a voter's ideal point on the scale. β_k is an unknown vector of *item difficulty* parameters which measure the probability of a certain candidate being chosen, irrespective of the underlying trait. In this context, this is the proportion of the votes that each candidate received. $F(\cdot)$ is a function mapping the equation to the probability line. Given my data, where voters can choose from any number of unordered candidates for each contest, $F(\cdot)$ is the softmax function, a multivariate generalization of the inverse logit function. This coerces the vector of probabilities for each candidate in the contest into a vector of probabilities that sum to one.

$$\pi_{jk} = Pr(y_{jk} = c|\alpha_j, \gamma_k, \beta_k) = F(\alpha_j\gamma_k - \beta_k) \tag{1}$$

Of particular importance to IRT models, and the categorical model in particular, are the identification restrictions. As it stands, the model is not identified. Simply put, the scales of α are not set and can be easily multiplied by any factor or shifted by any constant without changing the relative location of each parameter. Similarly, the sign of γ can vacillate with a corresponding switch in the sign of α and result in the same behavior. Therefore, a number of identification restrictions must be imposed. For a more full discussion of these conditions, see Jackman (2009), Clinton, Jackman, and Rivers (2004), and Rivers (2003). I choose to normalize α to mean 0 and standard deviation 1, which I impose both in post-processing and by setting a strong standard normal prior. For γ, typically the restriction that γ is positive is applied. However, because the categorical model also requires a reference category to be set, and I have no *a priori* way to determine which candidate has the "smallest" γ, I cannot force γ to be positive. Instead, I set the winning candidate (based on their vote totals in the sample) as the reference category, and let γ be unidentified during estimated. I then post-process the draws using the Rotation-Sign-Permutation algorithm described in Papastamoulis and Ntzoufras (2022). The implications of this choice are not important in the interpretation of the results, but they make estimation and convergence of the model more challenging.

I estimate this model on a smaller subset of the Colorado data, using only voters from Adams County, a large county that covers the northeast corner of Denver and some rural areas outside of Denver. This constitutes a sample size of $7,535$ voters with $247,917$ choices. The model is estimated under a Bayesian framework using a bespoke Stan model.[7] I follow standard procedure and take 1000 warmup draws then sample from 1000 draws across 4 chains. After applying RSP,[8] the model converges well. I show the distribution of the $\hat{R}$ statistic in Table C.1 and plot traceplots for 24 randomly selected parameters in Figure C.1. After estimation, I also drop candidates that received less than 5 votes from voters in the random sample.[9]

I validate my estimates in two ways. First, I aggregate estimated ideal points for each voter, depending on which presidential candidate they selected. I take the mean

7. Code snippets are found in Appendix B

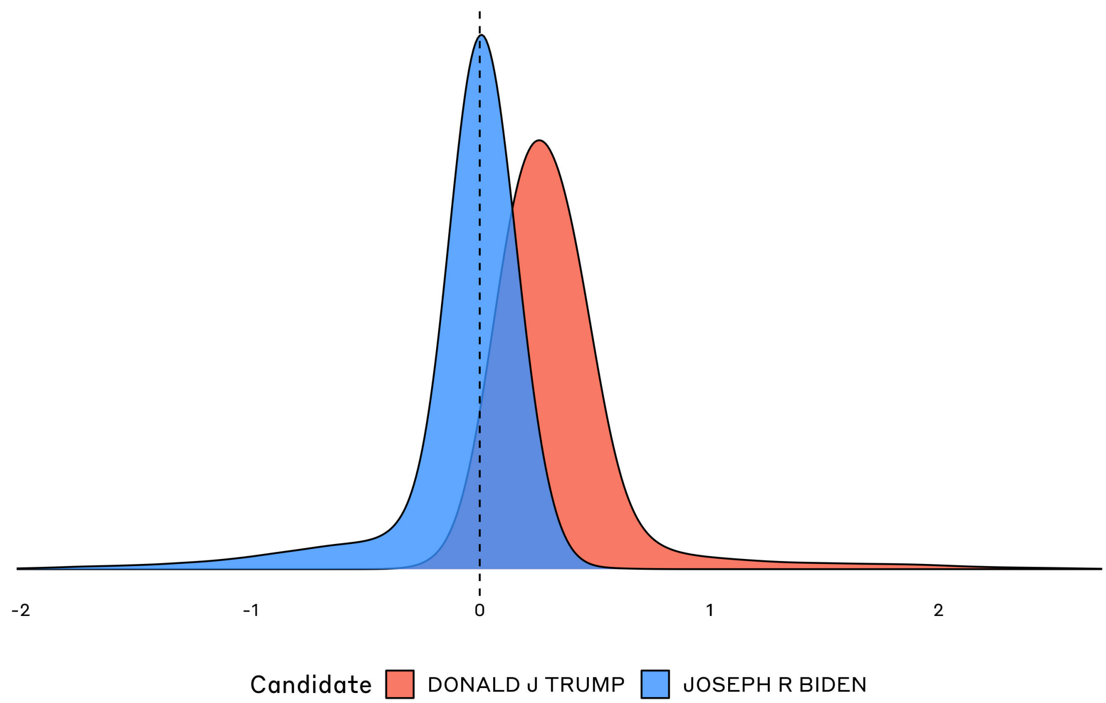
8. See Figure C.4 for a comparison of the draws before and after the application of Rotation-Sign-Permutation.

9. This drops the following candidates, with the contest they participated in in parentheses: Laura Ireland (US House 004), Steve Zorn (US House 007), Phil Collins (US President), Kyle Kenley (US President), Brock Pierce (US President), Brian Carroll (US President), Blake Huber (US President), Princess Khadijah M. Pres Jacob-Fambro (US President), and Joe McHugh (US President).

of the posterior draws for each voter, then plot the distribution of those means for the presidential candidates. In the process of plotting the distribution, which is normalized with a Gaussian kernel, I weight observations by the precision of the estimate – effectively upweighting voters who's ideal point the model is highly confident about and downweighting voters it is uncertain about. The resulting distribution for Trump and Biden voters is shown in Figure 2. I expect that Biden voters will mostly be distributed to the left of Trump voters, which the plot confirms. The plot provide facial evidence that the model is accurately representing reality at the aggregate level. One useful application of the categorical model is that I am not only able to plot the posterior distribution of Biden and Trump voters' ideal points, but also the distribution of ideal points of all voters who cast ballots for third-party candidates in the election. Typically, the number of voters for each third-party candidate, especially in the random subset I have chosen, would make these candidates unable to be modelled. However, Bayesian estimation ensures that information from other contests on the ballot allows me to still estimate ideal points for voters who selected third-party candidates. I aggregate those estimates in the same way as I do for Trump and Biden voters. The aggregated estimates are instead displayed using a boxplot, with a similar weighting procedure, since the kernel function for the density plots was overpowering the few number of observations for some of the candidates. These boxplots are found in Figure 3. Because there are low numbers of voters for each third-party candidate, I do not interpret these estimates, but instead leave them as a proof of concept for what interpretation with the full data could contribute.

I continue to test the results facially by plotting the posterior distribution of estimated ideal points for 15 random voters in Figure 4. I expect that for individual voters, those voters who voted straight-ticket Democrat (I temporarily ignore nonpartisan elections for this exercise) will be to the left of both voters who voted straight-ticket Republican and of those who split their tickets. The plot confirms this, the voters far on

Figure 2: Distribution of Ideal Points of Voters for Trump and Biden Voters



the left of the graph voted straight-ticket Democrat, while voters on the far right side of the graph voted straight-ticket Republican. Voters in the middle split their tickets among the partisan candidates. This plot also demonstrates an important point about the model. Voters in the middle, who split their tickets, communicate more information about their true ideal points than voters who voted straight-ticket, and thus have tighter posterior distributions. Taken together, the aggregate distribution of ideal points and the example individual ideal points suggests that the model accurately represents reality.

Conducting validation of the model on down-ballot elections is also important, but harder to do facially without deep contextual knowledge about each contest. Instead, I compare the weighted, mean of each voter's estimated ideal point (following the same weighting procedure as above) to a well-accepted measure in the literature, DIME scores (Bonica 2014). This comparison is non-trivial, since DIME scores and my estimates of ideal points are not on the same scale. Instead of directly comparing points, I

Figure 3: Distribution of Ideal Points of Voters for Third Party Presidential Candidates

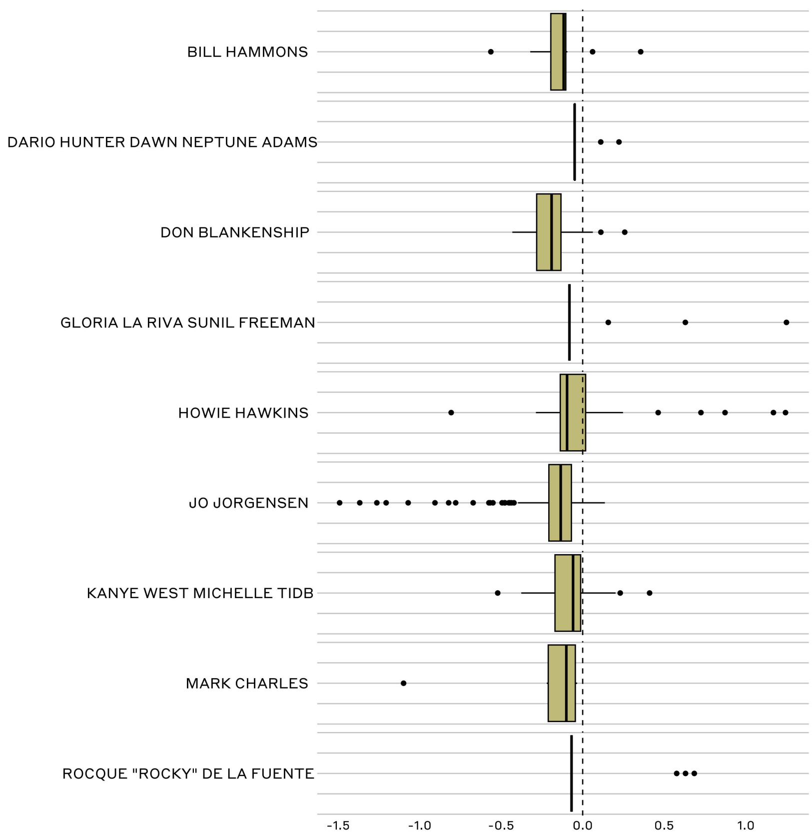
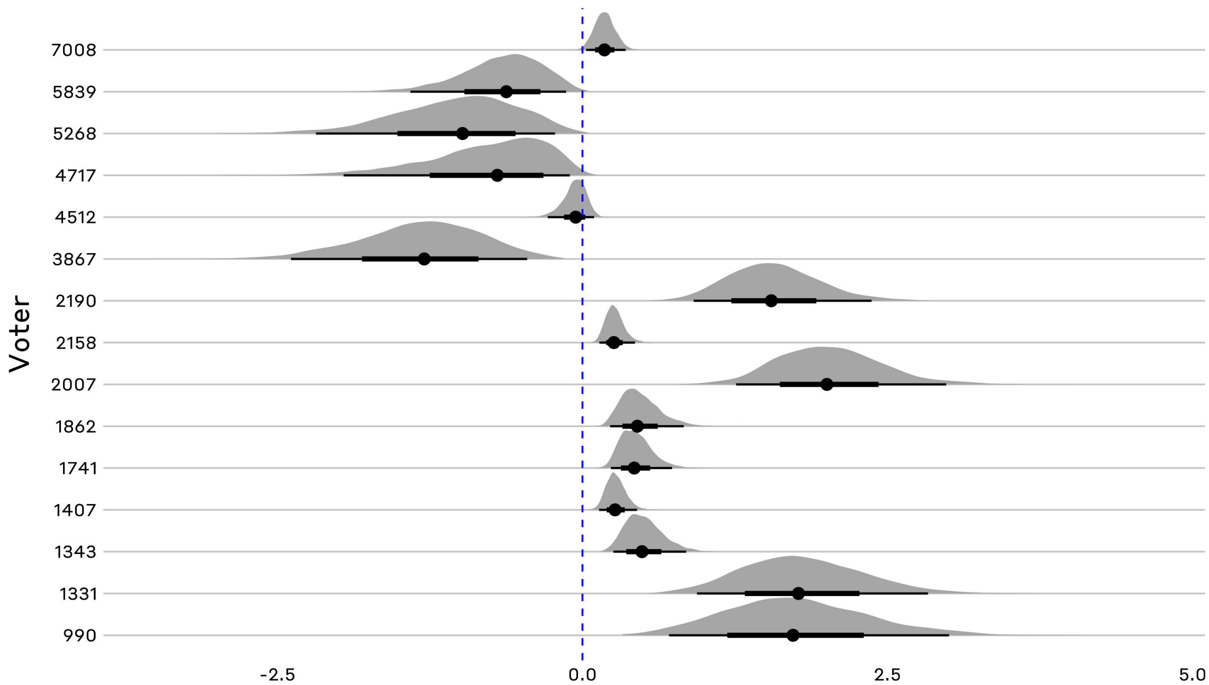


