Party Lines or Voter Preferences? Explaining Political Realignment

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September 19, 2024

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Abstract

This paper addresses how to disentangle demand factors (voters) from supply factors (politicians) in shaping political outcomes, focusing on the recent realignment of blue-collar voters away from left-wing parties. I develop a multidimensional political equilibrium model to jointly evaluate the contributions of changes in voter preferences and voter demographics (demand side) and party positions and party discipline (supply side) to the U.S. educational realignment between 2000 and 2020. I estimate candidate positioning using a multimodal text-and-survey model from campaign websites, finding that candidate polarization on cultural issues has been twice as large as on economic issues. To measure demand, I build a new panel of precinct-level election results and identify voter preferences from congressional district border discontinuities. Using a model of political competition where candidates balance electability against compliance with the party line, I show that House candidates' ability to adapt their positions to their constituents has been divided by three. The paper shows that realignment is driven mainly by changes in party positioning — particularly parties' stronger polarization on cultural than economic issues — rather than by shifts in voter preferences. Finally, I simulate support for counterfactual environmental positions, revealing that progressive environmental policies involving economic rather than cultural measures would attract more support from less-educated voters.

*I am extremely grateful to Suresh Naidu for his invaluable and supportive guidance throughout this project. I am also grateful for extensive guidance from Charles Angelucci, Vincent Pons, Pietro Tebaldi, and Francesco Trebbi. For comments that have improved this paper, I thank Elliott Ash, Pierre Bodéré, Matilde Bombardini, Nathan Canen, Alessandra Casella, Julia Cagé, Tristan du Puy, Amory Gethin, Alexis Ghersengorin, Gautam Gowrisankaran, Dan Hopkins, Matias Iaryczower, Karam Kang, Ethan Kaplan, Kei Kawai, Ilyana Kuziemko, Félix Loubaton, John Marshall, Sergio Montero, Sebastián Otero, Thomas Piketty, Andrea Prat, Carlo Prato, Bernard Salanié, Cailin Slattery, Andrey Simonov, Martin Vaeth, and Ebonya Washington. I am also grateful to seminar participants at Berkeley, Princeton, ASSA, APSA, the Stanford-Berkeley DEV-PE Conference, the Monash-Warwick-Zurich Text-as-Data Workshop, and the Columbia Industrial Organization, Political Economy, and Sustainable Development Colloquia. I am particularly indebted to Keyon Vafa for sharing and guiding me through the original TBIP code and Jeff Gortmaker for answering questions on PyBLP. I thank Isaiah Colmenero, Micol Galante, Pia Mahajan, Axel Martin, Jacob Posada, Lucas Puttre, and especially Ece Fisgin and Ignacio Ugalde, for excellent research assistance in collecting the precinct-level electoral results. Part of this paper was written while visiting UC Berkeley Haas School of Business - the hospitality of which is gratefully acknowledged. The research in this paper was supported by the Columbia Center for Political Economy. This paper received the IPUMS 2023 Best Student Spatial Work.

1 Introduction

This paper addresses how to disentangle demand factors (voters) from supply factors (politicians) in shaping political outcomes, focusing on the recent realignment of blue-collar voters away from left-wing parties. Traditionally the favored choice of less-educated voters, left-wing parties in Western Democracies have seen their base shift significantly toward a more educated electorate (Kitschelt and Rehm, 2019; Gethin, Martínez-Toledano, and Piketty, 2022; Kuziemko, Longuet-Marx, and Naidu, 2023). While this trend is widespread, the pace and intensity of this realignment in the United States stand out as particularly striking. Over the past 20 years, the proportion of voters with a high school diploma or less supporting the Democratic Party has dropped by more than 10 percentage points, while the share of college graduates voting Democratic has increased by a similar margin. This realignment has not only altered voting patterns but also catalyzed profound transformations in political polarization and policymaking, fundamentally reshaping the landscape of American democracy.

Previous work has advanced a broad range of explanations, including changes in economic conditions (Autor, Dorn, Hanson, and Majlesi, 2020; Choi, Kuziemko, Washington, and Wright, 2024; Gallego, Kurer, and Schöll, 2022), the rise of identity and immigration issues (Alesina and Tabellini, 2024; Norris and Inglehart, 2019), voters' increasing focus on cultural questions (Inglehart, 1997; Enke, Polborn, and Wu, 2021; Danieli, Gidron, Kikuchi, and Levy, 2022), or shifts in candidate positions (Rennwald and Evans, 2014; Kuziemko et al., 2023), as possible factors influencing political realignment. This article takes a distinctive approach by introducing a unified empirical framework to jointly assess any of these demand-side or supply-side explanations. Specifically, I estimate the contributions of the changes in voter preferences and voters' demographics (demand-side changes) and changes in party leadership positions and party discipline (supply-side changes) to this recent voter realignment episode. The analysis ultimately identifies supply-side factors as the decisive force behind political realignment.

Understanding the drivers of political realignment requires making progress on longstanding questions in political economy: How does the interaction between voters and parties determine political outcomes in equilibrium? How do voters respond to policies offered by their local candidates? And are candidates catering their positions to their constituents, or only following their parties' line? Answering these questions has proven difficult due to a series of independent empirical challenges.

The first challenge concerns the measurement of candidate positions themselves; grappling with the multidimensionality of ideological positioning and comparing these dimensions across multiple elections is particularly difficult (Poole and Rosenthal, 2011; Bateman and Lapinski, 2016). Additionally, previous studies have typically been limited to measures available only for incumbents, as obtaining reliable information on the positions of challengers has often been more complex. Second, to recover the distribution of voter preferences, it is necessary to observe multiple pairs of candidates, each offering their own platform, along with variation in voter choices for any given choice set (Berry and Haile, 2021). Third, identifying exogenous shifters for both demand and supply variation is essential to circumvent possible endogeneity concerns in the estimation of voters' and candidates' preferences (Berry and Haile, 2024). Finally, individual voting decisions are seldom observed and relying on aggregate voting data makes it difficult to recover individual preferences (King, 2013).

This paper makes progress on these issues in several ways. To begin with, I recover the position of each candidate in Congressional races on both cultural and economic dimensions by training a multimodal text-and-survey model based on candidate websites. These dimensions are both interpretable and comparable over time thanks to candidate survey questions asked repeatedly. Next, to measure demand, I construct a new panel dataset of precinct-level election results in Congressional races between 2000 and 2020 to capture extremely granular, within-district variation in voter preferences (170,000 precincts per year). Lastly, leveraging exogenous variation in candidate policy propositions using precincts that sit on district borders allows the identification and estimation of a structural model of heterogeneous voter demand for economic and cultural policy positions. The combination of these new elements enables the estimation of a multidimensional political equilibrium model of U.S. House elections, quantifying the influence of supply-side factors, such as party leadership positions and party discipline, as well as demand-side factors, such as voters' ideological preferences, voter demographics, and redistricting.

The key finding of the paper is that the educational realignment observed in the US between 2000 and 2020 is driven entirely by supply-side factors. This conclusion is built on three main points. First, the model reveals that less-educated voters prefer conservative cultural policies but progressive economic policies, and their preference for progressive economic policies has increased over time. Second, despite these shifts in economic preferences, parties have polarized twice more on cultural issues than economic ones. Together, these findings demonstrate that the differential polarization on cultural issues has alienated less-educated voters from Democratic candidates, despite their growing preference for progressive economic policies. These changes in voter preferences, however, led less-educated voters to support Democratic candidates more. In other words, without these demand-side changes, less-educated voters would have shifted even more toward Republican candidates, making political realignment even more pronounced. Below, I outline the empirical framework and intermediate results that support this conclusion.

Beginning with some descriptive results, the panel dataset of precinct-level data provides granular variation in vote shares,[1] allowing for the reproduction and extension of findings re-

[1]Each precinct comprises on average 1,200 registered voters, that is, about 50 times smaller than a typical county

lated to the recent political realignment. I show that realignment along educational lines has dominated realignment along any other demographic line such as income, race, religion, occupation, union affiliation, or age. In each successive election, the average gap in education between Democratic and Republican voters has increased by 2.5 months of schooling. Regarding candidate positioning, while the increasing polarization between the two parties is well-documented,[2] the candidate ideal point model reveals a much greater rise in political polarization on cultural issues compared to economic ones. In particular, I show that the magnitude of polarization on cultural issues has been twice as large as on economics issues, with two-thirds of this polarization driven by the Democratic Party. Importantly, this analysis applies to both election-winners and election-losers.

In the next stage of the analysis, I estimate a multidimensional political equilibrium model that captures two key aspects of the electoral process. First, politicians compete to maximize their chances of getting elected while simultaneously minimizing the ideological distance between their chosen positions and those of their party leadership. Second, heterogeneous voters select the candidate whose platform and characteristics give them the highest utility.

To recover voter preferences over candidate platforms, I estimate a structural model of voter behavior using granular variation in election results from precinct data combined with individual survey data (Berry, Levinsohn, and Pakes, 2004). I address the endogeneity of candidate positions by matching contiguous precincts on both sides of congressional district borders, within each state, following the approach used for counties in Dube, Lester, and Reich (2010) and Spenkuch and Toniatti (2018). Since candidates likely determine their strategies at the district level, and each individual precinct is insignificant from their perspective (with approximately 400 precincts per district), differences in candidate positions between contiguous precincts on either side of the border can be treated as effectively random, especially after conditioning on time-invariant precinct characteristics. While it is impossible to directly test for unobservables, I provide auxiliary evidence that, conditional on border-by-election fixed effects and precinct fixed effects, candidate positions are uncorrelated with a wide range of precinct-level demographics. By comparing candidate vote shares between these contiguous precincts, I can measure how voters respond to plausibly exogenous variation in candidate positioning, holding all demand-side characteristics constant.

I find that voters with higher levels of education prefer more progressive positions on cultural issues, but not on economic issues. Especially in later years, less-educated voters have adopted preferences in favor of more progressive economic positions, compared to more-educated voters. The educational gradient on cultural questions has also strengthened over time: education is

and more than 400 times smaller than a congressional district.

[2]See e.g., McCarty, Poole, and Rosenthal (2016), Gentzkow, Shapiro, and Taddy (2019) for elected representatives or Bonica (2013) for candidates.

increasingly a predictor of preferences for progressive cultural policies.

Further, I document a rise in party discipline in both parties. Using estimates of the distribution of ideological preferences in each electoral precinct, I recover supply-side parameters measuring the weights that candidates allocate to the probability of wining versus aligning with the party when choosing the positions they offer to voters. I show that party discipline has dramatically increased over time: the ability of a House candidate to adapt their positions to their constituents has been divided by three, resulting in an ultimate uniformization of candidates across districts.

Finally, with demand-side and supply-side estimates in hand, one can simulate multiple counterfactual scenarios to assess the contribution of each factor to the overall change in voter choices. Since candidate positions are an equilibrium outcome, I begin by decomposing the changes in candidate positions, especially the differential polarization on cultural issues, into multiple drivers. I show that at least 75% of these changes can be attributed to supply-side factors — particularly the polarization of party leadership and increased party discipline. In contrast, demand-side factors explain only 3.5% of the variation in candidate positions.

All these results lead to the paper's key result: when assessing changes in voter choices, I show that virtually all of the explained political realignment is driven by supply-side factors, particularly the rising polarization between the two parties on cultural issues compared to economic issues, driven in the most part by the Democratic Party. In contrast, changes in voter preferences have had the opposite effect: the growing preference for progressive economic policies among less-educated voters has mitigated the extent of realignment. In other words, while less-educated voters have increasingly supported progressive economic policies, traditionally offered by the Democratic Party, the parties, especially the Democratic Party, have become more polarized on cultural issues, pushing less-educated voters toward the Republican Party. These findings resonate with existing theories on cultural polarization as one of the reasons why democracy has struggled to curb rising inequality (Bonica, McCarty, Poole, and Rosenthal, 2013; Roemer, 1998; Hacker and Pierson, 2020).