Figure 4: Example Ideal Points from the Categorical Model



instead compare cutpoints between candidates after independently normalizing each data set to a mean of zero and variance of one. The definition of cutpoints flows from standard spatial models of voting (Enelow and Hinich 1984). In the standard binary choice model, respondents are assumed to have quadratic utility functions over the choices; i.e. $U_i(\zeta_j) = -\|\xi_i - \zeta_j\|^2 + \eta_{ij}$ and $U_i(\psi_j) = -\|\xi_i - \psi_j\|^2 + v_{ij}$, where $\xi_i \in \mathbb{R}^d$ is the ideal point of respondent i, η_{ij} and v_{ij} are the errors or stochastic elements of utility, and $\|\cdot\|$ is the Euclidean norm (c.f. Jackman 2009, 458). Utility maximization implies $y_{ij} = 1$ if $U_i(\zeta_j) > U_i(\psi_j)$ and $y_{ij} = 0$ otherwise (c.f. 458). Similarly, this model implies that the cutpoint between the two candidate choices (i.e. the point at which a respondent would find themselves indifferent between the two candidates), is defined as $(\xi_j + \psi_j)/2$ (c.f. 458).

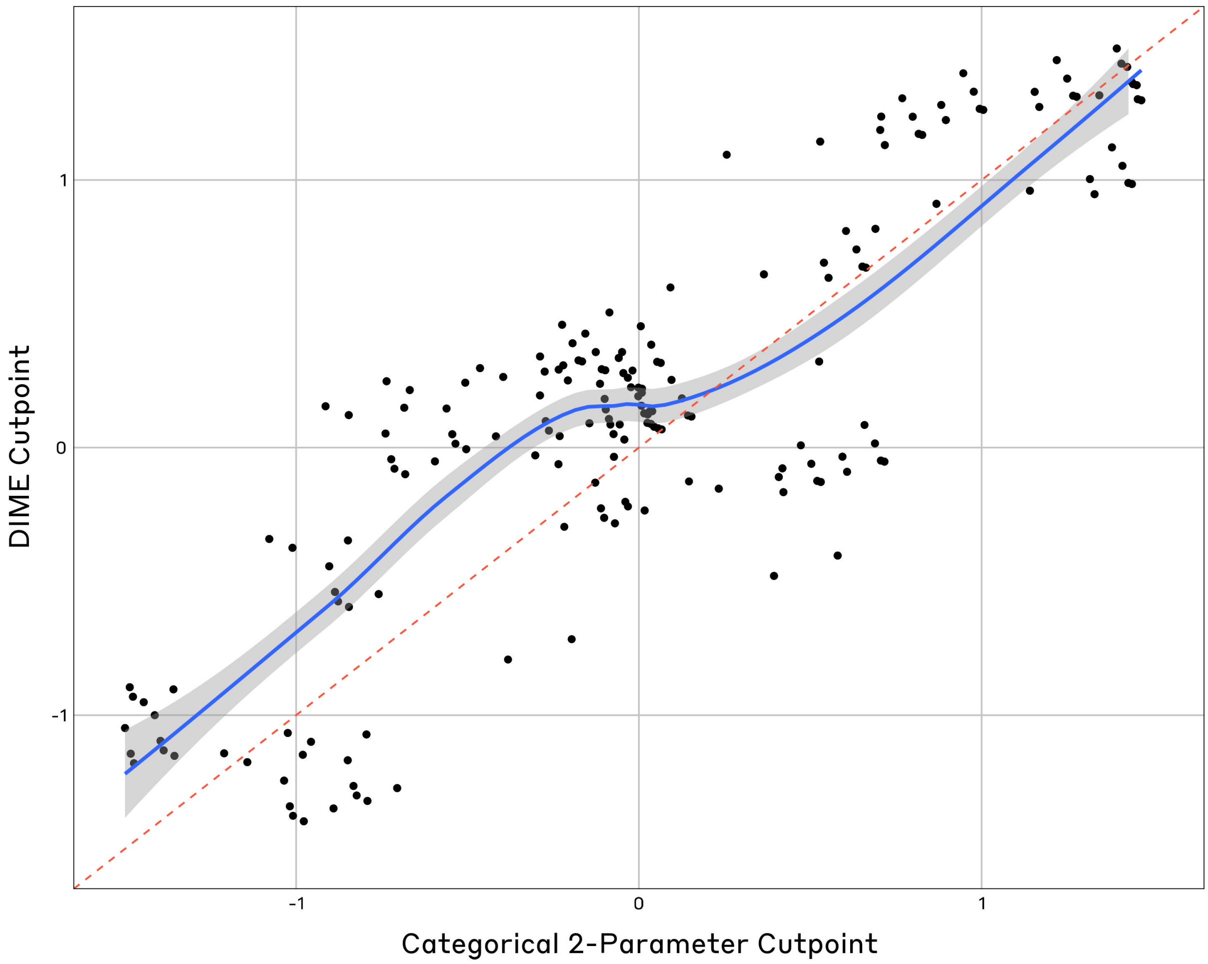
In the categorical model, the choices explode. Given a choice of candidate c, the utility a respondent derives from that candidate can be expressed as $U_i(\zeta_j^c) = -\|\xi_i - \zeta_j^c\|^2 + \eta_{ij}^c$. Then, a respondent chooses a specific candidate if the utility exceeds the utilities of all of the other proposals: $Pr(U_i(\zeta_j^c) > U_i(\zeta_j^{c'}))$, where $\zeta_j^{c'}$ implies all of the possible candidates except for candidate c. In these models, the cutpoint can be defined as a series of pairwise comparisons between each of the candidates, following the same formulation as in the binary choice model. In addition, because there are multiple proposals, there is a conceptual area of indifference where a single respondent would be indifferent between all of the possible candidates. With three candidates, one could imagine three different cutting planes (unique for each voter) defined by the utility functions from each candidate, and their intersection in the middle would be an area of indifference. As the number of candidates (and thus dimensions) increases, the number of cutting dimensions and comparisons increases exponentially.

For both my own scores, and for DIME scores, I compute cutpoints for all candidates that are present in both my data and in the DIME scores. Only 16% of candidates in my data are given scores in the DIME data. This is an additional advantage of my method, since it does not rely on candidates publicly reporting their campaign contributions or donating to other causes. The only requirement for a candidate to appear in my data is that they were present on the ballot. Nevertheless, I proceed by comparing cutpoints using the matching candidates. The cutpoints correlate well, at 0.88. The distribution of cutpoints are shown in Figure 5. The plot indicates that the categorical 2-Parameter IRT method correlates well with the widely accepted DIME scores, when they can be matched, which I treat as additional validation of my method.

Computational Extensions

The estimation of a complex Bayesian IRT model is a non-trivial task. Using the fully Bayesian method, fitting a model on the subset of Adams County, Colorado still takes approximately 10 hours using MIT's SuperCloud cluster. A fully Bayesian estimation of even a subset of the state of Colorado would take at least a week, and a reasonable subset of the nation could take several months. Therefore, I must explore potential

Figure 5: Comparison of the Cutpoints from the Categorical 2-Parameter Model and DIME Scores



Note: This figure plots the cutpoints between candidates, using two separate datasets. On the x-axis, average ideal points from my categorical 2-parameter IRT model for individual candidates are used to compute cutpoints between that candidate and all other candidates. On the y-axis, I use Bonica (2014) DIME scores as the average ideal point, then compute all cutpoints between a given candidate and all other candidates. The cutpoints between candidates are matched between the two datasets and plotted. In blue, a LOESS line of best fit is drawn. In dashed red is the 45° line.

alternatives to the fully Bayesian method. Since my model is already implemented in *Stan*, it is relatively easy to switch to faster approximation methods. I choose the *Pathfinder* method proposed in Zhang et al. (2022). "Pathfinder is a variational method for approximately sampling from differentiable log densities. Starting from a random initialization, Pathfinder locates normal approximations to the target density along a quasi-Newton optimization path, with local covariance estimated using the negative inverse Hessian estimates produced by the L-BFGS optimizer. Pathfinder returns draws from the Gaussian approximation with the lowest estimated Kullback-Leibler (KL) divergence to the true posterior" (CmdStan User Guide 2024, c.f.). *Pathfinder* is an order of magnitude faster (10 minutes vs 10 hours for the Adams County, Colorado sample) and produces results that correlate with the fully Bayesian results at 0.66, although this low correlation is primarily driven by the β parameter (For more detailed comparisons, see Figure C.5).

For future versions of this project, I intend to proceed in two different ways. First, I will solely use the *Pathfinder* method to estimate parameters for the model on a larger scale. This should provide reasonable approximations of what the true underlying parameters are. Second, I will also scale up the fully Bayesian models by using the parameters from the *Pathfinder* method as initial values, instead of randomly initializing values. This should increase the speed of convergence for the fully Bayesian method, allowing me to use less draws and arrive at similar results. I still need to test the computational speed and feasibility of these two methods.

Results

To estimate the degree to which voters rely on partisanship in nonpartisan races, I focus on the *item discrimination* parameter in the categorical 2-parameter model, $\gamma_{k(c)}$. Larger absolute values of γ for a given candidate relative to the baseline candidate in that contest indicate that a vote for that candidate provides us with more information as to the relative position of a certain voter on the first-dimension of the model. Simply put, I interpret larger γ values as a sign that voters treat a candidate as more partisan. I recognize that the use of this parameter implies a somewhat circular relationship, since I both define the latent space based on nonpartisan and partisan contests, but then also interpret the parameter as meaningful for this distinction. In future versions of this project I have two plans to help address this circularity: (1) estimating a model with multiple dimensions will allow more flexibility in the relationship and reduce some of the dependence. (2) I also intend to fit a future version of the model only on partisan elections since that more clearly defines the first dimension, and the discrimination parameter, as related to the degree of partisan voting in a contest. Then, I would use that fitted model and project nonpartisan elections into this space, enforcing the partisan dimension from the partisan contests. Nevertheless, even given these limitations, I do not anticipate that these extensions will dramatically change the substantive interepretation of my results.

The 95% credible intervals of the discrimination parameter, γ, for nonpartisan races are shown in Figure 6. The baseline categories are omitted for clarity, since all nonpartisan races in Adams County are "Yes/No" contests. The important takeaway from this figure is that the credible intervals for the discrimination parameters do not include zero. Moreover, the judicial contests are further from zero than the ballot initiatives. There is notable heterogeneity among the judicial contests, which I intend to explore more in future research.

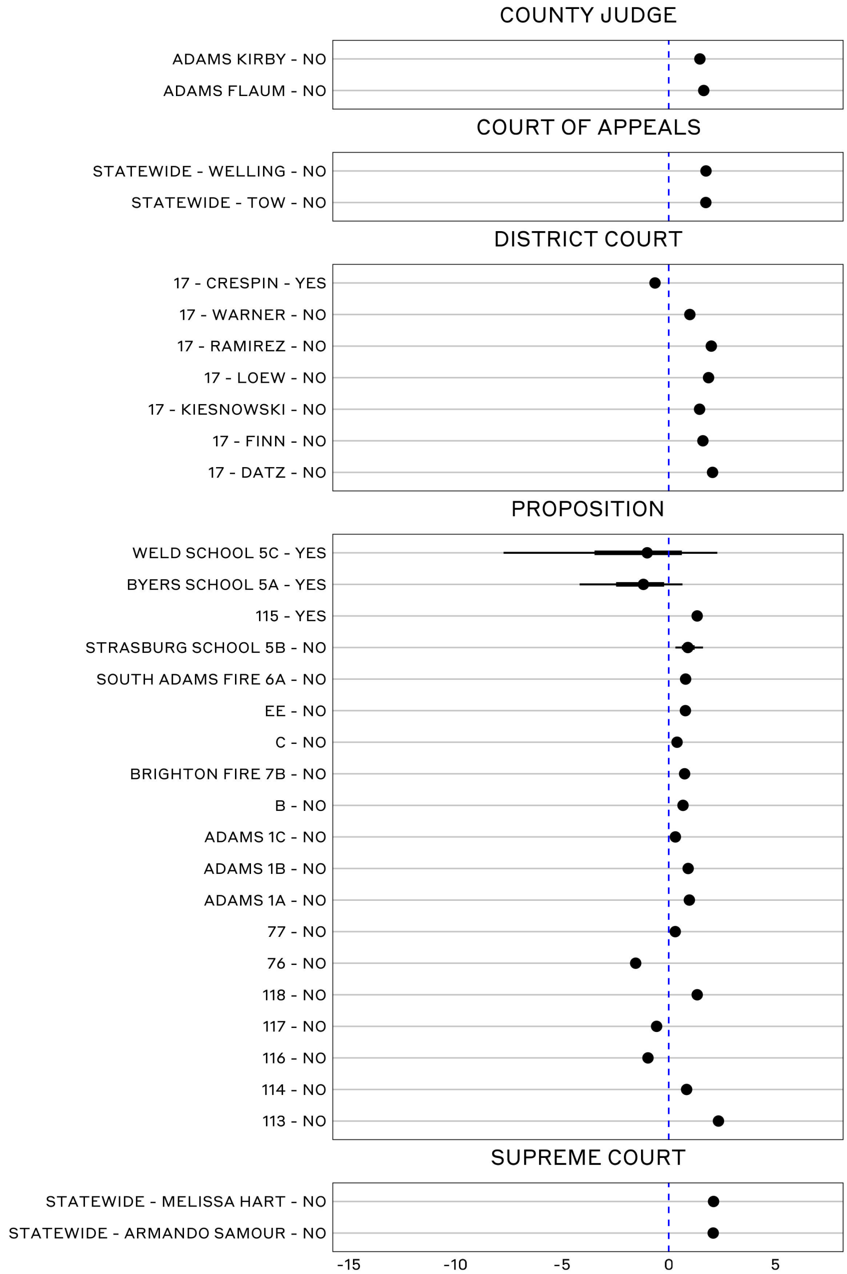
There is one limitation to this plot, which is that it gives us no sense how partisan these races are compared to prototypical partisan races. To that end, Figure 7 shows the same type of distributions for partisan elections. For this plot, baseline categories are included for reference since the partisan races have more than two candidates. As expected, these races also all have discrimination parameters different from zero. Because both figures are on the same scale I can compare the degree of partisan voting between partisan and nonpartisan races. As should be expected, on average, the absolute value of the discrimination parameter for partisan races is larger than the parameter in nonpartisan races. Although nonpartisan races do not appear to be truly ”nonpartisan” in the strict sense, they do appear to be less partisan than strictly partisan races. Although the results provide some support for the theory that nonpartisan contests do not activate partisan behavior among voters (which seems to be particularly true for ballot propositions), they mostly support the claim that voters also use partisanship to decide between candidates in nonpartisan races. However, they do not use partisanship as much as they would in an officially partisan race.

Conclusion

I present results to help adjudicate between two competing theories about partisanship in nonpartisan elections. I contribute new, more detailed answers to this question using an original data set of ballot-level data in Colorado. In addition, the method I demonstrate is able to estimate parameters for more candidates than previous methods because it relies on a candidate’s presence on the ballot, rather than their participation in roll call votes (Poole and Rosenthal 1985) or campaign contributions (Bonica 2018). My results suggest that although voters appear to use partisanship less in nonpartisan elections, it is nevertheless still present in nonpartisan elections. The goals of Progressive Era reformers to ”insulate government from the pressures of parties and political machines” seems to have been only partially successful.

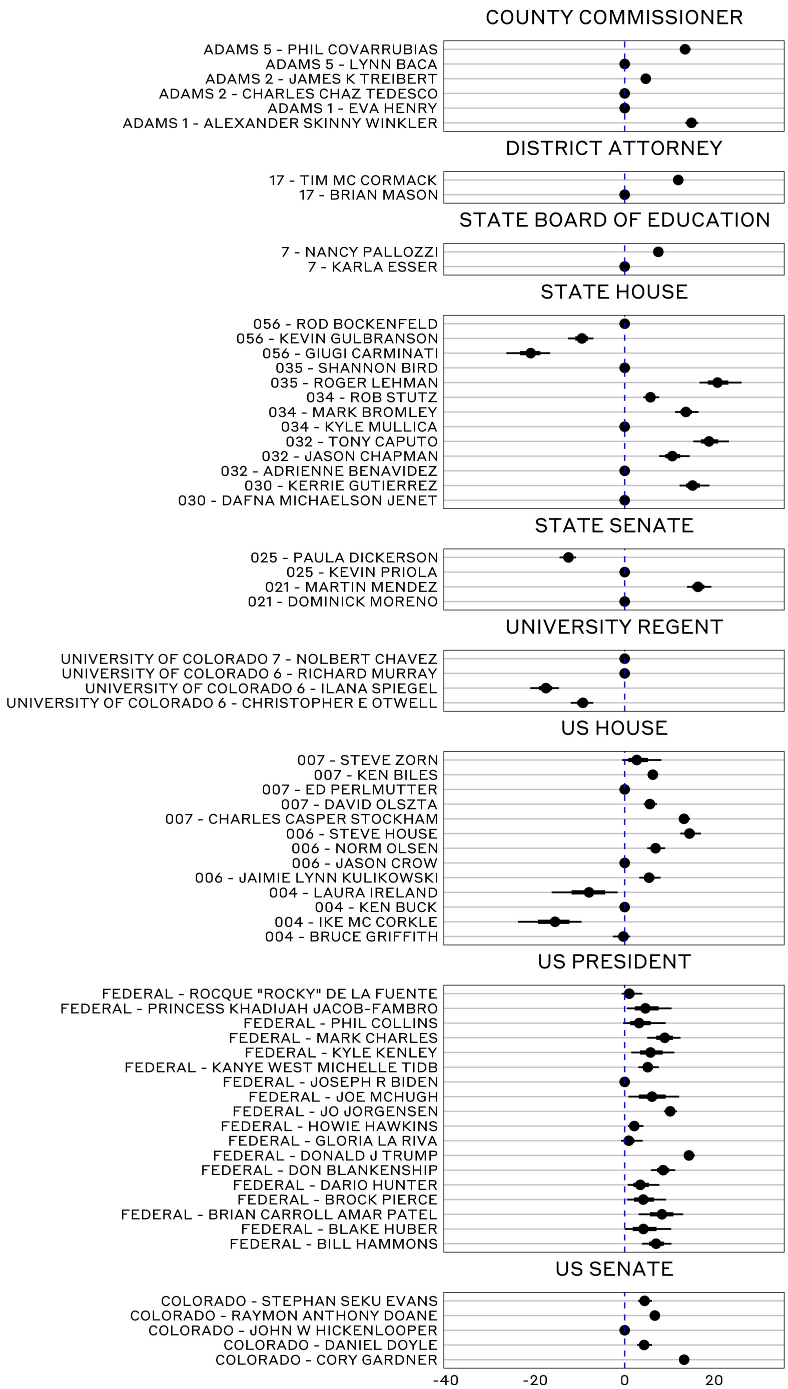
One question remains for future research – if not partisanship, what else are voters using to choose among candidates? Previous work has found that in the absence of party labels, voters may rely on other heuristics, including: race or ethnicity (Pomper 1966; Arrington 1978; Bullock 1984; Matson and Fine 2006; Boudreau, Elmendorf, and

Figure 6: Discrimination Parameters for Nonpartisan Elections



Note: This figure shows the posterior distribution for each discrimination parameter for all nonpartisan elections in Adams County, Colorado. The parameters are grouped by the type of contest, and the x-axis is allowed to vary for each type of contest. The baseline categories for each election are omitted. Although discrimination parameters in categorical models are generally interpreted as relative to the baseline, each nonpartisan election in this data is a "Yes/No" election so these posterior distributions can be interpreted more easily.

Figure 7: Discrimination Parameters for Partisan Elections



Note: This figure shows the posterior distribution for each discrimination parameter for all partisan elections in Adams County, Colorado. The parameters are grouped by the type of contest, and the x-axis is allowed to vary for each type of contest.

MacKenzie 2019; Crowder-Meyer, Gadarian, and Trounstine 2020; Burnett and Kogan 2022), issue positions (Abrajano, Nagler, and Alvarez 2005; Holman and Lay 2021), incumbency (Squire and Smith 1988; Schaffner, Streb, and Wright 2001; Trounstine 2011), ballot position (Mueller 1970; Miller and Krosnick 1998; Ho and Imai 2006), endorsements (Krebs 1998; Arceneaux and Kolodny 2009; DeLuca 2023), or personal reputation and traits (Raymond 1992; Banducci et al. 2008; Kirkland and Coppock 2018; Atkeson and Hamel 2020). How do these characteristics interact with the perceived partisanship of nonpartisan candidates or ballot initiatives? Future work should add information on these important covariates to help further understand why voters use partisanship more in some races rather than others.

In addition to expanding factors related to the degree of partisan voting in nonpartisan elections, future work should take advantage of the full dataset of ballot-level records. As I discuss in the methodology section, the estimation of Bayesian IRT models is non-trivial on even a subset of data from Adams County, Colorado. Including more voters, from more geographies, would increase the external validity of this research and let us draw more general conclusions about voter behavior in nonpartisan elections. A promising avenue could be machine learning techniques, like those deployed in Bonica (2018), to speed estimation.

References

Abi-Hassan, Sahar, Janet M. Box-Steffensmeier, Dino P. Christenson, Aaron R. Kaufman, and Brian Libgober. 2023. "The Ideologies of Organized Interests and Amicus Curiae Briefs: Large-Scale, Social Network Imputation of Ideal Points." *Political Analysis* 31, no. 3 (July): 396–413.

Abrajano, Marisa A., Jonathan Nagler, and R. Michael Alvarez. 2005. "A natural experiment of race-based and issue voting: The 2001 city of Los Angeles elections." *Political Research Quarterly* 58 (2): 203–218.

Adrian, Charles R. 1959. "A Typology for Nonpartisan Elections." *Western Political Quarterly* 12, no. 2 (June): 449–458.

———. 1952. "Some general characteristics of nonpartisan elections." *American Political Science Review* 46 (3): 766–776.

Aldrich, John Herbert. 2011. *Why Parties? A Second Look.* 2nd ed. Chicago: University of Chicago Press.

Alvarez, R. Michael, Thad E. Hall, and Ines Levin. 2018. "Low-information voting: Evidence from instant-runoff elections." *American Politics Research* 46, no. 6 (March): 1012–1038.

Alvarez, R. Michael, Thad E. Hall, and Morgan Llewellyn. 2008. "Who Should Run Elections in the United States?" *Policy Studies Journal* 36, no. 3 (August): 325–346.

Ansolabehere, Stephen, and Eitan Hersh. 2012. "Validation: What big data reveal about survey misreporting and the real electorate." Publisher: Cambridge University Press, *Political Analysis* 20 (4): 437–459.

Ansolabehere, Stephen, Shigeo Hirano, James M Snyder, and Michiko Ueda. 2006. "Party and incumbency cues in voting: Are they substitutes?" *Quarterly Journal of Political Science* 1, no. 2 (April): 119–137.