As a final step of my analysis, I employ the model to examine the political consequences of the differential polarization highlighted in previous sections on voters' support for environmental policies. Environmental issues present an interesting case study not only because they have recently become an important part of political discourse and public opinion (Dunlap, McCright, and Yarosh, 2016; Egan, Konisky, and Mullin, 2022) but also because they carry both economic and cultural significance (Besley and Persson, 2023). By projecting candidates' environmental positions on the cultural and economic dimensions, I show that Democratic candidates' environmental positions have a much stronger cultural than economic dimension, while the reverse is true for Republicans. In other words, Democratic candidates who have progressive environmental positions tend to be progressive on cultural issues rather than on economic issues, whereas Republican candidates show the opposite pattern: Republicans who are conservative on environmental issues are also conservative on economic issues, not on cultural issues. The environment stands out as the topic on which this divergence between the two parties is the most pronounced. Using the supply and demand model estimated in the previous sections, I show that current Democratic positions on the environment, which are heavily cultural, deter less-educated voters. In contrast, an equally progressive environmental policy with a stronger economic focus, such as a "Green New Deal," would generate more support from less-educated voters. In a companion paper (Bombardini, Finan, Longuet-Marx, Naidu, and Trebbi, 2024), we adapt the framework developed in this paper specifically to environmental issues, and precisely examine how demand and supply of environmental policy respond to changes in environmental conditions and employment opportunities in the environmental sector.

Related Literature This article relates and contributes to five distinct strands of the literature in economics and political science.

First, it sheds new light on political realignment in the U.S. by using official granular election results. While previous studies (e.g., Kitschelt and Rehm (2019); Gethin et al. (2022); Kuziemko et al. (2023) among others) have relied on survey data to document the evolution of political cleavages, I complement these *stated preferences* approaches by bringing evidence from *revealed preferences*. Using the universe of precinct-level data also prevents biases in sample selection and allows me to bring more nuance to the extent of political realignment, along many dimensions and at various geographical scale.

This article relates and contributes to the literature focusing on positioning politicians ideologically. The data and framework proposed in this paper offer four distinguishing features compared to the existing literature. First, this article relies on information extracted directly from candidates' campaign materials, rather than using their behavior once elected - such as roll-call votes (Poole and Rosenthal, 1985; Martin and Quinn, 2002) and speeches in Congress (Gentzkow, Shapiro, and Taddy, 2019; Enke, 2020), or the behaviors of other agents as proxy for candidate ideology, such as campaign contributions (Bonica, 2013; Hall and Snyder, 2015). Tausanovitch and Warshaw (2017) show that these various measures are only weakly correlated with each other and therefore do not necessarily capture the actual ideological variation presented to voters. Second, observing information on candidates and not only elected members allows me to observe the behaviors of the two opponents at each election, a critical component in estimating a model of political competition. Previous articles that have used candidate survey data (Ansolabehere, Snyder, and Stewart, 2001; Shor and Rogowski, 2018) had to rely on the sub-sample of survey respondents. By using candidate websites in addition to surveys, I do not have to restrict my sample to survey respondents. Candidate websites have been used in the literature to derive unidimensional measures of ideology (Le Pennec, 2024; Di Tella, Kotti, Le Pennec, and Pons, 2023; Meisels, 2023). The third advantage of the framework developed in this paper is that I am able to assign a position to each candidate on multiple political dimensions. Importantly, these dimensions are both interpretable and comparable over time, thanks to survey questions asked repeatedly over time. Lastly, the combination of survey and website data allows me to estimate ideal points without using party labels, contrary to a large share of the existing literature. Ideal points based on party labels often fail to accurately position extreme candidates and instead provide a measure of ideology that reflects how central each politician is within their party (Noel, 2014, 2016). In addition, relying on party labels to define ideology, as party dynamics and their ideologies evolve constantly, limits the ability to make meaningful comparisons over time.

Third, this work relates to articles that estimate structural models of voter preferences from aggregate election results (Coate and Conlin, 2004; Rekkas, 2007; Strömberg, 2008; Gordon and Hartmann, 2013; Sieg and Yoon, 2017; Ujhelyi, Chatterjee, and Szabo, 2021; Kawai and Sunada, 2022; Iaryczower, Montero, and Kim, 2022; Cox, 2023; Cox and Shapiro, 2024). To the best of my knowledge, Iaryczower et al. (2022) is the only paper that recovers individual voter preferences over candidate ideological positions. They estimate preferences using candidate variation in ideology across municipalities in Brazil and rely on campaign contributions to measure candidate ideology. This paper recovers the distribution of voter preferences over candidate ideology in the U.S. and recovers preferences over multiple political dimensions. A strength of the method in this paper is the observation of electoral results at a much more granular level than the one at which candidate supply is determined, with nearly 500 precincts per congressional district, allowing for considerable variation in voter choices within a given choice set.

Fourth, the supply estimates from my political equilibrium model contribute new evidence to the literature on political common agency, where politicians must balance the competing demands of both their party and constituents. Ansolabehere, Snyder, and Stewart (2001), looking at U.S. House Elections between 1874 and 1996, show that candidates have relatively low ability to accommodate their positions to their local constituents, as party discipline is very strong. While they have to rely on past election results to measure ideology, I can use the estimated distribution of ideology in each district, recovered from the demand estimation. I measure the extent of the rise of party discipline, leading to both polarization and uniformization of candidates within party. These findings complement what Canen, Kendall, and Trebbi (2020, 2021) have estimated in the U.S. Congress who show that about 65% of polarization in Congress can be attributed to party discipline. Cox and Shapiro (2024) recover the parameters underlying House candidates' choice of positions in the context of financial pressure from party leadership and special interest groups. Other papers, such as Mian, Sufi, and Trebbi (2010), Bombardini, Li, and Trebbi (2023), or Iaryczower, Lopez-Moctezuma, and Meirowitz (2024) have also recovered the weights that US politicians have been giving to their constituents vs. ideological components while making decisions in Congress. My framework contributes to this literature in two main ways. First, the approach adopted in this paper allows me to measure how sensitive candidates are to voters' actual policy preferences rather than relying on proxies such as Presidential vote share or economic vulnerability to certain policies. These sensitivity weights can then be directly compared to the weights candidates give to toeing the party line on ideological grounds. Second, it allows for the analysis of candidate responsiveness to constituents and party discipline before the election, rather than limiting the study of these factors to post-election behaviors.

Lastly, this article contributes to the literature that seeks to disentangle demand and supply changes from shifts in voting behavior. Krasa and Polborn (2014) take an approach opposite to the one adopted in this paper, estimating both voter preferences and presidential candidate positions from survey data to decompose the rise in polarization between changes in candidate positions and changes in voter preferences, ultimately finding very little change in voter preferences. Many articles have used the Comparative Manifesto Project (CMP) to construct measures of party positions (Adams, Clark, Ezrow, and Glasgow, 2004; Elff, 2009; Evans and Tilley, 2012; Rennwald and Evans, 2014; Danieli, Gidron, Kikuchi, and Levy, 2022). However, none of these articles is able to obtain plausibly exogenous variation in candidate position to recover voter preferences. Even with micro-data, one often needs cross-market variation, as it is done in this paper, to recover voter preference parameters (Berry and Haile, 2021) and differentiate changes in choice sets from changes in preferences. The framework proposed in this article uses exogenous variation in candidate position, provided by the multiplicity of elections and the granularity of the electoral results. Danieli et al. (2022), in their study of the rise of radical right parties in Europe, decompose the phenomenon into demand- and supply-side elements and find that most of the change can be explained by demand-side factors. In particular, their findings highlight that voters have increasingly prioritized cultural issues in recent elections compared to the early 2000s. I also find a rise of polarization on cultural questions, especially along educational lines; however, I document a non-negligible polarization on economic questions, which in the U.S operates in the other direction than the cultural gradient and thus can easily be overlooked. In contrast to the setting exploited in Danieli et al. (2022), there has been no party entry in the U.S., which constrains the bundling of cultural and economic issues that can be offered to voters.

The remaining of this paper is organized as follows: Section 2 outlines the conceptual framework of the paper, Section 3 presents the data, the methods to measure candidates, and provides descriptive statistics, Section 4 describes the estimation of demand-side parameters, Section 5 describes the estimation of the supply-side parameters, Section 6 decomposes changes in candidate positions and voting behavior between demand-side and supply-side factors, Section 7 studies positioning and voting on environmental issues, and Section 8 concludes and discusses the results.

2 Empirical Model

2.1 Setup

I consider a static model of local political competition where two candidates compete to maximize their vote shares while complying with party discipline. Citizens engage in sincere voting based on candidates' ideology and voting is compulsory.[3]

The setup is characterized by two types of agents. There is a set of voters $\mathcal{I}$, each indexed by i with observable characteristics $\mathbf{w_{it}}$. Voters choose between two candidates, D and R (indexed by j), who choose their k-dimensional political platforms, $\mathbf{x_{Dt}} \in \mathbb{R}^k$ and $\mathbf{x_{Rt}} \in \mathbb{R}^k$, respectively.

Each voter votes for the candidate that maximizes their utility $u_{it}(\mathbf{x_{jt}}; \mathbf{w_{it}})$. I write the probability that voter i votes for the Democratic candidate in election t as:

$$\begin{aligned} \Pr_{Dt}(\mathbf{w_{it}}) &= \Pr\left(u_{it}(\mathbf{x_{Dt}}; \mathbf{w_{it}}) \geq u_{it}(\mathbf{x_{Rt}}; \mathbf{w_{it}})\right) && (1) \\ &= s_{iDt}\left(\mathbf{x_{Dt}}, \mathbf{x_{Rt}}; \mathbf{w_{it}}\right). && (2) \end{aligned}$$

The total vote share obtained by the Democratic candidate can be written as:

$$s_{Dt} = \int_{\mathbf{w}} s_{iDt}\left(\mathbf{x_{Dt}}, \mathbf{x_{Rt}}; \mathbf{w_{it}}\right) dF_t(\mathbf{w_{it}}), \tag{3}$$

where $F_t(\mathbf{w_{it}})$ is the distribution of voters' observable characteristics in election t. The Republican vote share is $s_{Rt} = 1 - s_{Dt}$.

The vector $\mathbf{x_{jt}} \in \mathbb{R}^k$ is chosen by the local candidate ($j = \{D, R\}$) in order to maximize the probability of being elected on the one hand, and to comply with the national leadership of their party on the other. Candidates seek to be elected as they derive a rent $Q > 0$ from being in office.

[3] While voter turnout decisions are undoubtedly important, this paper focuses on the choice between Democratic and Republican candidates, as this has been the primary emphasis of most of the existing literature. Note that, from a candidate's perspective, what matters is not the absolute number of votes but the relative vote share compared to the opponent, which differs from most economic markets. Appendix Section G provides estimates from an alternative demand model that includes an endogenous turnout decision. The estimates from the specification with turnout are similar to those under compulsory voting, though of smaller magnitude.

$$\Pi_{jt}(\mathbf{x_{jt}}) = \underbrace{P_j(\mathbf{x_{jt}}, \mathbf{x_{-jt}})}_{\text{probability of winning}} Q - \underbrace{\lambda_{jt}||\mathbf{x_{jt}} - \mathbf{N_{jt}}||^2}_{\text{distance from national party platform}} + \underbrace{\boldsymbol{\eta}'_{\boldsymbol{jt}}\mathbf{x_{jt}}}_{\text{own ideological shock}} . \quad (4)$$

where the parameter λ_{jt} captures candidates' cost of deviating from the party line. The parameter λ_{jt} captures the strength of party discipline. It captures the extent to which each candidate has the ability to deviate from the national party platform to adapt to their local conditions.