Anzia, Sarah F. 2021. "Party and ideology in american local government: An appraisal." *Annual Review of Political Science* 24, no. 1 (May): 133–150.

Arceneaux, Kevin, and Robin Kolodny. 2009. "Educating the least informed: Group endorsements in a grassroots campaign." *American Journal of Political Science* 53 (4): 755–770.

Arrington, Theodore S. 1978. "Partisan Campaigns, Ballots, and Voting Patterns: The Case of Charlotte." *Urban Affairs Quarterly* 14, no. 2 (December): 253–263.

Atkeson, Lonna Rae, and Brian T. Hamel. 2020. "Fit for the Job: Candidate Qualifications and Vote Choice in Low Information Elections." *Political Behavior* 42, no. 1 (March): 59–82.

Bailey, Michael A., and Forrest Maltzman. 2011. *The Constrained Court: Law, Politics, and the Decisions Justices Make.* Princeton: Princeton University Press, December.

Banducci, Susan A., Jeffrey A. Karp, Michael Thrasher, and Colin Rallings. 2008. "Ballot Photographs as Cues in LowInformation Elections." *Political Psychology* 29, no. 6 (December): 903–917.

Barberá, Pablo. 2015. "Birds of the same feather tweet together: Bayesian ideal point estimation using Twitter data." Publisher: Cambridge University Press, *Political analysis* 23 (1): 76–91.

Bertelli, Anthony M., and Christian R. Grose. 2011. "The Lengthened Shadow of Another Institution? Ideal Point Estimates for the Executive Branch and Congress." *American Journal of Political Science* 55, no. 4 (October): 767–781.

Bledsoe, Timothy, and Susan Welch. 1987. "Patterns of Political Party Activity among U.S. Cities." *Urban Affairs Quarterly* 23, no. 2 (December): 249–269.

Bonica, Adam. 2018. "Inferring Roll-Call Scores from Campaign Contributions Using Supervised Machine Learning." *American Journal of Political Science* 62, no. 4 (October): 830–848.

———. 2014. "Mapping the Ideological Marketplace." *American Journal of Political Science* 58 (2): 367–386.

Bonneau, Chris W., and Damon M. Cann. 2015. "Party Identification and Vote Choice in Partisan and Nonpartisan Elections." *Political Behavior* 37, no. 1 (March): 43–66.

Bonneau, Chris W., and Melinda Gann Hall. 2009. *In Defense of Judicial Elections.* Routledge, June.

Boudreau, Cheryl, Christopher S. Elmendorf, and Scott A. MacKenzie. 2019. "Racial or spatial voting? The effects of candidate ethnicity and ethnic group endorsements in local elections." *American Journal of Political Science* 63, no. 1 (January): 5–20.

Bullock, Charles S. 1984. "Racial Crossover Voting and the Election of Black Officials." *The Journal of Politics* 46, no. 1 (February): 238–251.

Burnett, Craig M., and Vladimir Kogan. 2022. "Do nonpartisan ballots racialize candidate evaluations? Evidence from Who Said What experiments." *Party Politics* 28, no. 3 (May): 541–553.

Burnett, Craig M., and Lydia Tiede. 2014. "Party labels and vote choice in judicial elections." *American Politics Research* 43, no. 2 (September): 232–254.

Campbell, Angus, Philip E Converse, Warren E Miller, and Donald E Stokes. 1960. *The American Voter.* Chicago: University of Chicago Press.

Clinton, Joshua, Simon Jackman, and Douglas Rivers. 2004. "The Statistical Analysis of Roll Call Data." *American Political Science Review* 98, no. 2 (May): 355–370.

Clinton, Joshua D., Anthony Bertelli, Christian R. Grose, David E. Lewis, and David C. Nixon. 2012. "Separated Powers in the United States: The Ideology of Agencies, Presidents, and Congress." *American Journal of Political Science* 56, no. 2 (April): 341–354.

CmdStan User Guide. 2024. *Pathfinder for Variational Inference.*

Crawford, Evan. 2022. "Who prefers nonpartisan elections? The role of individual party ID and county partisanship." *Research & Politics* 9, no. 1 (January).

Crosson, Jesse M., Alexander C. Furnas, and Geoffrey M. Lorenz. 2020. "Polarized pluralism: organizational preferences and biases in the American pressure system." Publisher: Cambridge University Press, *American Political Science Review* 114 (4): 1117–1137.

Crowder-Meyer, Melody, Shana Kushner Gadarian, and Jessica Trounstine. 2020. "Voting can be hard, information helps." *Urban Affairs Review* 56 (1): 124–153.

de Benedictis-Kessner, Justin, Daniel Jones, and Chris Warshaw. 2023. "How partisanship in cities influences housing policy." *SSRN Electronic Journal* (February).

de Benedictis-Kessner, Justin, and Christopher Warshaw. 2016. "Mayoral Partisanship and Municipal Fiscal Policy." *The Journal of Politics* 78, no. 4 (October): 1124–1138.

Delli Carpini, Michael X., and Scott Keeter. 1996. *What Americans know about politics and why it matters.* 3. [pr.] New Haven: Yale Univ. Press.

DeLuca, Kevin. 2023. "Editor's Choice: Measuring Candidate Quality using Local Newspaper Endorsements." In *APSA Preprints.* May.

DeSantis, Victor S, and Tari Renner. 1991. "Contemporary Patterns and Trends in Municipal Government Structure." In *The Municipal Year Book,* 57–69. Washington, DC: International City/County Management Association.

Downs, Anthony. 1957. *An Economic Theory of Democracy.* New York: Harper.

Einstein, Katherine Levine, and David M. Glick. 2018. "Mayors, partisanship, and redistribution: Evidence directly from US mayors." *Urban Affairs Review* 54 (1): 74–106.

Einstein, Katherine Levine, and Vladimir Kogan. 2016. "Pushing the City Limits: Policy Responsiveness in Municipal Government." *Urban Affairs Review* 52, no. 1 (January): 3–32.

Enelow, James M., and Melvin J. Hinich. 1984. *The spatial theory of voting: An introduction.* CUP Archive.

Fiorina, Morris P. 1981. *Retrospective voting in American national elections.* New Haven: Yale University Press.

Garlick, Alex. 2015. "The letter after your name: Party labels on virginia ballot." *State Politics & Policy Quarterly* 15, no. 2 (June): 147–170.

Green, Donald P., Bradley Palmquist, and Eric Schickler. 2002. *Partisan Hearts and Minds: Political Parties and the Social Identities of Voters.* Yale ISPS series. New Haven London: Yale University Press.

Grumbach, Jacob M. 2022. *Laboratories Against Democracy: How National Parties Transformed State Politics.* Princeton, New Jersey: Princeton University Press.

Herrmann, Michael, and Holger Döring. 2023. "Party Positions from Wikipedia Classifications of Party Ideology." *Political Analysis* 31, no. 1 (January): 22–41.

Hertel-Fernandez, Alex. 2019. *State Capture: How Conservative Activists, Big Businesses, and Wealthy Donors Reshaped the American States and the Nation.* New York: Oxford University Press.

Highton, Benjamin, and Cindy D. Kam. 2011. "The Long-Term Dynamics of Partisanship and Issue Orientations." *The Journal of Politics* 73, no. 1 (January): 202–215.

Ho, Daniel E., and Kosuke Imai. 2006. "Randomization inference with natural experiments: An analysis of ballot effects in the 2003 california recall election." Publisher: [American Statistical Association, Taylor & Francis, Ltd.] *Journal of the American Statistical Association* 101 (475): 888–900.

Holman, Mirya R., and J. Celeste Lay. 2021. "Are you picking up what I am laying down? Ideology in low-information elections." *Urban Affairs Review* 57, no. 2 (March): 315–341.

Hopkins, Daniel J. 2018. *The increasingly United States: How and why American political behavior nationalized.* University of Chicago Press.

Jackman, Simon. 2009. *Bayesian Analysis for the Social Sciences.* Hoboken, NJ: Wiley.

Jensen, Amalie, William Marble, Kenneth Scheve, and Matthew J. Slaughter. 2021. "City limits to partisan polarization in the American public." Publisher: Cambridge University Press, *Political Science Research and Methods* 9 (2): 223–241.

Kam, Cindy D. 2005. "Who Toes the Party Line? Cues, Values, and Individual Differences." *Political Behavior* 27, no. 2 (June): 163–182.

Kirkland, Patricia A., and Alexander Coppock. 2018. "Candidate choice without party labels: New insights from conjoint survey experiments." *Political Behavior* 40, no. 3 (September): 571–591.

Klein, David, and Lawrence Baum. 2001. "Ballot information and voting decisions in judicial elections." *Political Research Quarterly* 54 (4): 709–728.

Krebs, Timothy B. 1998. "The determinants of candidates' vote share and the advantages of incumbency in city council elections." *American Journal of Political Science,* 921–935.

Kritzer, Herbert M. 2021. "Polarization and Partisanship in State Supreme Court Elections." *Judicature* 105 (3): 64–75.

Kuriwaki, Shiro. 2023. *Ticket splitting in a nationalized era.* Preprint. SocArXiv, March.

Kuriwaki, Shiro, Jeffrey B Lewis, and Michael Morse. 2024. *The Still Secret Ballot: The Limited Privacy Cost of Transparent Election Results.* Working Paper. February.

Kuriwaki, Shiro, Mason Reece, Kate Murray, Joseph Loffredo, Kevin E. Acevedo Jetter, Zachary Djanogly Garai, Luka Bulic Braculj, et al. 2024. *A Multi-State Database of Cast Vote Records.* Working Paper.

Lai, Angela, Megan A. Brown, James Bisbee, Joshua A. Tucker, Jonathan Nagler, and Richard Bonneau. 2024. "Estimating the Ideology of Political YouTube Videos." *Political Analysis* (February): 1–16.

Lau, Richard R., and David P. Redlawsk. 2001. "Advantages and Disadvantages of Cognitive Heuristics in Political Decision Making." *American Journal of Political Science* 45, no. 4 (October): 951.

Lauderdale, Benjamin E., and Tom S. Clark. 2012. "The Supreme Court's many median justices." Publisher: Cambridge University Press, *American Political Science Review* 106 (4): 847–866.

Lewis, Jeffrey B. 2001. "Estimating Voter Preference Distributions from Individual-Level Voting Data." *Political Analysis* 9, no. 3 (January): 275–297.

Lewis, Jeffrey B, Keith Poole, Howard Rosenthal, Adam Boche, Aaron Rudkin, and Luke Sonnet. 2024. *Voteview: Congressional Roll-Call Votes Database.*

Lim, Claire S.H., and James M. Snyder. 2015. "Is more information always better? Party cues and candidate quality in U.S. judicial elections." *Journal of Public Economics* 128 (August): 107–123.

Martin, Andrew D., and Kevin M. Quinn. 2002. "Dynamic ideal point estimation via Markov chain Monte Carlo for the US Supreme Court, 1953-1999." Publisher: Cambridge University Press, *Political analysis* 10 (2): 134–153.

Matson, Marsha, and Terri Susan Fine. 2006. "Gender, Ethnicity, and Ballot Information: Ballot Cues in Low-Information Elections." *State Politics & Policy Quarterly* 6 (1): 49–72.

Miller, Joanne M., and Jon A. Krosnick. 1998. "The impact of candidate name order on election outcomes." Publisher: [Oxford University Press, American Association for Public Opinion Research], *The Public Opinion Quarterly* 62 (3): 291–330.

Mondak, Jeffery J. 1993. "Public opinion and heuristic processing of source cues." *Political Behavior* 15, no. 2 (June): 167–192.

Moskowitz, Daniel J. 2021. "Local News, Information, and the Nationalization of U.S. Elections." *American Political Science Review* 115, no. 1 (February): 114–129.

Mueller, John E. 1970. "Choosing among 133 candidates." *The Public Opinion Quarterly* 34 (3): 395–402.

Oliver, J. Eric, Shang E Ha, and Zachary Callen. 2012. *Local elections and the politics of small-scale democracy.* Princeton: Princeton University Press.

Papastamoulis, Panagiotis, and Ioannis Ntzoufras. 2022. "On the identifiability of Bayesian factor analytic models." *Statistics and Computing* 32, no. 2 (April): 23.