The need to comply with the position of the national leadership is not modeled explicitly, yet it can be justified by a variety of political and institutional factors. First, party leaders reward candidates who follow the party line, both before and after the election. Second, it is costly for local candidates to come up with their own political strategy. I treat the evolution of the national leadership platforms as exogenous. Exogeneity here is intended as relative to the determinants of the local elections I study, and can be justified by the limited impact of each congressional district with respect to federal concerns.

A Nash equilibrium in election t is characterized by a collection of positions $(\mathbf{x_{Dt}}, \mathbf{x_{Rt}})$ and vote shares (s_{Dt}, s_{Rt}) such that (i) $\mathbf{x_{jt}}$ maximizes $\Pi_{jt}(\mathbf{x_{jt}})$ and (ii) $s_{jt} = \int_{\mathbf{w}} s_{ijt}\left(\mathbf{x_{Dt}}, \mathbf{x_{Rt}}; \mathbf{w_{it}}\right) dF_t(\mathbf{w_{it}})$, for $j \in \{D, R\}$.

As is well known, such duopoly models with spatial competition in multiple dimensions do not necessarily admit a unique equilibrium (Hotelling, 1929; Caplin and Nalebuff, 1991). In Appendix F, I show that for sufficiently large λ, a multidimensional political equilibrium always exists and is unique. In particular, I can confirm that with the parameters estimated from the data, the model always admits a unique equilibrium.

2.2 Empirical Goal

The overall objective of this paper is to decompose the change in individual vote between two periods into changes in $s_{ijt}(\cdot)$ and $\mathbf{w_{it}}$ on the demand side and changes in $\mathbf{N_t} = (\mathbf{N_t^D}, \mathbf{N_t^R})$ and λ_{jt} on the supply side. Importantly, I evaluate the impact of changes in leadership positions exclusively through the resulting adjustments made by local candidates, rather than through any direct influence that leadership changes might exert on local candidates' vote shares. Consequently, this paper merely decomposes changes in local voting determinants, for which there is identifying variation, and does not address changes in voters' overall propensity to vote for a party, independent of local candidates' positions.

To make these decompositions, I proceed in five steps. First, I obtain measures of $\mathbf{x_{jt}}$ and $\mathbf{N_t}$ using an ideal point model of candidate ideology. Second, granular precinct-level data allow me to obtain precise measures of the observed vote shares S_{jt}. Third, using precincts that sit on the district border, I isolate variation in $\mathbf{x_t}$ to estimate $s_{ijt}(\cdot)$ conditional on t and voter characteristics $\mathbf{w_{it}}$. Fourth, I recover the supply-side parameter λ_{jt} underlying candidates' choice of $\mathbf{x_t}$ given demand. Finally, the parameters recovered in the first four steps allow me to conduct a variety of counterfactual exercises. One natural counterfactual exercise involves decomposing the extent to which the changes in positions were generated by an endogenous response to changing preferences or by the need to adhere to trends in the national parties' platforms. Another corresponds to simulate various voting behaviors either by changing party platforms while fixing voter preferences, or by changing voter preferences while fixing party platforms.

I will start by discussing the measurement of $\mathbf{x_t}$, $\mathbf{N_t}$, and s_t and document the time series variation whose decomposition is my main object of interest. I will then introduce an econometric specification for the primitives in the framework above, and discuss exclusion restrictions that are sufficient for identification.

3 Data and Descriptive Statistics

3.1 Panel of Precinct-level Election results

I collect precinct-level electoral results from 2000 to 2020. Precincts are the smallest geographical unit at which election results are available in the U.S. Each precinct has an average population of 1,100 registered voters. There are about 175,000 precincts in the U.S., with on average 400 precincts per congressional district, which allows me to obtain considerable variation within congressional districts. Despite these election results being made public by county or state officials, there has been so far no unified dataset that contains the precinct-level Congressional results for the entire period that includes the geographical boundaries of each precinct. I therefore combined data from more than 50 different sources, such as Secretaries of State and County officials, in order to obtain results for the largest possible number of states over the period. The list of sources is described in Appendix Section dedicated to the description of the electoral data (see Appendix C).

Figure 1 shows the distribution of precincts in the U.S. for the 2020 election. Using precinct-level data instead of county-level data offers three advantages. First, precincts are much smaller and more demographically homogeneous than counties, reducing concerns about ecological fallacy and facilitating the estimation of individual preferences. Second, unlike counties, precincts are designed to have roughly equal populations everywhere, which allows for significant variation in both urban and rural areas. In contrast, using county-level voting data provides very scarce within-congressional district variation in urban areas. For instance, there are 16 congressional districts in Los Angeles county alone and Manhattan spans 3 distinct districts. In comparison, these counties have 4,312 and 1,266 precincts, respectively. The third advantage of precinct over county data is that the granular variation provides a stronger basis for identification assumptions, as I will describe in Section 4.

Since precinct boundaries are changing over time, building a panel of electoral precincts is challenging. I therefore apportion all votes to the 2010 block-group-level, which have approximately the same population as electoral precincts. This offers the benefit of creating a consistent panel dataset with geographies that can be compared across elections. This is also the most granular level at which census demographic variables are available and will be used in the analysis. Appendix C describes the strategy implemented to apportion the electoral results to the block group level by using the spatial overlaps of precincts with each census blocks (35 blocks per block-groups). In order to maintain a balanced panel of states across the two periods of analysis, I include only those states that are available in both the pre-2010 and post-2010 periods. Table A.5 in the Appendix presents the sample of states included in the analysis.

I then combine election results with census demographics at the block-grouplevel from NHGIS IPUMS (Manson, Schroeder, Van Riper, Kugler, and Ruggles, 2021) using the decennial census and the American Community Survey (ACS).

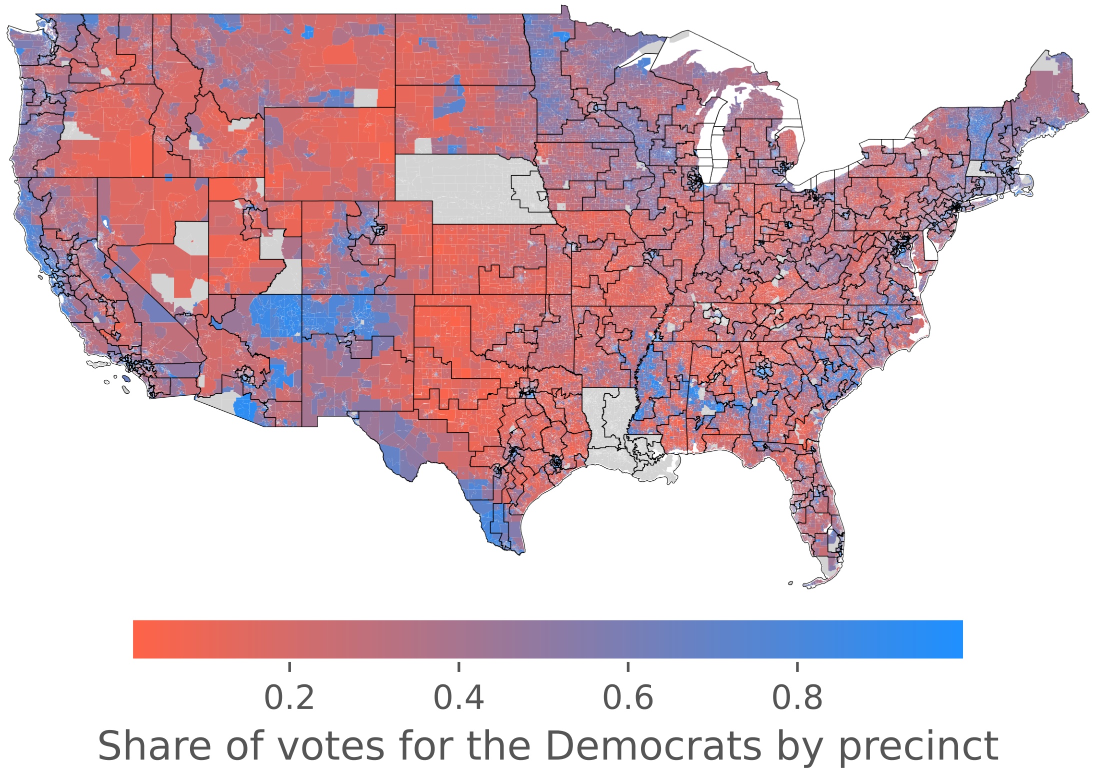
In order to estimate individual-level preferences and not only aggregate preferences, I need the full distribution of demographics along three dimensions: education, race, and age. This requires having both the average, the variance, and the covariance of each of these demographic variables at the block-group-level. Since only marginal distributions are reported in the decennial census and the ACS, I recover the joint distribution at the block-group level from a multi-scale model combining block-group level and tract level demographic counts with PUMA-level individual data from the ACS. Appendix D details the strategy to recover the full distribution of demographics in each block-group.

In the remainder of this paper, I will refer to white and non-white voters with a specific definition. The census asks both about race and ethnicity, and people can be classified as belonging to multiple races. In order to have demographic groups with sufficiently large sizes in most precincts, I classify both "Hispanic white" and "Hispanic non-white" as non-white and individuals with multiple races as "non-white". The group of "white" voters is therefore constituted of "Non-Hispanic whites", with a single race. Under this definition, the average share of whites is 75% in 2000 and 68% in 2020.

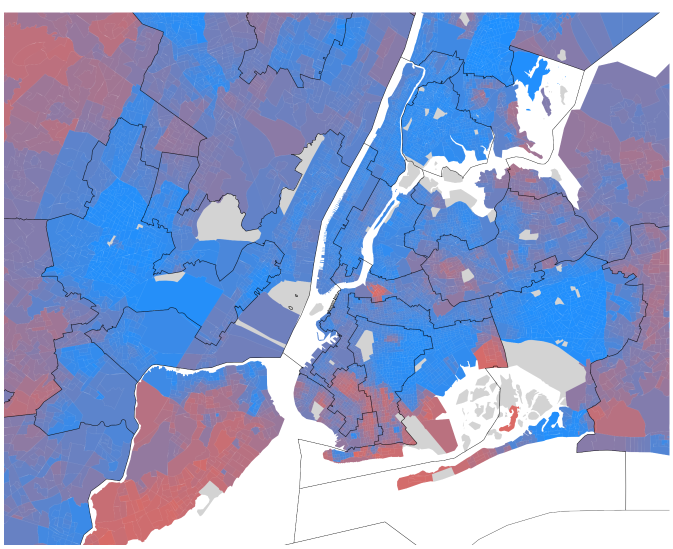
In addition to census demographics, I also collected the share of unionized workers using localized contract-level data from the Federal Mediation and Conciliation Service (FMCS), which gives establishment levels data on unionization. I geocode each establishment to obtain its census block, I then apportion employment from the workplace to the voting place using LEHD Origin-Destination Employment Statistics (LODES) data which give block-to-block job flows. This strategy allows me to obtain a block-group level estimate of *voters* that are part of a labor union. I also collected the share of voters that belong to any church, and specifically that belong to an Evangelical Church, using a combination of data from The Census of Religious Bodies and data from Axle.

In what follows, I will keep using the term *precinct* as the unit of observation, with minor abuse of language.