Peterson, Erik. 2017. "The Role of the Information Environment in Partisan Voting." *The Journal of Politics* 79, no. 4 (October): 1191–1204.

Peterson, Paul E. 1981. *City limits.* Chicago: University of Chicago Press.

Pomper, Gerald. 1966. "Ethnic and Group Voting in Nonpartisan Municipal Elections." *Public Opinion Quarterly* 30 (1): 79.

Poole, Keith T., and Howard Rosenthal. 1985. "A spatial model for legislative roll call analysis." Publisher: JSTOR, *American journal of political science,* 357–384.

Raymond, Paul. 1992. "The American Voter in a Nonpartisan, Urban Election." *American Politics Quarterly* 20, no. 2 (April): 247–260.

Rivers, Douglas. 2003. *Identification of Multidimensional Item Response Models.*

Rock, Emily, and Lawrence Baum. 2010. "The impact of high-visibility contests for U.S. state court judgeships: Partisan voting in nonpartisan elections." *State Politics & Policy Quarterly* 10 (4): 368–396.

Schaffner, Brian F., and Matthew Streb. 2002. "The partisan heuristic in low-information elections." *Public Opinion Quarterly* 66 (4): 559–581.

Schaffner, Brian F, Matthew Streb, and Gerald Wright. 2001. "Tearns Without Uniforms: The Nonpartisan Ballot in State and Local Elections." *Political Research Quarterly* 54, no. 1 (March): 7–30.

Sievert, Joel, and Seth C. McKee. 2019. "Nationalization in US Senate and gubernatorial elections." *American Politics Research* 47 (5): 1055–1080.

Squire, Peverill, and Eric R.A.N. Smith. 1988. "The effect of partisan information on voters in nonpartisan elections." *The Journal of Politics* 50, no. 1 (February): 169–179.

Svara, James H. 2003. "Two decades of continuity and change in American city councils." *Washington, DC: National League of Cities.*

Tausanovitch, Chris, and Christopher Warshaw. 2013. "Measuring Constituent Policy Preferences in Congress, State Legislatures, and Cities." *The Journal of Politics* 75, no. 2 (April): 330–342.

Taylor, Jon, and William D. Schreckhise. 2003. "The impact of issue voting on a local nonpartisan election." *State and Local Government Review* 35, no. 3 (September): 174–182.

Trounstine, Jessica. 2011. "Evidence of a Local Incumbency Advantage." *Legislative Studies Quarterly* 36, no. 2 (May): 255–280.

Weinschenk, Aaron, Mandi Baker, Zoe Betancourt, Vanessa Depies, Nathan Erck, Quinne Herolt, Amanda Loehrke, Cameron Makurat, Hannah Malmberg, and Clarice Martell. 2021. "Have state supreme court elections nationalized?" *Justice System Journal* 41 (4): 313–322.

Weinschenk, Aaron C. 2022. "The nationalization of school superintendent elections." *Social Science Quarterly* 103, no. 3 (May): 597–606.

Zhang, Lu, Bob Carpenter, Andrew Gelman, and Aki Vehtari. 2022. "Pathfinder: Parallel quasi-Newton variational inference." *Journal of Machine Learning Research* 23 (306): 1–49.

Software References

Arel-Bundock, Vincent. 2022. "modelsummary: Data and Model Summaries in R." *Journal of Statistical Software* 103 (1): 1–23.

Barrett, Tyson, Matt Dowle, Arun Srinivasan, Jan Gorecki, Michael Chirico, and Toby Hocking. 2024. *data.table: Extension of 'data.frame'.* R package version 1.15.0. https://CRAN.R-project.org/package=data.table.

Bürkner, Paul-Christian. 2018. "Advanced Bayesian Multilevel Modeling with the R Package brms." *The R Journal* 10 (1): 395–411.

———. 2021. "Bayesian Item Response Modeling in R with brms and Stan." *Journal of Statistical Software* 100 (5): 1–54.

———. 2017. "brms: An R Package for Bayesian Multilevel Models Using Stan." *Journal of Statistical Software* 80 (1): 1–28.

Gabry, Jonah, Daniel Simpson, Aki Vehtari, Michael Betancourt, and Andrew Gelman. 2019. "Visualization in Bayesian workflow." *J. R. Stat. Soc. A* 182 (2): 389–402.

Gabry, Jonah, Rok Češnovar, and Andrew Johnson. 2023. *cmdstanr: R Interface to 'CmdStan'.* Https://mc-stan.org/cmdstanr/, https://discourse.mc-stan.org.

Kay, Matthew. 2023. *tidybayes: Tidy Data and Geoms for Bayesian Models.* R package version 3.0.6. http://mjskay.github.io/tidybayes/.

Landau, William Michael. 2021. "The targets R package: a dynamic Make-like function-oriented pipeline toolkit for reproducibility and high-performance computing." *Journal of Open Source Software* 6 (57): 2959. https://doi.org/10.21105/joss.02959.

Pedersen, Thomas Lin. 2024. *patchwork: The Composer of Plots.* R package version 1.2.0. https://CRAN.R-project.org/package=patchwork.

R Core Team. 2023. *R: A Language and Environment for Statistical Computing.* Vienna, Austria: R Foundation for Statistical Computing. https://www.R-project.org/.

Richardson, Neal, Ian Cook, Nic Crane, Dewey Dunnington, Romain François, Jonathan Keane, Dragoș Moldovan-Grünfeld, Jeroen Ooms, Jacob Wujciak-Jens, and Apache Arrow. 2023. *arrow: Integration to 'Apache' 'Arrow'.* R package version 14.0.0.2. https://CRAN.R-project.org/package=arrow.

Stan Development Team. 2024a. *Stan Reference Manual.*

Stan Development Team. 2024b. *Stan User's Guide.* https://mc-stan.org/docs/stan-users-guide/..

Ushey, Kevin, and Hadley Wickham. 2024. *renv: Project Environments.* R package version 1.0.4. https://CRAN.R-project.org/package=renv.

Vehtari, Aki, Andrew Gelman, Daniel Simpson, Bob Carpenter, and Paul-Christian Bürkner. 2021. "Rank-normalization, folding, and localization: An improved Rhat for assessing convergence of MCMC (with discussion)." *Bayesian Analysis.*

Wickham, Hadley, Mara Averick, Jennifer Bryan, Winston Chang, Lucy D'Agostino McGowan, Romain François, Garrett Grolemund, et al. 2019. "Welcome to the tidyverse." *Journal of Open Source Software* 4 (43): 1686.

Appendix for ”Ideal Points”

A Binary Outcomes

Lewis (2001) estimates voter ideal points using CVRs, but only relies on ballot questions. Ballot questions are inherently encoded as Yes/No choices, which means they can be easily represented by an IRT binomial model. I also begin with a binomial model, but depart slightly from Lewis. Instead of focusing on ballot questions, I intentionally choose partisan races since they are more informative on the ideological location of a voter. To do this, I create a binary variable, where a 1 indicates that the voter selected the Republican candidate in the race.[1] This necessitates that I subset the data to only partisan races, which does not reduce the number of voters but it does reduce the number of choices to 682, 858 (25% of the total). Equation 1 then becomes:

$$\pi_{jk} = Pr(y_{jk} = 1|\alpha_j, \gamma_{k(c)}, \beta_{k(c)}) = F(\alpha_j \gamma_{k(c)} - \beta_{k(c)}) \tag{2}$$

For the binary model, I set $F(\cdot)$ to be the inverse logistic function. The likelihood is shown in Equation 3, given the common independence assumption across voters and races (Clinton, Jackman, and Rivers 2004). In addition, because there are no unique candidate effects, only effects at the race level, I drop the indexing by candidate within each race and only reference the race itself.

$$\mathcal{L} = \prod_{j=1}^{J} \prod_{k=1}^{K} \pi_{jk}^{y_{jk}} (1 - \pi_{jk})^{1-y_{jk}} \tag{3}$$

As it stands, the model is not identified. Simply put, the scales of α are not set and can be easily multiplied by any factor or shifted by any constant without changing the relative location of each parameter. Similarly, the sign of γ can vacillate with a corresponding switch in the sign of α and result in the same behavior. Therefore, a number of identification restrictions must be imposed. For a more full discussion of these conditions, see Jackman (2009), Clinton, Jackman, and Rivers (2004), and Rivers (2003). I choose to normalize the latent trait to mean 0 and standard deviation 1, which I impose both in post-processing and by setting a strong standard normal prior. I also impose the restriction that γ must always be positive, thus fixing its sign.

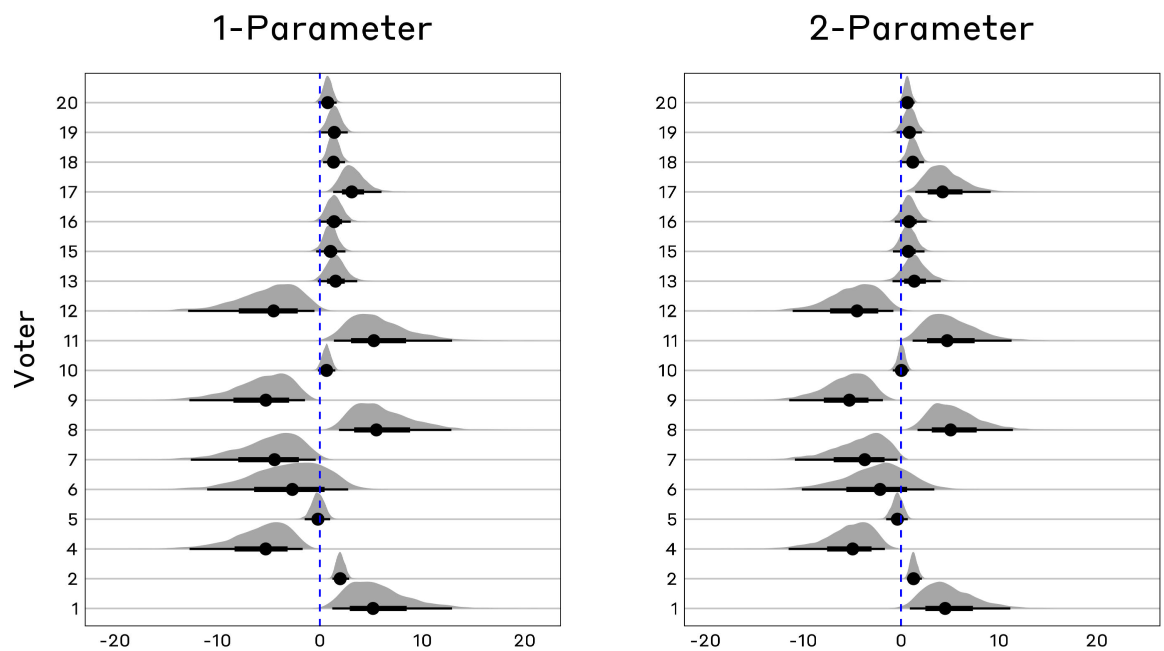
I start by fitting a simple 1-Parameter model. I estimate the previous Bernoulli model using *brms*.[2] All models are run for 4 chains, with 1000 warm-up iterations and then 1000 sampling iterations. Trace plots are too numerous to display in full, but samples can be found in Figure C.2, all of which indicate good convergence. In addition, Table C.1 displays summaries of the $\hat{R}$ value for every parameter in the model.

1-Parameter models treat each race as equally important in determining the ideal point of a voter, so I only look at those ideal points. I randomly select some voters and plot their estimated ideal points in the left panel of Figure A.1. The plot acts as a simple validation check; voters far on the left side of 0 cast straight-ticket Democrat ballots whereas voters on the far right cast straight-ticket Republican ballots. Voters in

1. This choice ensures that ideal points on the right side of the scale will indicate greater likelihood to select the Republican candidate, thus matching the standard perception of American political parties.

2. Relevant code snippets can be found in Appendix B

Figure A.1: Example Ideal Points from the Bernoulli Model



the middle cast more split-ticket ballots. The different exact estimates are due to the differing impact of casting a ballot for the Republican in a specific race versus another, which is driven entirely by the difficulty parameter in the 1-Parameter model but by both the difficulty and discrimination parameter in the 2-Parameter model.

I then proceed after the 1-Parameter model to also fit a 2-Parameter model, which allows the discrimination parameters to vary and be estimated, but requires them to be positive. Again, Figure C.3 and Table C.1 show that the models converge well. As can be seen in the right panel of Figure A.1, the estimates match up closely to the estimates from the 1-Parameter model. That there isn't much difference makes sense given the context of US elections, where most voters choose the same party up and down the ballot (Kuriwaki 2023), so no single race is likely to be more informative than others on their location on a latent scale. To confirm this, I directly plot the difficulty and discrimination parameters for a random set of races from the 2-Parameter model in Figure A.2 and display the full estimates in Table A.1. Although many of the races are significantly different from 0, most of the races are similarly discriminatory. I don't want to read too much into these parameters, but the lack of wild variation suggests that they are all acting in a similar way to one another in the Bernoulli model.

Table A.1: Distribution of β in the 2-Parameter Bernoulli Model

Race	**Mean β**	**SD β**	**Mean γ**	**SD γ**
City Council - Castle Rock 1	7.51	1.69	0.10	0.06

City Council - Castle Rock 2	7.57	1.72	0.09	0.06
City Council - Castle Rock 4	7.38	1.76	0.10	0.06
City Council - Castle Rock 6	7.62	1.68	0.09	0.06
County Clerk - Alamosa	0.38	0.16	0.12	0.03
County Commissioner - Adams 1	1.81	0.09	0.44	0.08
County Commissioner - Adams 2	10.16	1.41	0.06	0.03
County Commissioner - Adams 5	1.30	0.08	0.40	0.07
County Commissioner - Alamosa 1	−0.30	0.17	0.19	0.05
County Commissioner - Alamosa 3	−0.04	0.17	0.15	0.04
County Commissioner - Arapahoe 1	2.85	0.26	1.08	0.21
County Commissioner - Arapahoe 3	2.82	0.34	1.60	0.32
County Commissioner - Arapahoe 5	4.41	0.60	1.47	0.34
County Commissioner - Archuleta 1	0.21	0.14	0.06	0.02
County Commissioner - Archuleta 2	0.15	0.14	0.08	0.02
County Commissioner - Bent 1	−0.50	0.31	0.05	0.02
County Commissioner - Boulder 1	1.48	0.08	0.31	0.06
County Commissioner - Boulder 2	1.78	0.09	0.34	0.06
County Commissioner - Chaffee 1	1.01	0.16	0.13	0.03
County Commissioner - Cheyenne 3	−4.66	1.50	0.12	0.10
County Commissioner - Clear Creek 3	7.64	1.75	0.07	0.04
County Commissioner - Conejos 1	−0.10	0.20	0.09	0.03
County Commissioner - Conejos 3	0.91	0.24	0.10	0.03
County Commissioner - Costilla 3	6.63	1.86	0.08	0.05
County Commissioner - Custer 2	−0.97	0.24	0.02	0.01
County Commissioner - Custer 3	−0.13	0.21	0.01	0.01
County Commissioner - Delta 3	−0.58	0.13	0.16	0.03
County Commissioner - Dolores 3	0.41	0.42	0.12	0.06
County Commissioner - Douglas 2	1.69	0.14	0.86	0.16
County Commissioner - Douglas 3	0.60	0.10	0.67	0.12
County Commissioner - Eagle 1	0.73	0.14	0.17	0.04
County Commissioner - Eagle 2	0.66	0.13	0.15	0.03
County Commissioner - El Paso 2	−0.12	0.09	0.24	0.04
County Commissioner - El Paso 3	0.34	0.09	0.23	0.04
County Commissioner - El Paso 4	0.16	0.10	0.22	0.04
County Commissioner - Elbert 1	−6.91	1.29	0.07	0.04
County Commissioner - Elbert 3	−0.33	0.18	0.38	0.09
County Commissioner - Gilpin 1	0.51	0.31	0.21	0.07
County Commissioner - Gilpin 3	1.49	0.43	0.27	0.09
County Commissioner - Grand 1	0.37	0.15	0.08	0.02
County Commissioner - Grand 2	0.02	0.18	0.20	0.05
County Commissioner - Gunnison 1	0.46	0.16	0.16	0.04
County Commissioner - Gunnison 2	7.95	1.65	0.07	0.04
County Commissioner - Hinsdale 1	6.15	1.96	0.10	0.07
County Commissioner - Hinsdale 3	−1.76	0.67	0.08	0.05

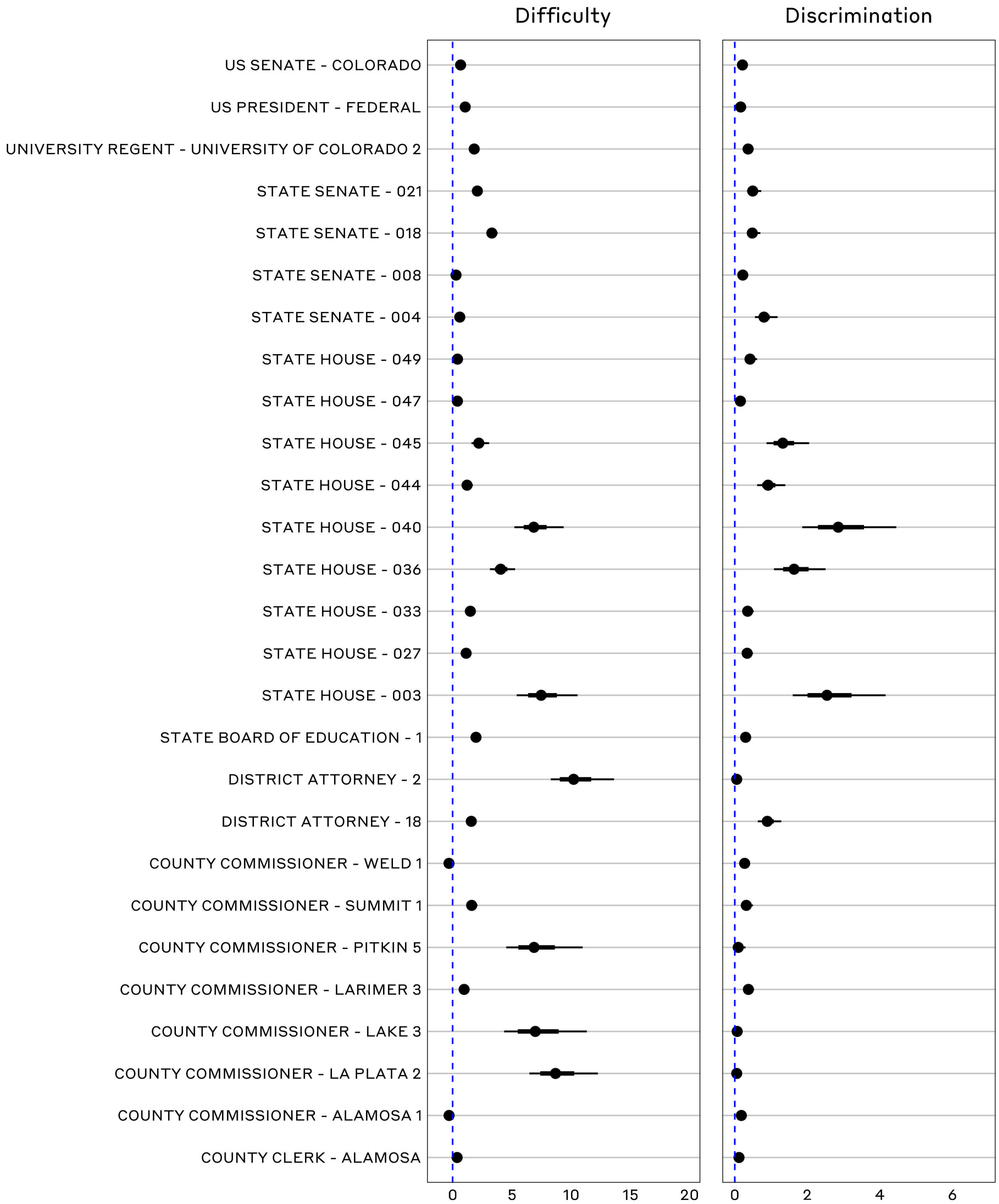
County Commissioner - Huerfano 1	0.55	0.23	0.09	0.03
County Commissioner - Huerfano 2	1.27	0.28	0.12	0.04
County Commissioner - Jefferson 1	1.08	0.06	0.33	0.06
County Commissioner - Jefferson 2	1.18	0.07	0.40	0.07
County Commissioner - Kit Carson 3	−0.77	0.23	0.07	0.03
County Commissioner - La Plata 2	8.86	1.52	0.06	0.03
County Commissioner - La Plata 3	8.87	1.58	0.06	0.03
County Commissioner - Lake 2	0.73	0.23	0.12	0.04
County Commissioner - Lake 3	7.22	1.84	0.07	0.04
County Commissioner - Larimer 2	1.06	0.08	0.40	0.07
County Commissioner - Larimer 3	0.98	0.08	0.38	0.07
County Commissioner - Mesa 1	−0.16	0.08	0.22	0.04
County Commissioner - Mesa 3	−0.20	0.07	0.19	0.03
County Commissioner - Mineral 2	−0.37	0.63	0.17	0.17
County Commissioner - Mineral 3	0.02	0.47	0.06	0.03
County Commissioner - Montezuma 3	0.07	0.13	0.13	0.03
County Commissioner - Morgan 1	−0.96	0.13	0.06	0.01
County Commissioner - Otero 1	−0.59	0.17	0.16	0.04
County Commissioner - Ouray 1	7.24	1.77	0.08	0.05
County Commissioner - Ouray 3	7.21	1.79	0.08	0.05
County Commissioner - Park 2	−0.32	0.15	0.09	0.02
County Commissioner - Pitkin 4	7.84	1.72	0.07	0.04
County Commissioner - Pitkin 5	7.11	1.65	0.11	0.07
County Commissioner - Pueblo 1	9.27	1.52	0.06	0.03
County Commissioner - Routt 2	7.49	1.75	0.07	0.04
County Commissioner - Saguache 1	0.68	0.28	0.17	0.05
County Commissioner - San Miguel 3	6.95	1.73	0.08	0.05
County Commissioner - Summit 1	1.62	0.23	0.33	0.08
County Commissioner - Summit 2	1.02	0.17	0.24	0.05
County Commissioner - Summit 3	8.22	1.64	0.06	0.04
County Commissioner - Weld 1	−0.30	0.11	0.28	0.05
County Commissioner - Weld 3	0.34	0.11	0.26	0.05
County Commissioner - Weld At-Large	−0.24	0.06	0.28	0.05
County Commissioner - Yuma 2	0.03	0.20	0.04	0.01
County Commissioner - Yuma 3	0.15	0.20	0.03	0.01
County Treasurer - Grand	0.01	0.15	0.12	0.03
District Attorney - 1	0.92	0.06	0.36	0.06
District Attorney - 11	0.02	0.08	0.16	0.03
District Attorney - 16	−0.16	0.13	0.13	0.03
District Attorney - 17	1.16	0.07	0.41	0.08
District Attorney - 18	1.58	0.10	0.92	0.17
District Attorney - 2	10.41	1.42	0.06	0.03
District Attorney - 8	1.00	0.08	0.38	0.07
Sheriff - Hinsdale	−4.06	1.53	0.15	0.13