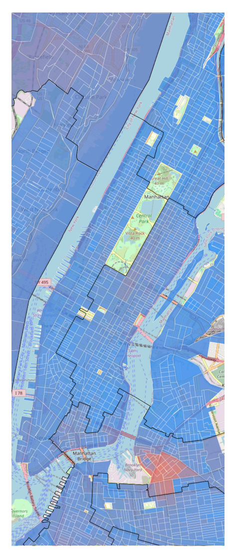
Lastly, in order to have additional individual-level demographic heterogeneity, I use individual vote-choice survey data from the Cooperative Election Survey (CES), The American National Election Survey (ANES), the General Social Survey (GSS), and from Gallup, obtained from Kuziemko et al. (2023).



(a) Continental United States



(b) New York City, NY



(c) Manhattan, NY

Figure 1: Precinct-level democratic vote share in 2020 in NYC

Notes: The figure shows the 2020 distribution of democratic vote share in each precinct. Congressional district borders are shown in black. Precinct results have been spatially interpolated at the block-group level as described in Section 3.

3.2 Descriptive Statistics on Voting Patterns

I start by providing new evidence of political realignment using this novel panel of precinct-level electoral results. Most of the existing evidence on realignment has been documented through survey data (Kitschelt and Rehm, 2019; Gethin et al., 2022; Kuziemko et al., 2023). Using aggregate election results presents three advantages. First, it allows me to study the revealed instead of stated preferences of voters, as survey respondents might misreport their votes. Second, it also prevents some sample bias issues associated with survey methodologies. Lastly, it gives more power to study precise phenomena and detect non-linearities. Naturally, relying on aggregate results also has some drawbacks. The main issue is to recover individual voting behavior from aggregate election results, referred to as the ecological inference problem (King, 2013). I discuss these challenges and the strategy proposed to overcome them in Section 4.

I start by analyzing the variables along which political realignment has been the most pronounced. I use 11 variables about the demographic composition of precincts, the distribution of occupations, and religious or labor union affiliation. To compare the magnitude of realignment, I run linear regressions of Democratic vote shares on demographic variables interacted with a time trend. I normalize each demographic variable to have a mean of zero and a standard deviation of one to have comparable coefficients across dimensions. Specifically, I run the following regression:

$$S_{dem,p,t} = \sum_{w} \beta_1^w w_{p,t} + \beta_2^w w_{p,t} \times year_t + \mu_t + \epsilon_{p,t}, \tag{5}$$

where $S_{dem,p,t}$ is the vote share obtained by the House Democratic candidate in precinct p at election t, $w_{p,t}$ are demographic variables of precinct p along one dimension, μ_t are election fixed effects. Figure 2 reports both the estimates from the joint regression including all demographic variabgles, Appendix Figure A.4 reports the unconditional estimates from regressing one coefficient at a time. Positive values indicate a realignment toward the Democratic Party ($\beta_2 > 0$) while negative values indicate a realignment toward the Republican Party. The figure shows that education, income, race, and rurality have the highest unconditional impact on political realignment. The effect of education dominates the effect of any other demographic variable, and is even stronger among white voters. Additionally, other variables, such as age and the share of Evangelicals, also play a significant role, with areas with older voters and a higher proportion of Evangelicals tending to shift away from the Democratic Party over time.

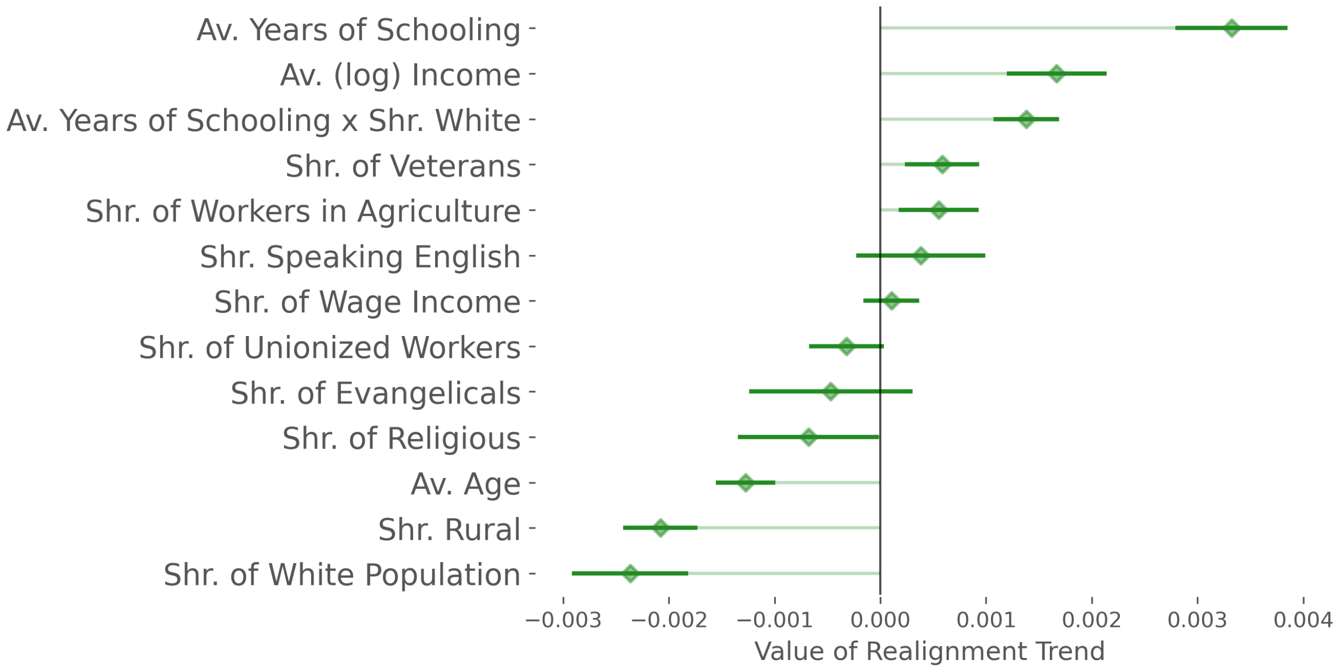


Figure 2: "Horse race" of demographics in political realignment: Education is driving voters' re-alignment.

Notes: The figure shows, for each demographic variable $w_{p,t}$, the coefficients β_2^w from the following linear regression: $S_{dem,p,t} = \sum_w \beta_1^w w_{p,t} + \beta_2^w w_{p,t} \times year_t + \mu_t + \epsilon_{p,t}$ where $S_{dem,p,t}$ is the share of vote obtained by Democratic candidates in precinct p at time t, $year_t$ is the year of the election, and μ_t are election fixed-effects. The bars around each marker show the 95% confidence intervals with standard errors clustered at the precinct level and at the congressional district by year. Appendix Figure A.4 shows the results from a regression of each demographic variable separately.

I now turn to measures of political realignment focusing on educational lines. Figure 3 shows the linear relationship between precinct-level education and Democratic voting. In each successive election, the average gap in education between Democratic and Republican voters has increased by 2.5 months of schooling. Importantly, the rise in this correlation has preceded the election of Donald Trump in 2016, with no specific jump in the educational gradient in that year.

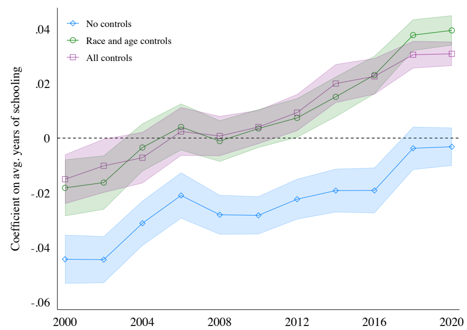


Figure 3: Increasing correlation between precinct-level education and Democratic vote shares.

Notes: The figure shows the coefficient β_t from the following regression: $S_{dem,p,t} = \beta_t edu_{pt} + \mu_t + \epsilon_{pt}$. The coefficients in blue are unconditional while the coefficients in green are from a regression controlling for the precinct-level share of white and the precinct-level average age by year. The coefficients in purple also control for average income, share of unionized workers, share of religious people, share of veterans share of veterans, share of workers in agriculture, share of the population that lives in rural areas, separately for each year. Standard errors are clustered by congressional district by year and by precincts.

Precinct-level election results allow me to delve further into this relationship and investigate some non-linearities. Figure A.5 shows the average Democratic vote share for each 5% quantile of the education distribution. The figure shows a strong U-shape relationship between education and vote shares, with most changes over time occurring at the tails of the distribution.

Figure A.6 shows the evolution of the education gradient both within and between congressional districts. The relationship within district is strongly negative, with more educated precincts inside each congressional district voting more for the Republican candidates, with little change over time. This negative relationship contrasts with the pattern observed between districts, where more educated districts have been consistently voting more for the Democratic Party, echoing findings from Gelman (2009) for income. Overall, the precinct-level U-shape relationship can be thought as a weighted average of those two opposite relationships, between and within districts.

3.3 Candidate ideological positioning

In order to recover candidate ideologies on multiple dimensions, I combine candidate survey data from VoteSmart with text data from candidate websites obtained from the United States Election Web Archive, maintained by the Library of Congress. Appendix Figures A.1 and A.2 show examples of what the raw data looks like.

Project Votesmart is a non-partisan organization that has been sending surveys to candidates since the 1990s. These surveys include a very large number of questions about the candidate political stances on multiple topics. The response rate has started to go down in the late 2000s and Project Votesmart has started to perform some internal research using candidate statements, press releases, and interest group ratings to impute answers for candidates who have not answered the survey. When candidates' position about an issues in unclear from these statements, the answer is left unknown.

Since some questions change over time, I then match questions between election cycles with each other only if the framing of the question is almost identical. I include questions that have been asked in at least two elections and I do not include questions that ask about policies from specific politicians and relationships with specific countries. I have a total of 132 distinct questions from 2000 to 2020. Each question belongs to one of the 15 topics: abortion, crime, education, environment, gun regulation, campaign finance, immigration, international relations and security, diversity questions, employment, trade, taxes, health care, social security, and welfare. I then classify each of these themes into two main categories: cultural and economic issues. Appendix Section E details the classification.

In order to obtain an ideal point for each candidate, I apply a Bayesian item response model, similar to Clinton, Jackman, and Rivers (2004), Jessee (2009), and Shor and Rogowski (2018), detailed in Appendix Section E. The model estimates each candidate's underlying ideology, along with a difficulty parameter for each survey question that characterizes its position in the ideological space and a discrimination parameter that indicates how polarizing the question is. The model is estimated by Marginal Maximum Likelihood, separately for cultural and economic issues. I assign standard normal priors to the ideal points. By definition, all candidates answered the set of questions only partially since not all questions were asked every year. I also obtain the standard errors of each ideal point.

I complement these survey-based ideal points with data from candidate websites. Using the Web Election Archive, I scrape candidates' website on the first day of November before the election. I process and transform the text to extract valuable information using embedding vectors (Dai, Olah, and Le, 2015), as described in more detail in Appendix Section E.

I then train a machine learning regressor using the text features with an Extreme Gradient Boosting algorithm (Chen, He, Benesty, Khotilovich, Tang, Cho, Chen, Mitchell, Cano, Zhou, et al., 2015). I obtain a mean squared error (MSE) of 0.17 for the economic prediction and 0.21 for the cultural dimension (19% and 21% of a standard deviation, respectively).

Finally, I combine the information from survey and websites using the relative uncertainty of both measures. Candidates without any survey answer (27%) are assigned their website ideal points only (x_{jk}^{website}), similarly candidates for whom I do not have the website are assigned their survey ideal point only (18%). For all those with both survey and website ideal points (46%), I take a weighted average of the two measures using their relative uncertainty as the weighting factor:

$$x_{jk} = \omega_{jk} x_{jk}^{\text{survey}} + (1 - \omega_{jk}) x_{jk}^{\text{website}}, \tag{6}$$

with $\omega_{jk} = \frac{MSE(x_k^{\text{website}})}{se(x_{jk}^{\text{survey}})^2 + MSE(x_k^{\text{website}})}$.

Appendix Figure A.18 shows the correlation between the survey-based x_{jk}^{survey} and website-based ideal points (x_{jk}^{website}) on each topic, which is above 90% overall and above 70% within party.

I do not observe the ideology of about 9% of the sample of candidates which are therefore excluded from the analysis.

Appendix I describes an alternative estimation of politicians' ideology based on an unsupervised probabilistic topic model, adapted from Vafa, Naidu, and Blei (2020). The estimated dimensions of the two methods have a correlation of about 0.5 (see Appendix Figure A.26), both between and within party.

Figure 4 shows the distribution of candidate positions on the cultural and economic dimensions. The distribution of Democratic and Republican candidates are clearly distinct from each other. However, contrary to measures such as DW-Nominate, the distribution of candidates from the two parties overlap substantively, with the most conservative Democratic candidates located to the right of the most progressive Republican candidates. Canen et al. (2021) found similar polarization patterns in Congress, once accounting for party discipline from party leaders. Importantly, while the overall Spearman (rank) correlation between the cultural and economic topic is 0.88, the within-party correlations are much smaller: 0.49 among Democrats and 0.46 among Republicans.[4] These relatively low correlations suggest that candidates' cultural and economic positions vary independently, with some candidates being significantly more progressive on one dimension than the other.

Appendix Figure A.8 compares my measures with commonly used measures of ideology, such as DW-Nominate (Poole and Rosenthal, 1985), two-dimensional positions from Canen et al. (2021), which are both available for election-winners only, and the contribution-based measure of ideology from Bonica (2014) which are also available for election-losers. Both the cultural and economic dimensions are highly correlated with other measures.

[4] The overall covariance between cultural and economic positions is $\mathbb{C}(x_{j,\text{cult}}, x_{j,\text{econ}}) = 0.623$, which can be decomposed into: $\mathbb{E}\big[\mathbb{C}(x_{j,\text{cult}}, x_{j,\text{econ}}|p(j))\big] = 0.074$ and $\mathbb{C}\big[\mathbb{E}(x_{j,\text{cult}}|p(j)), \mathbb{E}(x_{j,\text{econ}}|p(j))\big] = 0.549$, where $p(j)$ denotes the party of each candidate.

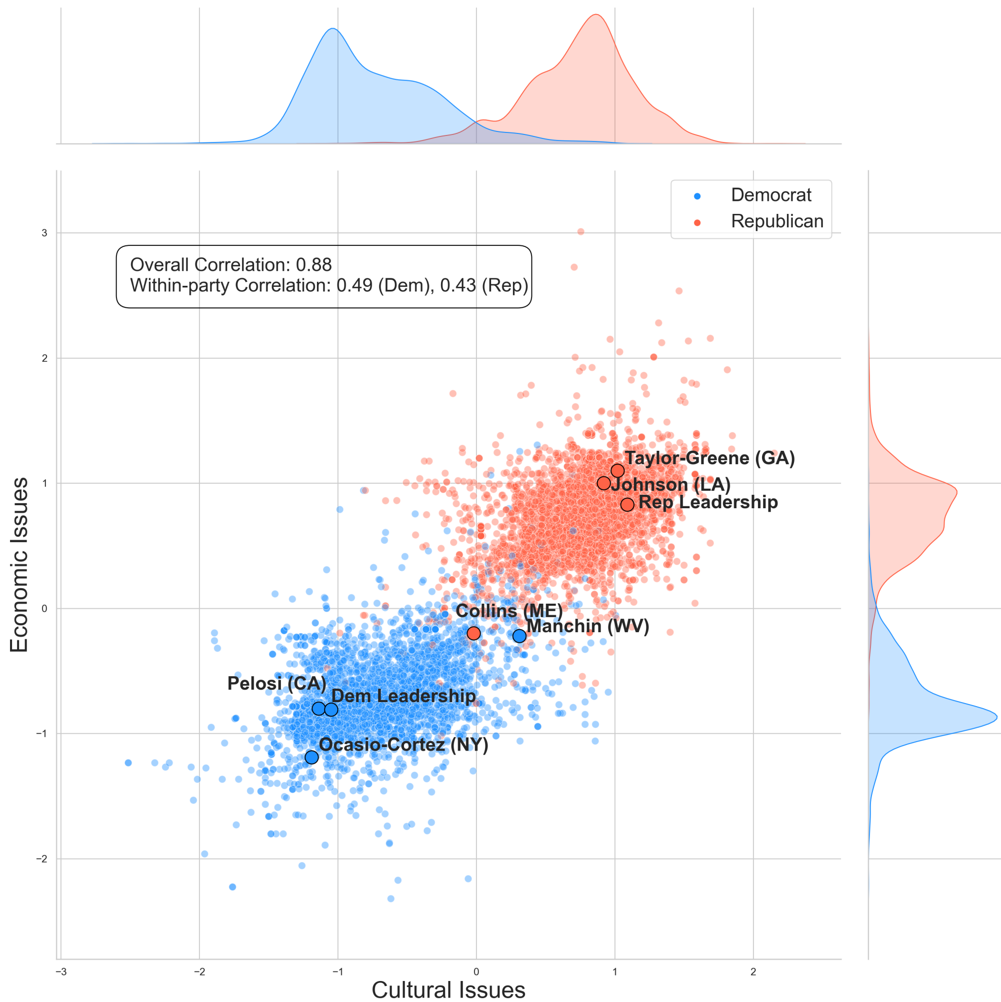


Figure 4: Distribution of candidate ideal points

Notes: Each dot shows one House candidate's estimated two-dimensional ideal point from the multimodal text-and-survey model on cultural and economic issues for each election. Famous candidates' positions as as the party leadership position in 2020 are added to the graph. The partial densities are plotted on each axis. The graph excludes third parties and independent candidates. The correlation between the two dimensions is 0.88 in the whole sample and the within-party correlations are 0.49 for the Democratic Party and 0.43 for the Republican Party. Appendix Figure A.19 shows the difference in positions between Democratic and Republican candidates in each Congressional race.

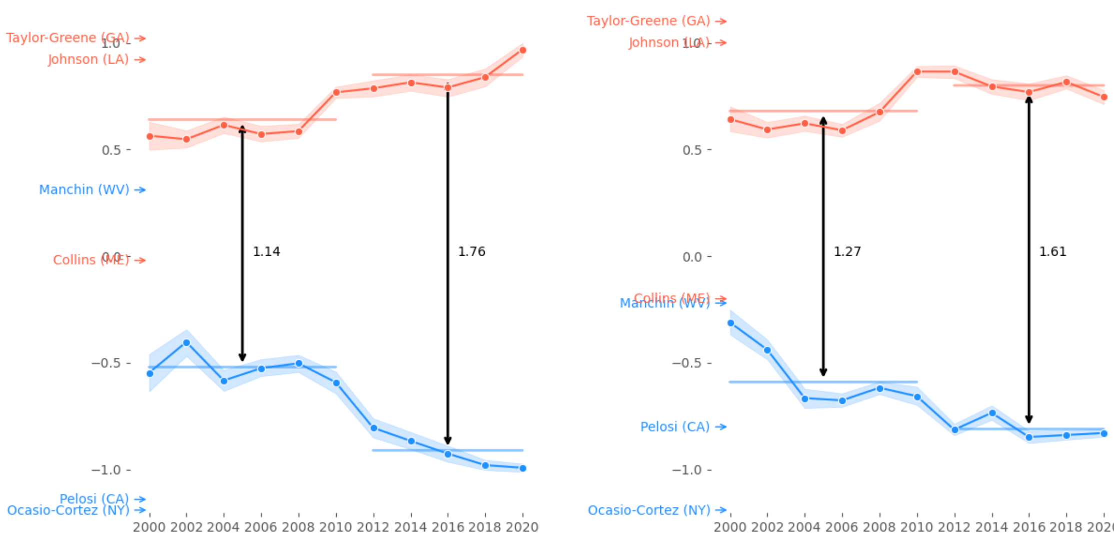
3.4 Differential Polarization on Cultural Issues

Figure 5 shows the evolution of candidate ideal points on both cultural and economic issues over time. The average distance between the two parties has increased in both dimensions, with a much more dramatic divergence on cultural issues compared to economic issues. The average distance between a Democratic and a Republican candidate on cultural issues has doubled between 2000 and 2020, while it has risen by around 50% on economic issues. Figure reports the average differences between the two parties between from 2000 to 2010 and from 2012 to

2020.

The overall dynamic of polarization align with similar findings from other types of data (rollcall votes, speeches in Congress, campaign contributions, etc.). To the best of my knowledge, this paper is the first one to document a differential polarization on cultural rather than economic issues, looking at both election winners and losers. Appendix Figure A.10 shows the same relationship separately for election-winners and election-losers, echoing findings from Moskowitz, Rogowski, and Snyder (2018).

Notably, the rise in political polarization between the two main parties has almost mechanically led to an increase in the overall correlation between candidates' cultural and economic ideal points. However, when looking within party, the correlation between candidate positions across the two dimensions has decreased over time. In 2000-2010, candidates' cultural and economic positions had a 0.44 Spearman correlation coefficient for Democratic candidates and a 0.49 coefficient for Republican candidates. This rank correlation went down to 0.29 for Democratic candidates and 0.24 for Republican candidates in 2012-2020. This decline in the correlation indicates that as the two parties moved further apart, candidates began to differentiate themselves more across the two dimensions.



(a) Cultural Positions

(b) Economic Positions

Figure 5: Differential Polarization on Cultural vs. Economic Issues

Notes: The figure shows the evolution of the average position of candidates in each party on each dimension, with the 95% confidence interval. The average distance between the two parties on cultural issues increased from 1.14 in the first period (2000-2010) to 1.76 in the second period (2012-2020). On economic issues, the average distance increased from 1.27 to 1.61. Famous candidates' positions in 2020 on both dimensions are added to the graph.

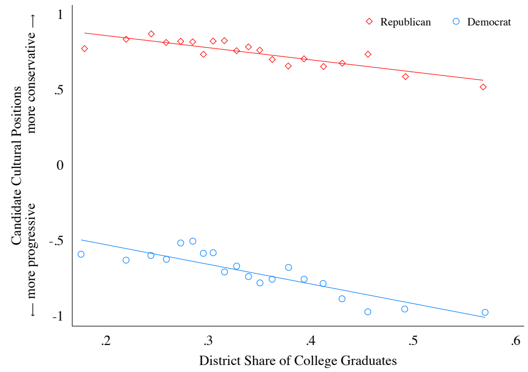
3.5 Determinants of candidate positioning

This section examines the extent to which the demographic composition of a candidate's congressional district impacts their ideal points. Following the logic of classic spatial models such as Downs (1957) and the Median Voting Theorem, one should expect candidates to adapt their positions to the ideology of their constituents.