State Board Of Education - 1	1.97	0.05	0.30	0.05
State Board Of Education - 3	0.11	0.03	0.19	0.03
State Board Of Education - 7	1.40	0.07	0.26	0.05
State House - 001	1.55	0.19	0.32	0.07
State House - 002	2.10	0.17	0.29	0.06
State House - 003	7.61	1.30	2.62	0.66
State House - 004	2.22	0.21	0.27	0.06
State House - 005	2.58	0.25	0.36	0.07
State House - 006	2.54	0.22	0.34	0.07
State House - 009	2.50	0.23	0.39	0.08
State House - 010	3.98	0.41	0.56	0.12
State House - 011	1.87	0.19	0.40	0.08
State House - 012	2.74	0.27	0.51	0.11
State House - 013	1.62	0.13	0.30	0.06
State House - 014	0.37	0.11	0.25	0.05
State House - 015	0.15	0.12	0.26	0.05
State House - 016	0.72	0.15	0.31	0.06
State House - 017	1.29	0.17	0.23	0.05
State House - 018	1.62	0.18	0.29	0.06
State House - 019	−1.04	0.12	0.27	0.05
State House - 020	0.18	0.13	0.30	0.06
State House - 021	0.62	0.15	0.26	0.05
State House - 022	1.13	0.17	0.39	0.08
State House - 023	2.51	0.23	0.42	0.08
State House - 024	2.06	0.23	0.48	0.10
State House - 025	1.10	0.15	0.41	0.08
State House - 027	1.14	0.13	0.35	0.07
State House - 028	1.85	0.18	0.36	0.07
State House - 029	2.31	0.24	0.44	0.09
State House - 030	1.02	0.18	0.49	0.10
State House - 032	2.51	0.29	0.48	0.11
State House - 033	1.50	0.14	0.36	0.07
State House - 034	1.93	0.21	0.39	0.08
State House - 035	2.22	0.25	0.49	0.10
State House - 036	4.10	0.55	1.68	0.37
State House - 037	3.38	0.42	1.45	0.30
State House - 038	5.26	0.64	1.77	0.38
State House - 039	0.17	0.13	0.46	0.09
State House - 040	6.97	1.06	2.93	0.68
State House - 041	4.21	0.70	1.98	0.48
State House - 043	2.12	0.37	1.32	0.29
State House - 044	1.23	0.23	0.94	0.20
State House - 045	2.25	0.38	1.36	0.30
State House - 046	1.04	0.10	0.17	0.03

State House - 047	0.41	0.09	0.16	0.03
State House - 048	−0.32	0.10	0.27	0.05
State House - 049	0.42	0.13	0.43	0.08
State House - 050	8.64	1.57	0.06	0.03
State House - 051	−3.52	0.27	0.12	0.03
State House - 052	1.35	0.15	0.39	0.08
State House - 053	8.90	1.57	0.06	0.03
State House - 054	−0.63	0.07	0.23	0.04
State House - 056	2.08	0.28	1.02	0.21
State House - 057	−1.36	0.19	0.15	0.04
State House - 058	−0.40	0.08	0.17	0.03
State House - 059	0.61	0.08	0.17	0.03
State House - 060	−0.11	0.08	0.20	0.04
State House - 061	0.94	0.09	0.21	0.04
State House - 062	0.75	0.09	0.15	0.03
State House - 063	0.15	0.10	0.26	0.05
State House - 064	−0.92	0.11	0.31	0.07
State Senate - 004	0.61	0.15	0.82	0.16
State Senate - 008	0.29	0.09	0.23	0.04
State Senate - 010	0.69	0.11	0.30	0.06
State Senate - 012	0.17	0.10	0.29	0.05
State Senate - 014	1.66	0.12	0.40	0.08
State Senate - 017	1.51	0.12	0.38	0.07
State Senate - 018	3.32	0.24	0.49	0.10
State Senate - 019	1.93	0.14	0.40	0.07
State Senate - 021	2.09	0.19	0.50	0.10
State Senate - 023	0.46	0.08	0.31	0.06
State Senate - 025	0.41	0.10	0.37	0.07
State Senate - 026	6.20	0.72	2.16	0.46
State Senate - 027	3.69	0.35	1.50	0.30
State Senate - 028	8.02	1.11	3.38	0.77
State Senate - 029	9.19	1.51	0.07	0.04
State Senate - 031	1.95	0.13	0.31	0.06
State Senate - 033	9.10	1.50	0.07	0.04
State Senate - 035	−0.20	0.06	0.16	0.03
University Regent - University Of Colorado 2	1.83	0.06	0.37	0.07
University Regent - University Of Colorado 6	2.93	0.17	1.32	0.24
University Regent - University Of Colorado 7	10.34	1.41	0.06	0.03
US House - 001	2.44	0.07	0.35	0.06
US House - 002	1.99	0.06	0.39	0.07
US House - 003	0.35	0.03	0.19	0.03
US House - 004	−0.01	0.04	0.33	0.06
US House - 005	0.26	0.04	0.24	0.04
US House - 006	3.68	0.18	1.21	0.22

US House - 007	1.69	0.06	0.33	0.06
US President - Federal	1.06	0.02	0.17	0.03
US Senate - Colorado	0.68	0.02	0.22	0.04

Figure A.2: Example Discrimination and Difficulty Parameters in the Bernoulli Model



Note: This plot displays the posterior distributions of the difficulty (β) and discrimination (γ) parameters from the 2-Parameter Bernoulli model. These are a random sample of 27 races from the model.

B Code for Estimation

A brms code

I use `brms` to estimate the Bernoulli models. For the 1-Parameter model, I use the random-effects formulation of an IRT model, as shown below, where I include a random effect for the race and for each group of voters. This approach is recommended by Bürkner (2021). I also set relatively uninformative priors on the distributions of each variable.

```
bf(
    choice_rep ~ 1 + (1 | race) + (1 | cvr_id),
    family = brmsfamily("bernoulli", link = "logit")
)
```

Again, as recommended by Bürkner (2021), I use a random-effects formulation for the 2-Parameter Bernoulli model as well. The code for this estimation is shown below, with the priors set at their default, relatively uninformative values.

```
bf(
    choice_rep ~ exp(loggamma) * alpha - beta,
    nl = TRUE,
    alpha ~ 0 + (1 | cvr_id),
    beta ~ 1 + (1 | race),
    loggamma ~ 0 + (1 | race),
    family = brmsfamily("bernoulli", link = "logit")
)
```

B Stan code

```
data {
    int<lower=1> J; // number of voters
    int<lower=1> K; // number of races
    int<lower=1> C; // number of candidates
    array[J, K] int<lower=0, upper=C> votes;
    array[K] int<lower=0, upper=C> sizes;
}
parameters {
    real mu_beta;
```

```
    vector[J] alpha;
    vector[C] beta_raw;
    vector[C] gamma_raw;
    real<lower=0> sigma_beta;
    real<lower=0> sigma_gamma;
}
transformed parameters {
    vector[C] beta = rep_vector(0, C);
    vector[C] gamma = rep_vector(0, C);
    {
        int pos_p = 0;
        for (k in 1:K){
        for (c in 2:sizes[k]){
            beta[pos_p + c] = beta_raw[pos_p + c] + mu_beta;
            gamma[pos_p + c] = gamma_raw[pos_p + c];
        }
        pos_p += sizes[k];
        }
    }
}
model {
    mu_beta ~ student_t(3, 0, 2.5);
    alpha ~ std_normal();
    sigma_beta ~ student_t(3, 0, 2.5);
    sigma_gamma ~ student_t(3, 0, 2.5);
    int pos_t = 1;
    for (k in 1:K) {
        int s = sizes[k];
        if (s == 0){
        continue;
        }
        segment(beta_raw, pos_t, s) ~ normal(0, sigma_beta);
        segment(gamma_raw, pos_t, s) ~ normal(0, sigma_gamma);
        vector[s] gamma_s = segment(gamma, pos_t, s);
        vector[s] beta_s = segment(beta, pos_t, s);
        for (j in 1:J){
        if (votes[j, k] > 0){
            calc = gamma_s .* alpha[j] - beta_s;
            votes[j, k] ~ categorical_logit(calc);
        }}
        pos_t += s;
    }
}
```

C Supplementary Figures and Tables

Table C.1: Distribution of the $\hat{R}$ Diagnostic

Model	Mean	Median	% $<$ 1.1	Max
Bernoulli 1-Parameter	1.00	1.00	99.8%	1.37
Bernoulli 2-Parameter	1.00	1.00	100.0%	1.10
Categorical 2-Parameter	1.01	1.00	98.1%	1.63

Note: This table displays the distribution of the Gelman-Rubin $\hat{R}$ diagnostic, commonly used to assess the convergence of Bayesian models (Gelman and Rubin 1992). For all three models, the $\hat{R}$ was computed for each parameter in the model, then simple descriptive statistics are reported – the mean, median, max $\hat{R}$, and the percent of $\hat{R}$s below 1.1.

Figure C.1: Traceplots for 24 random parameters in the Categorical 2-Parameter Model

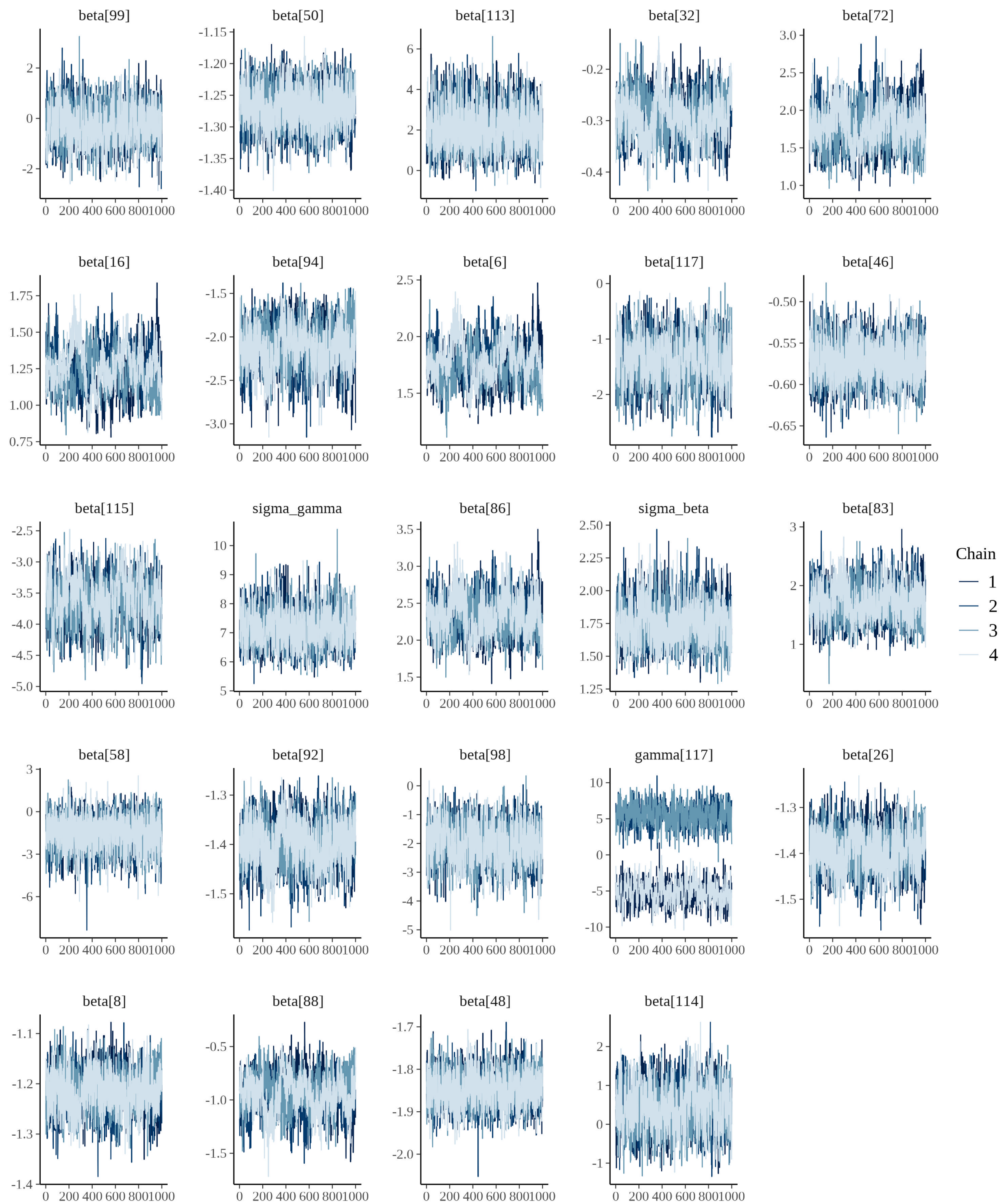


Figure C.2: Traceplots for 24 random parameters in the Bernoulli 1-Parameter Model