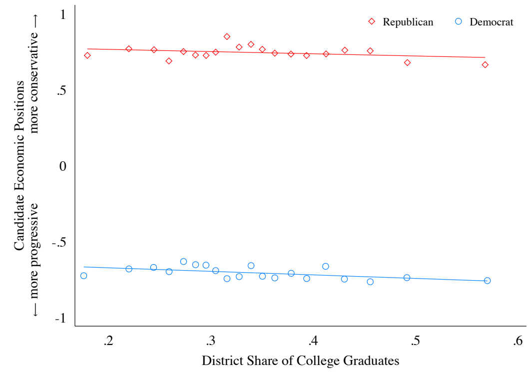
Figure 6 below provides evidence of such relationships, focusing on district's educational composition. Congressional districts are ranked by their average levels of education. For each 5% quantile, the figure shows the average position of both the Democratic and Republican candidates. The first two panels, which show unconditional relationships, reveal important differences between candidates along educational lines. On cultural issues, Democratic candidates running in the most educated districts tend to be one standard deviation more progressive on cultural issues than those in the least educated districts. Republican candidates follow the same pattern, with slightly less adaptation. Adaptation on economic issues along educational lines is less pronounced, with only a very small negative slope on these unconditional graphs.

The third and fourth panels display the same relationships, but controlling for candidates' position on the other dimension. The negative relationship between candidates' cultural positions and district education holds true for both Democratic and Republican candidates. The economic dimension exhibits the opposite pattern: both Democratic and Republican candidates tend to offer more conservative economic positions in more-educated districts, once accounting for their cultural positions. Appendix Figure A.9 presents similar results for other demographic variables, showing that candidates offer more conservative cultural positions to districts with a larger share of white voters, with more Evangelicals, with fewer unionized workers, and more veterans. Candidates also tend to offer more progressive economic positions to district with more unionized workers.

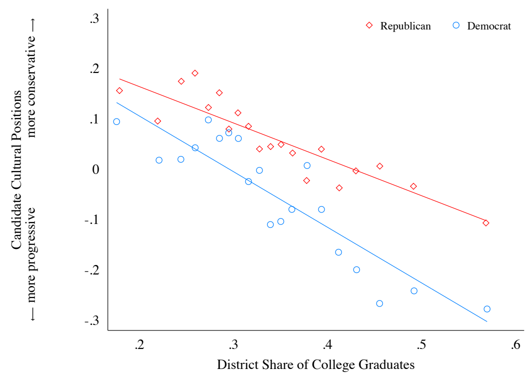
All these patterns provide suggestive evidence that candidates might be adjusting their positions to the demand of their constituents. Section 5 precisely estimates the weight that candidates allocate to their constituents in their choice of positions.



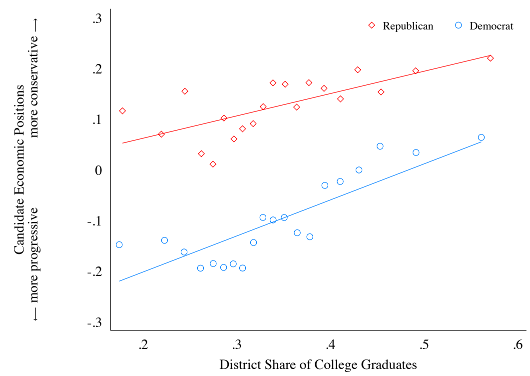
(a) Cultural Issues



(b) Economic Issues



(c) Cultural Issues, controlling for Economic



(d) Economic Issues, controlling for Cultural

Figure 6: Candidate positions and congressional district composition

Notes: Each panel shows the relationship between candidate positions and the district share of college graduates. Each dot represents 5% of the education distribution and shows the average position of candidates, separately for Democrats and Republicans for the districts in this quantile. The two first panels present at unconditional candidate positions, with cultural issues on the left and economic issues on the right. The two last panels show the same relationship but controlling for the position on the other dimension. Figure A.9 shows the same relationship for other demographic variables.

4 Estimation of voter preferences

4.1 Model

The model of vote choice features individual voters with heterogeneous preferences over candidate characteristics. Since voting is compulsory (cf. footnote 1) and there are only two candidates ($j \in \{D, R\}$), voters make a binary choice which I model as resulting from maximizing a random indirect utility with heterogeneous preferences and allowing for unobserved candidate heterogeneity (Berry et al., 2004). I give the following functional form to the utility of voter i, who resides in precinct $p(i)$, itself located in district d, when choosing the Democratic candidate in election t:

$$u_{it}=\sum_k \beta_{ikt}x_{d(i)kt}+\alpha_{it}+\xi_{p(i)t}+\epsilon_{it} \tag{7}$$

where $x_{d(i)kt}=x_{Dd(i)kt}-x_{Rd(i)kt}$ is the difference in positions on each topic between the two candidates, α_{it} is voter i's utility of voting for the Democratic rather than the Republican candidate, independently of their positions, $\xi_{p(i)t}$ is a precinct-level taste shock in favor of the Democratic candidate, and ϵ_{it} is an individual-level taste shock, which I assume follows a type-I extreme value distribution.

To capture the heterogeneity in voter preferences over ideology and over partisan preferences, I decompose the voter preference parameters as:

$$\begin{aligned}\alpha_{it} &= \alpha_t+\mathbf{w}'_{\mathbf{it}}\boldsymbol{\alpha}^{\mathbf{w}}_{\boldsymbol{t}}+\sigma^{\alpha}_t\nu_{0it} && (8)\\ \beta_{ikt} &= \beta_{kt}+\mathbf{w}'_{\mathbf{it}}\boldsymbol{\beta}^{\mathbf{w}}_{\boldsymbol{kt}}+\sigma^{\beta}_{kt}\nu_{kit} && (9)\end{aligned}$$

for each ideological dimension k. $\mathbf{w_{it}}$ is a vector of observed voter characteristics (years of schooling, race, the interaction between education and race, and age), $\boldsymbol{\alpha}^{\mathbf{w}}_{\boldsymbol{t}}$ and $\boldsymbol{\beta}^{\mathbf{w}}_{\boldsymbol{kt}}$ are vectors of dimension $|\mathbf{w}|$ capturing how voters' partisan and ideological preferences vary with demographics, $\boldsymbol{\nu_{it}}\sim P_\nu=\mathcal{N}(0,I_{K+1})$ adds some non-demographic based individual heterogeneity in partisan and ideological preferences, which is captured by the parameters σ^{α}_t and σ^{β}_{kt}. The distribution of demographics in each precinct p and election t is denoted by $F_t(\mathbf{w};p(i))$.

The share of votes received by the Democratic candidate in each precinct p is obtained by integrating over both demographic characteristics and unobserved heterogeneity:

$$s_{Dpt}=\int_w\int_\nu \frac{\exp\left(\sum_k \beta_{ikt}x_{d(i)kt}+\alpha_{it}+\xi_{p(i)t}\right)}{1+\exp\left(\sum_k \beta_{ikt}x_{d(i)kt}+\alpha_{it}+\xi_{p(i)t}\right)}dP_\nu dF_t(\mathbf{w};p(i)). \tag{10}$$

I follow Berry et al. (2004) (BLP) and recover a GMM estimator with both aggregate and individual moments, using Conlon and Gortmaker (2023).

Note that if I assume that voters are homogeneous within precincts $\left(\mathbf{w_{it}}=\mathbf{w_{p(i)t}}\right)$, as in Berry (1994), I can take the log-odds ratio of the Democratic vote share and express the predicted vote share of the democratic candidate as a function of candidate characteristics which can be recovered with Ordinary Least Squares, conditional on the fixed effects:

$$\log(\frac{S_{jpt}}{1-S_{jpt}}) = \alpha_t + \mathbf{w'_{pt}}\boldsymbol{\alpha_t^{w}} + \sum_k \beta_{kt} x_{d(p)kt} + \mathbf{w'_{pt}}\boldsymbol{\beta_{kt}^{w}} x_{d(p)kt} + \xi_{pt}, \tag{11}$$

where S_{jpt} denote observed vote shares. I report the estimates from the simpler specification along with the BLP results.

4.2 Identification

The demand-side estimation proceeds in two steps. I first recover voter preferences over candidates' endogenous characteristics (ideology) using a subset of electoral precincts located around the congressional district border. In the second step, using the estimates from the first step, I recover voter party preferences (candidates' exogenous characteristics) on the whole sample.

First Step The first step recovers the parameters β_{ikt} which capture voters' heterogeneous preferences over candidate positions. Since candidate positions are likely correlated with voters' taste shocks, naive identification strategies would give biased demand estimates. To address this, I propose an identification strategy that controls for unobserved voter taste shocks correlated with candidate positions. The identification strategy exploits the fine-grained structure of election data and the hierarchical nature of political competition, where candidates make decisions at a more aggregate geographic level than individual voters. Consequently, candidates target constituencies larger than individual precincts. Given that each precinct is small relative to the district (approximately 400 precincts per district), candidates likely base their position choices on aggregate district taste shocks rather than on specific precinct-level taste shocks. The identification strategy relies on spatial discontinuity in candidate positioning that should not correlate with any underlying voter discontinuity. For each precinct located on the edge of its congressional district, I pair it with contiguous precincts on the other side of the border. This approach yields pairs of adjacent precincts separated by the congressional district boundary, which plausibly share the same taste shock. I can then account for, at each election, any unobserved taste shock that does not have a discontinuity at the district border, I denote the average taste for Democratic candidates in the *pair* $g(p)$ of precinct p at election t by $\xi_{g(p)t} = \frac{1}{P_{g(p)}} \sum_{p' \in g(p)} \xi_{p't}$, where $P_{g(p)}$ is the number of precinct in the *pair*. Additionally, I control for precinct fixed effects, which handle any unobserved elements specific to each precinct that remain constant over time, denoted by $\xi_p = \frac{1}{T}\sum_t \xi_{pt}$, where T is the total number of elections.

$$\mathbb{E}[x_{d(p)kt} \cdot \xi_{pt} \big| \xi_{g(p)t}, \xi_p] \quad = \quad 0. \tag{12}$$

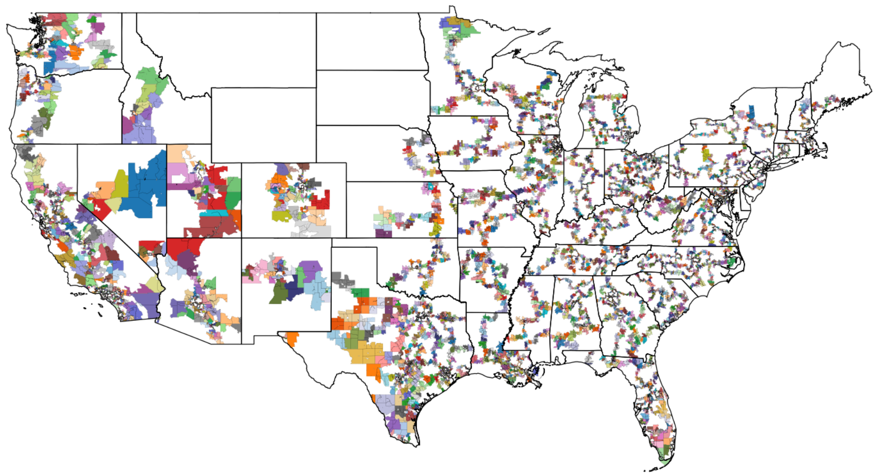
The assumption is based on the reasoning that differences in candidate positions across neighboring districts are not correlated with temporary, unobserved differences between their adjacent precincts. The assumption is justified by both the insignificance of each precinct from the candidate's perspective (about 400 precincts per district) and the absence of discontinuity at the district border in other dimensions than those related to elections. Importantly, I only use district borders within state, implying that there are no differences in legislation passed on both sides of the border and voters are voting for the same upper-level offices on both sides of the district border. Congressional districts are obviously not drawn at random and state legislators might be aware of some precinct-level unobserved taste shocks when deciding which precincts to include in each district. For the identifying assumption to hold, temporary deviations between precincts on both sides of the border should not be taken into account in redistricting. Table 1 shows that while in an OLS specification, precinct demographics are strongly correlated with candidate positions, this correlation disappears after conditioning on precinct-pair-by-election and precinct fixed effects. The table presents balance tests of demographic variables on both sides of the congressional border, conditional on the fixed effects. The table regresses candidate difference in positions on precinct-level demographics. One out of 22 coefficients is significant at the 5% level, as would be expected. No coefficient is significant at the 1% level.