Figure C.3: Traceplots for 24 random parameters in the Bernoulli 2-Parameter Model

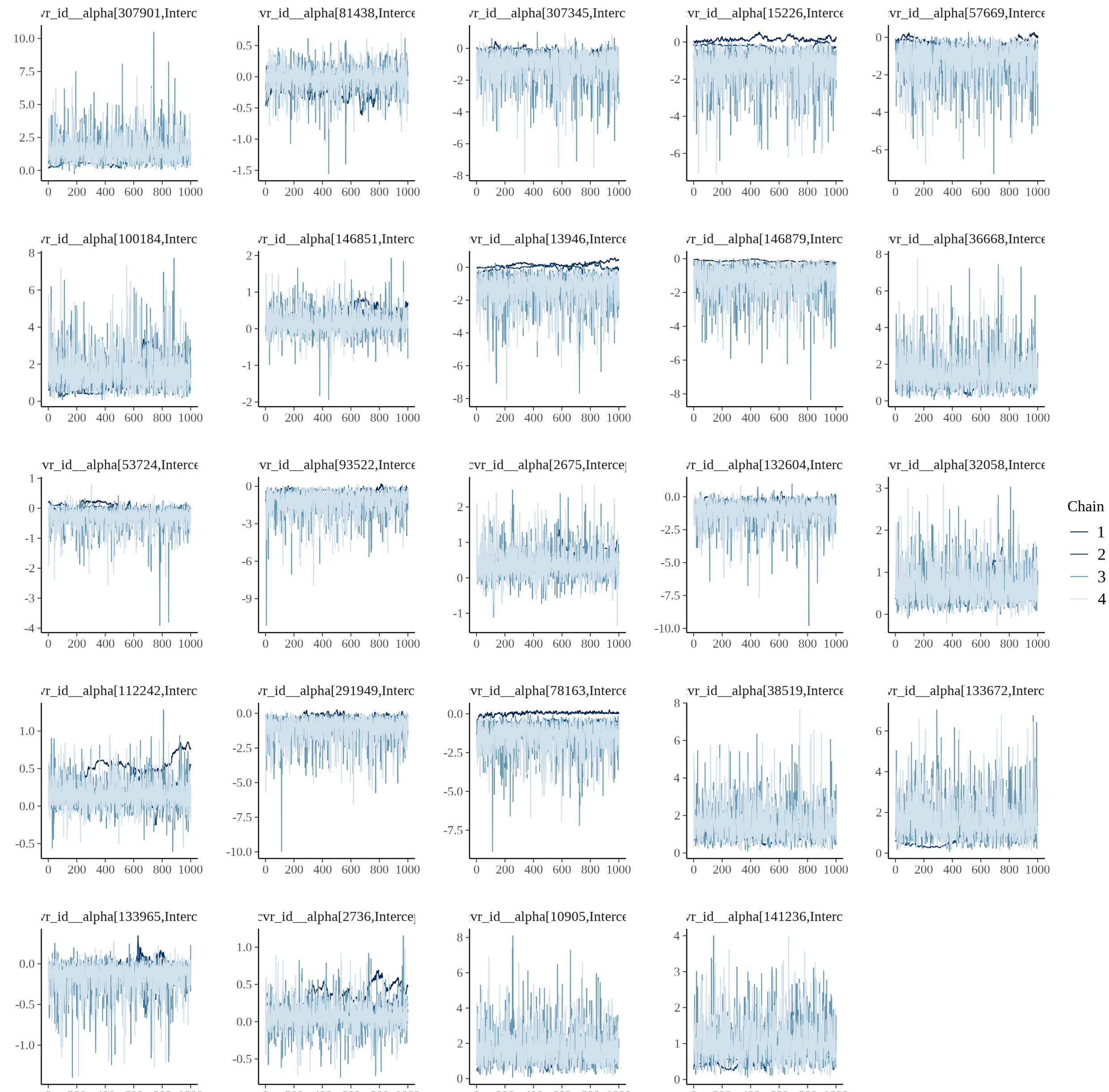
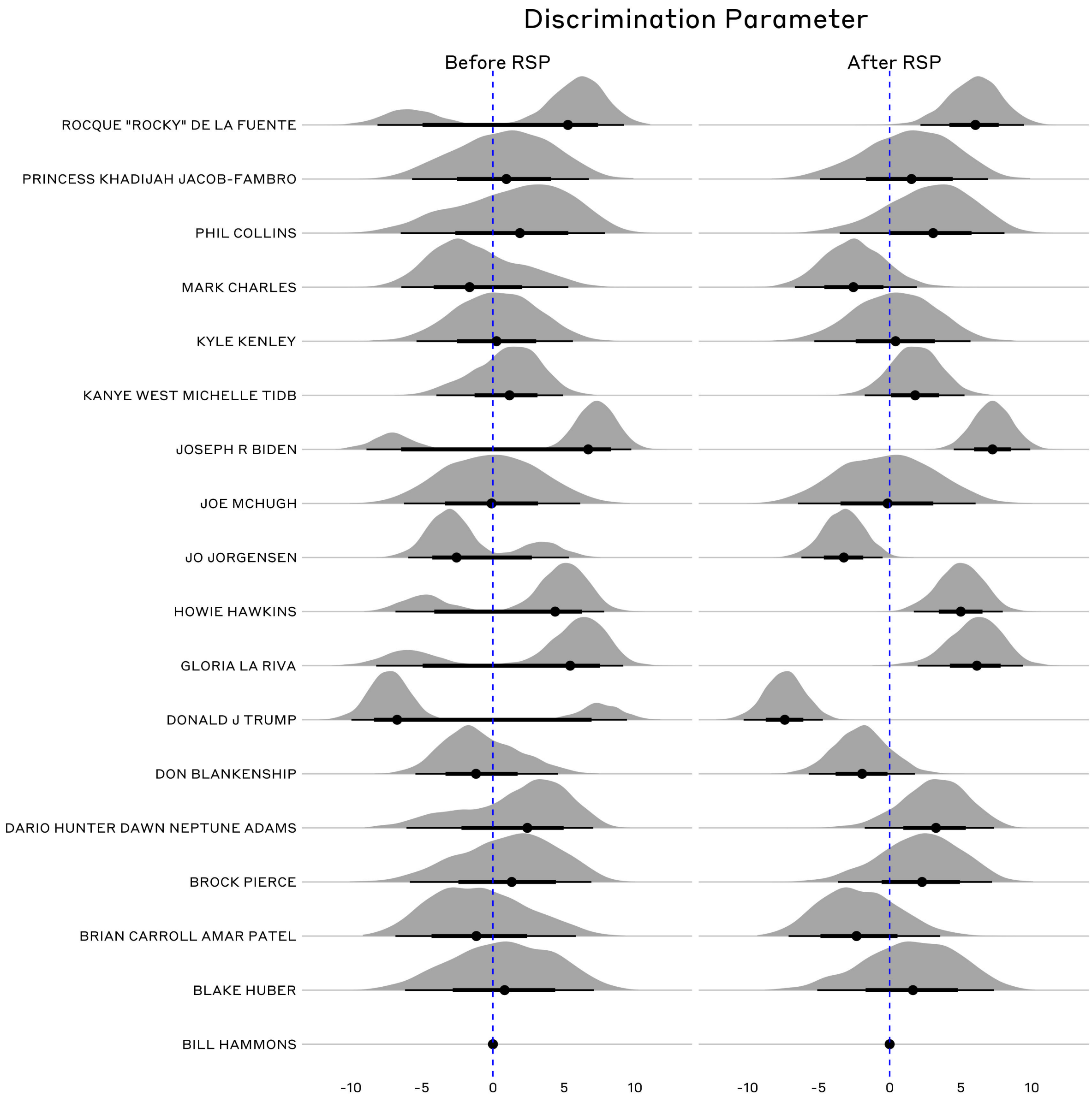
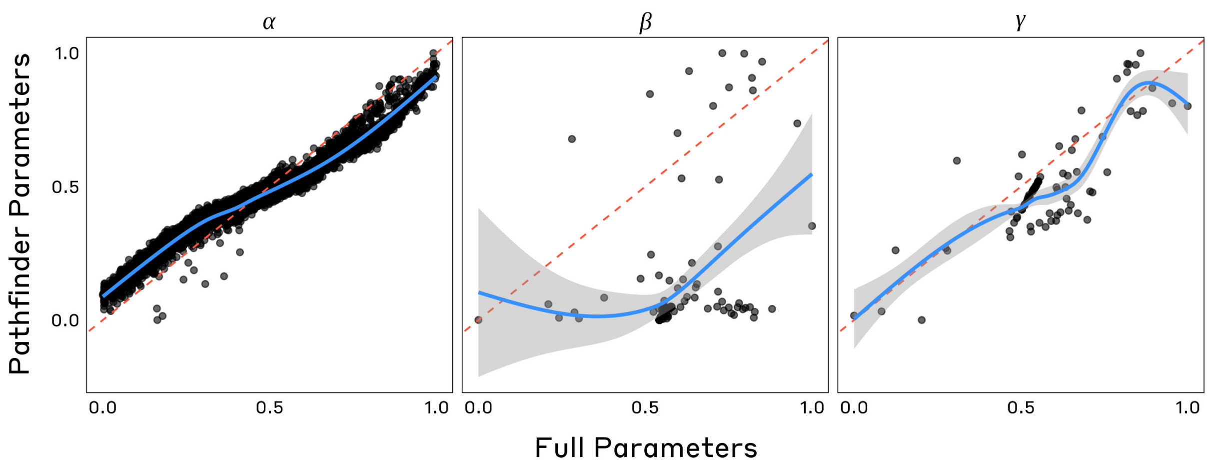


Figure C.4: Comparison of the Discrimination Parameters for US Presidential Candidates in the Categorical 2-Parameter Model



Note: This plot displays the distribution of discrimination parameters for each candidate in the US Presidential election, all in reference to the base category, "Bill Hammons". In the left panel, distributions before the application of the Rotation-Sign-Permutation algorithm (Papastamoulis and Ntzoufras 2022), which are clearly bimodal, and in the right panel, distributions after applying the algorithm. Although only presidential candidates are shown here, all candidates in all races are treated with the algorithm.

Figure C.5: Comparison of Parameters from the *Pathfinder* method and the fully Bayesian method



Note: This figure compares parameters from the *Pathfinder* method and the fully Bayesian, Hamiltonian Monte Carlo, method. On the x-axis are the estimates from the fully Bayesian method and on the y-axis are estimates from Pathfinder. Parameter values have been standardized to the [0, 1] interval to facilitate easier comparison. The estimates are disaggregated by the parameter being estimated. In blue is a smoothed GAM fit to the points, and in red is the 45 degree line.

Appendix References

Bürkner, Paul-Christian. 2021. "Bayesian Item Response Modeling in *R* with *brms* and *Stan*." *Journal of Statistical Software* 100 (5).

Clinton, Joshua, Simon Jackman, and Douglas Rivers. 2004. "The Statistical Analysis of Roll Call Data." *American Political Science Review* 98, no. 2 (May): 355–370.

Gelman, Andrew, and Donald B. Rubin. 1992. "Inference from iterative simulation using multiple sequences." *Statistical Sciences* 7:457–511.

Jackman, Simon. 2009. *Bayesian Analysis for the Social Sciences.* Hoboken, NJ: Wiley.

Kuriwaki, Shiro. 2023. *Ticket splitting in a nationalized era.* Preprint. SocArXiv, March.

Lewis, Jeffrey B. 2001. "Estimating Voter Preference Distributions from Individual-Level Voting Data." *Political Analysis* 9, no. 3 (January): 275–297.

Papastamoulis, Panagiotis, and Ioannis Ntzoufras. 2022. "On the identifiability of Bayesian factor analytic models." *Statistics and Computing* 32, no. 2 (April): 23.

Rivers, Douglas. 2003. *Identification of Multidimensional Item Response Models.*