Figure 7 illustrates the distribution of precincts located on district borders for the 2018 elections and depicts the precinct-pair-by-election-fixed-effects. The process of creating precinct groups is not trivial, as each precinct might be contiguous to several others. Instead of simple pairs, I construct precinct groups as follows, (1) For each precinct $p \in d_1$ located on the border between d_1 and d_2, in each election, I identify the closest precinct belonging to the neighboring district $p' \in d_2$, using the distance between their population-weighted centroids. (2) If p is also p''s closest precinct in district d_1, then p and p' form a pair. (3) If, however, p' is closer to another precinct $p'' \in d_1$ than to p, then p, p', and p'' form a group together. (4) I continue extending these chains until they close, meaning until the last added precinct already has its closest precinct included in the group. This approach ensures that the matching process is independent of the order in which it is performed. Figure A.11 in appendix offers a visual representation of the methodology.

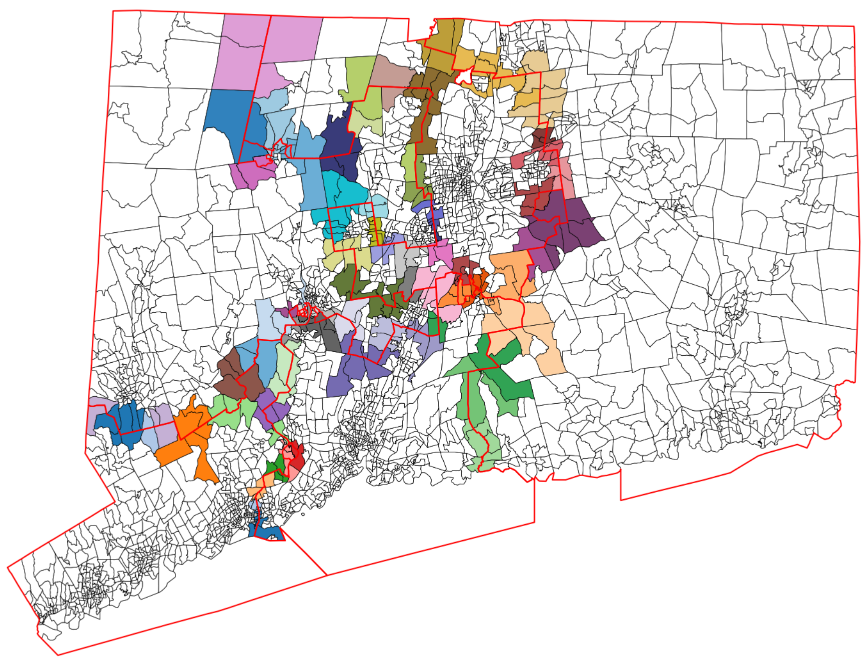
For simplicity, I will continue to use the term precinct *pairs* throughout the rest of the paper to denote these precinct groups. The median number of precincts in each of these "pairs" is 4. This strategy, which leverages spatial discontinuities, has been used in past studies to estimate the impacts of minimum wage (Card and Krueger, 1994; Dube et al., 2010), school valuations (Black, 1999), and advertising effects (Spenkuch and Toniatti, 2018).[5]

[5] Dube et al. (2010) and Spenkuch and Toniatti (2018) create a dataset at the county-pair level where each county has as many observations as it has contiguous neighbors. When the treatment effect is assumed to be homogeneous and standard errors are clustered at the state-pair level (or district-pair level in my case), the multiplication of

the number of observations does not affect the coefficients but in my case, the treatment effect is assumed to be very heterogeneous and it seems more reasonable to keep the number of observations constant and create groups of precincts.



(a) Continental U.S.



(b) Connecticut

Figure 7: Precinct "pairs" distribution for the 2018 elections (116^{th} Congress).

Notes: The first panel shows all the precincts (block-groups) in the U.S. that sit on a Congressional district border. I use only borders within the same state and therefore exclude at-large districts. The second panel zooms on the distribution of precinct groups in Connecticut. There are 5 congressional districts in Connecticut. Each color shows a different group of precincts.

The moments used for the identification of the parameters in the first step, for each political dimension $k = \{cultural, economic\}$, for each demographic characteristic $w_{pt} = \{education_{pt}, race_{pt}, education_{pt} \times race_{pt}, age_{pt}\}$ are:

$$\begin{aligned} \mathbb{E}[x_{d(p)kt} \cdot \xi_{pt} | \xi_{g(p)t}, \xi_p] &= 0 \\ \mathbb{E}[\big(x_{d(p)kt} \cdot w_{pt}\big) \cdot \xi_{pt} | \xi_{g(p)t}, \xi_p] &= 0 \\ \mathbb{E}[w_{pt} \cdot \xi_{pt} | \xi_{g(p)t}, \xi_p] &= 0 \\ \mathbb{E}[x^2_{d(p)kt} \cdot \xi_{pt} | \xi_{g(p)t}, \xi_p] &= 0 \\ \mathbb{E}[\big(x^2_{d(p)kt} \cdot w_{pt}\big) \cdot \xi_{pt} | \xi_{g(p)t}, \xi_p] &= 0 \end{aligned} \tag{13}$$

Figure A.12 in the Appendix presents Monte Carlo simulations of the demand specification, demonstrating that the coefficients are properly identified.

Appendix G demonstrates robustness of the results to using an alternative identification strategy using a different source of variation. I estimate the same parameters with congressional district by election fixed effects instead of precinct-pair by election fixed effects. With precinct-pair by election fixed effects, I compare arguably similar precincts that were facing a choice between different candidates. In contrast, with district by election fixed effects, I compare different precincts facing a choice between the same candidates. This alternative specification gives very consistent estimates of voter preferences.

Second Step By design, the first step does not leave any identifying variation for characteristics that do not exhibit a discontinuity at the district border ($\Delta w_{pt} \approx 0$). In particular, since precincts within the same pairs have very similar voter demographics, voters' party preferences (α_{it}) are left essentially unidentified in the first step.[6]

Given that a candidate's party affiliation is considered exogenous, it is not necessary to limit the analysis to precincts at the district border to identify party preferences. Consequently, in the second step, I utilize the entire sample, not just those precincts. This second step incorporates the estimates from the first step regarding voter preferences over candidate ideology and uses the following moments to recover preferences over partisan affiliations in a BLP framework:

$$\mathbb{E}[w_{pt} \cdot \xi_{pt}] = 0 \tag{14}$$

for each demographic characteristic w_{pt} (years of schooling, race, the interaction between years of schooling and race, and age). Essentially, this second step recovers the demographic heterogeneity in party preferences, accounting for the ideological preferences estimated in the first

[6]Note that I still estimate voter preferences over party in the first step to account for small differences in voter demographics that might subsist within precinct pairs.

step.

	DemCult - RepCult		DemEcon - RepEcon	
	(1)	(2)	(3)	(4)
Av. Edu	-0.023**	-0.006	-0.005	-0.007
	(0.009)	(0.005)	(0.008)	(0.005)
Shr. White	0.084***	0.001	0.017	0.006
	(0.013)	(0.022)	(0.012)	(0.020)
Av. (log) Income	-0.056***	0.001	-0.002	0.002
	(0.010)	(0.005)	(0.008)	(0.005)
Av. Age	-0.065***	0.013**	-0.019***	-0.001
	(0.006)	(0.005)	(0.005)	(0.005)
Pop	-0.012***	-0.002	-0.009***	-0.005
	(0.003)	(0.003)	(0.003)	(0.004)
Shr. Unionized	0.032***	0.003	0.007	-0.006
	(0.009)	(0.007)	(0.007)	(0.006)
Shr. Farmers	0.006	-0.002	-0.002	-0.000
	(0.006)	(0.002)	(0.006)	(0.002)
Shr. Wage Income	-0.005	-0.001	0.001	-0.001
	(0.004)	(0.004)	(0.003)	(0.003)
Shr. Speaking English	-0.027**	0.007	-0.027**	0.002
	(0.013)	(0.009)	(0.011)	(0.008)
Shr. Rural	-0.018***	-0.010	-0.004	0.016
	(0.007)	(0.015)	(0.006)	(0.014)
Shr. Veterans	0.079***	-0.000	0.049***	-0.000
	(0.007)	(0.002)	(0.006)	(0.002)
Precinct-pair x Year FE		X		X
Precinct FE		X		X
F-statistic	30.257	0.999	7.188	0.547
Observations	226,509	226,509	226,509	226,509

Table 1: Conditional balanceness of "treatment" across congressional district borders.

Notes: This table shows the coefficients from a regression of candidates' differences in positions on precinct-level demographic variables, columns (1) and (3) are simple OLS regressions and columns (2) and (4) are conditional on precinct fixed effects and precinct by election fixed effects. Standard errors clustered both by congressional district by year and by precinct are reported in parentheses. The joint F-statistic

4.3 Incorporation of micro-level variation

The precinct-level election results provide aggregate variation in vote shares. As precincts are relatively homogeneous demographically (1,200 registered voters on average), one can hope to recover demographic heterogeneity in vote choice based on aggregate vote share at the precinct-level. There is, however, a longstanding debate in social science about the ability of inferring individual-level preferences from aggregate election results (King, Tanner, and Rosen, 2004).

The Monte carlo simulations in Appendix show that, with very granular voting data and rich heterogeneity in voter preferences, one can recover consistent estimates of the true individual-level demand parameters. In addition to aggregate variation, one could also use individual-level variation to help estimate the demographic hetereogeneity parameters. I therefore collect large sample (N=400,000) survey data from ANES, CES, Gallup, and GSS containing voters' demographics, voters' congressional district and voters' House candidate choice (if any). As in Petrin (2002) and Conlon and Gortmaker (2023), I can build new moments from this individual-level data that I can stack with my vector of moments from aggregate data. I add a vector $g_M(\theta)$ of micro-moments which are functions of the model parameters. I include as micro-moments the interaction between all the demographics of interest (education, white dummy, and their interaction, and age) and their partisan choice as well as the ideological position for their chosen candidate. I stack these moments with the aggregate moments from precinct-level data ($g_A(\theta)$, giving a vector of moments $g(\theta) = \begin{pmatrix} g_A(\theta) \\ g_M(\theta) \end{pmatrix}$.

The full list of moments is shown in Appendix G. Note that the GMM weighting matrix is block-diagonal as the covariance between aggregate and micro-moments is assumed to be zero.

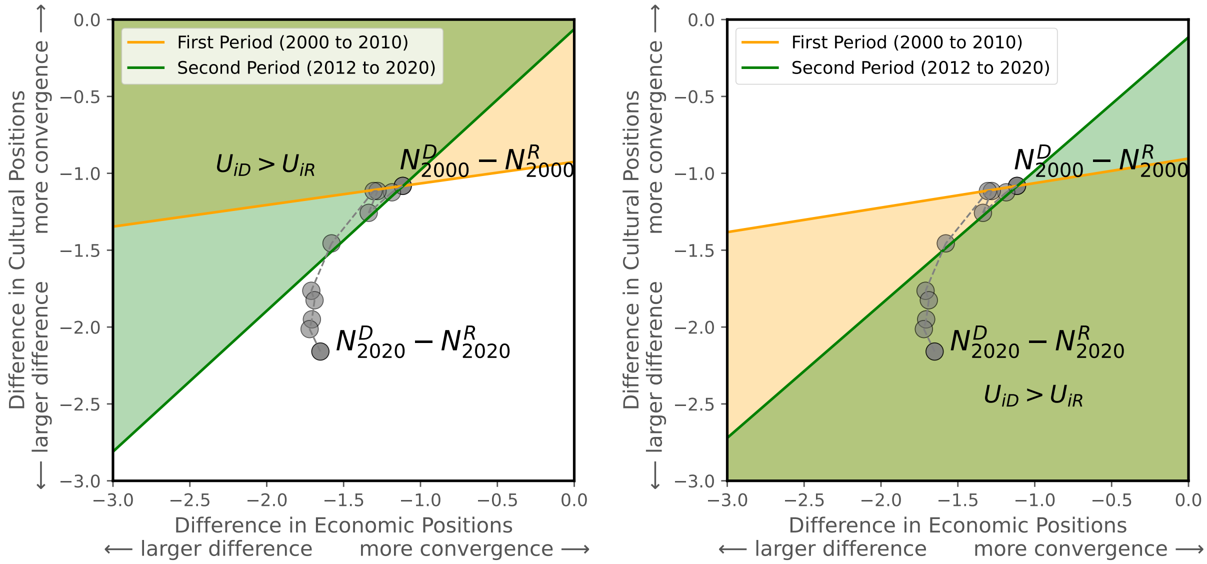
4.4 Demand Estimates

I estimate the specification with and without within-precinct heterogeneity, corresponding to equations 10 and 11. Table 2 reports the results with within-precinct heterogeneity, the corresponding estimates without within-precinct heterogeneity are reported in Appendix Table A.2. The two tables give very similar estimates. The main parameters of interest are β_{cult} and β_{econ} and in particular the heterogeneity in these dimensions across educational lines, denoted by $\beta_{edu,k}$. Overall, the ideological coefficients for white voters are typically larger in magnitude and more precise compared to those for non-white voters, suggesting that ideology plays a relatively greater role in shaping the choices of white voters than it does for non-white voters. The impact of education on white voters' preferences for cultural and economic policies diverges: higher levels of education are associated with more progressive preferences on cultural issues but more conservative preferences on economic issues. The coefficients are larger for cultural issues, indicating a stronger educational gradient in that dimension. Over time, the coefficients on both dimensions increase, with a more pronounced rise in the economic dimension. Note that the parameter α_i captures all the elements that affect voters' utility of voting for a Democratic candidate that do not vary by candidate. α_i therefore reflects preferences for various characteristics, such as pure partisanship and the ideology of upper-level candidates (e.g., Senate and Presidential candidates) who may exert a *coattail effect* on voters' choice of House candidate (Calvert and Ferejohn, 1983). While I consider α_i a potential confounder for ideology that must be controlled for, I do not attribute a structural interpretation to it. However, it is important to note the changes in α_i over time, with educated voters becoming more likely to vote for Democratic candidates and white voters becoming less likely to do so. Appendix Figure A.13 illustrates the variation in Democratic candidate vote shares for different positions, shown separately for more-educated and less-educated voters. Positive slopes indicate that voters from that group prefer more conservative policies on that dimension.

To summarize the demand-side changes in ideological preferences, I represent each voter's ideological preferences with an indifference curve, which shows the combination of candidate positions that would leave the voter indifferent between voting for the Democratic or Republican candidate, normalizing non-ideological effects. Voter i indifference curve is given by:

$$x_{\text{cult}} = -\frac{\beta_{i,\text{econ}}}{\beta_{i,\text{cult}}} x_{\text{econ}}, \tag{15}$$

where x_{cult} (resp. x_{econ}) is the difference in positions between the Democratic and the Republican candidate on cultural (resp. economic) issues. The set of positions for which voter i votes for the Democratic candidate depends on the sign of $\beta_{i,\text{cult}}$. If $\beta_{i,\text{cult}} > 0$, for any positions such that $x_{\text{cult}} \geq -\frac{\beta_{i,\text{econ}}}{\beta_{i,\text{cult}}} x_{\text{econ}}$, i will vote for the Democratic candidate, and the opposite if $\beta_{i,\text{cult}} < 0$. Figure 8 shows the average indifference curve of less-educated and more-educated voters, separately for 2000 to 2010 and 2012 to 2020. Both curves are upward slopping, indicating that $\beta_{i,\text{cult}}$ and $\beta_{i,\text{econ}}$ are of opposite signs. The shaded areas indicate the set of positions where each voter type would choose the Democratic candidate. The difference in leadership positions for each year are added to the graph. I evaluate the indifference curves for a voter that would initially be indifferent between the Democratic and the Republican leadership. Less-educated voters tend to vote for the Democratic candidate when candidates are positioned in the upper left corner, where there is low differentiation on cultural issues but a strong differentiation on economic issues, with the Democratic candidate being much more progressive. Conversely, more-educated voters support the Democratic candidate when candidates are located in the lower right corner, where they are similar on economic issues but highly differentiated on cultural issues. Over time, the slope for both less-educated and more-educated voters has increased, reflecting the growing educational gradient on economic issues. Over the years, the leadership of both parties has moved further apart, particularly on cultural issues, their vertical shift is twice as large as their horizontal shift. The main takeaway from the figure is that although the shift in less-educated voters' preferences has brought them closer to the Democratic Party (the green curve is closer to $N^D_{2020} - N^R_{2020}$ than the orange curve), the significant shift in leadership positions has reduced the likelihood of these voters choosing the Democratic candidate.



(a) Less-educated voters

(b) More-educated voters

Figure 8: Voters' indifference curves

Notes: The Figure shows the average indifference curves of voters with Low (upper panel) and High (lower panel) levels of education for different combinations of candidate positions at the two periods. For each voter i, the indifference curve is given by $x_{\text{cult}} = -\frac{\alpha_i}{\beta_{i,\text{cult}}} - \frac{\beta_{i,\text{econ}}}{\beta_{i,\text{cult}}} x_{\text{econ}}$, where x_{cult} (resp. x_{econ}) is the difference in positions between the Democratic and the Republican on cultural (resp. economic) issues. The shaded areas show the combinations of positions for which voters choose to vote for the Democratic candidate. Less-Educated voters choose the Democratic candidate for any couples of positions located to the Upper-Left of the indifference curve. More-Educated voters choose the Democratic candidate for any couple of positions located to the Lower-Right of the indifference curve. $N_t^D - N_t^R$ represents the difference in positions between the two leaderships in each year t.

Coefficients	Parameters	Estimates	Standard Errors
First Period: 2000-2010			
CultDem - CultRep	β_{cult}	0.0110	(0.0259)
EconDem - EconRep	β_{econ}	-0.0397	(0.0342)
Yrs. Schooling × Non-white	$\alpha_{edu,NW}$	-0.1576	(0.0210)
Yrs. Schooling × White	$\alpha_{edu,W}$	0.0249	(0.0163)
White	α_{W}	-2.2885	(0.1196)
(CultDem - CultRep) × Yrs. Schooling × Non-white	$\beta_{edu,NW,\text{cult}}$	-0.0042	(0.0069)
(CultDem - CultRep) × Yrs. Schooling × White	$\beta_{edu,W,\text{cult}}$	-0.0357	(0.0051)
(CultDem - CultRep) × White	$\beta_{W,\text{cult}}$	0.0414	(0.0447)
(CultDem - CultRep) × Age	$\beta_{age,\text{cult}}$	-0.0007	(0.0005)
(EconDem - EconRep) × Yrs. Schooling × Non-white	$\beta_{edu,NW,\text{econ}}$	-0.0268	(0.0072)
(EconDem - EconRep) × Yrs. Schooling × White	$\beta_{edu,W,\text{econ}}$	0.011	(0.0061)
(EconDem - EconRep) × White	$\beta_{W,\text{econ}}$	0.1352	(0.0266)
(EconDem - EconRep) × Age	$\beta_{age,\text{econ}}$	-0.0016	(0.0035)
Unobserved partisan heterogeneity	σ^{α}	0.0562	(0.1437)
Unobserved cultural heterogeneity	$\sigma^{\beta}_{\text{cult}}$	-0.0107	(0.1277)
Unobserved economic heterogeneity	$\sigma^{\beta}_{\text{econ}}$	0.0118	(0.8791)
Second Period: 2012-2020			
CultDem - CultRep	β_{cult}	0.0438	(0.0135)
EconDem - EconRep	β_{econ}	-0.0685	(0.0132)
Yrs. Schooling × Non-white	$\alpha_{edu,NW}$	-0.0502	(0.0140)
Yrs. Schooling × White	$\alpha_{edu,W}$	0.2288	(0.0160)
White	α_{W}	-3.0364	(0.0779)
(CultDem - CultRep) × Yrs. Schooling × Non-white	$\beta_{edu,NW,\text{cult}}$	0.0112	(0.0149)
(CultDem - CultRep) × Yrs. Schooling × White	$\beta_{edu,W,\text{cult}}$	-0.0444	(0.0039)
(CultDem - CultRep) × White	$\beta_{W,\text{cult}}$	-0.0623	(0.4851)
(CultDem - CultRep) × Age	$\beta_{age,\text{cult}}$	0.0003	(0.0027)
(EconDem - EconRep) × Yrs. Schooling × Non-white	$\beta_{edu,NW,\text{econ}}$	0.0249	(0.0053)
(EconDem - EconRep) × Yrs. Schooling × White	$\beta_{edu,W,\text{econ}}$	0.0314	(0.0041)
(EconDem - EconRep) × White	$\beta_{W,\text{econ}}$	-0.084	(0.0751)
(EconDem - EconRep) × Age	$\beta_{age,\text{econ}}$	0.0023	(0.0046)
Unobserved partisan heterogeneity	σ^{α}	0.0847	(0.1541)
Unobserved cultural heterogeneity	$\sigma^{\beta}_{\text{cult}}$	0.1171	(0.1924)
Unobserved economic heterogeneity	$\sigma^{\beta}_{\text{econ}}$	0.0336	(0.0751)

Table 2: Estimated demand-side parameters with demographic heterogeneity

Notes: The table shows the estimated coefficients from Equation 10, including precinct and precinct-pair by election fixed effects. The reported α coefficients include both the variation from the demographics in the initial specifications and the variation captured by the fixed effects. Standard errors are clustered by congressional district by election. The same Table using an alternative set of fixed effects: congressional district by election fixed effects and precinct fixed effects is provided in Appendix.

5 Estimating candidates' supply of ideology

5.1 Model

After having recovered the demand-side parameters, which give the distribution of ideological preferences in each congressional district, I can estimate how each candidate chooses the policy to offer to their constituents using equilibrium conditions. I estimate a canonical candidate competition model (see e.g., Wittman (1983)) where candidates are facing pressure to adhere to the party line. I write each candidate's objective function as Π_{jt}, which depends on the candidate's probability of winning and earning the rent of being in office $Q > 0$, the distance between their chosen position and the party leadership, and their own ideological shock.

$$\Pi_{jt}(\mathbf{x_{jt}}) = \underbrace{P_j(\mathbf{x_{jt}}, \mathbf{x_{-jt}})}_{\text{probability of winning}} Q - \underbrace{\lambda_{jt}||\mathbf{x_{jt}} - \mathbf{N_{jt}}||^2}_{\text{distance from national party platform}} + \underbrace{\boldsymbol{\eta}'_{jt}\mathbf{x_{jt}}}_{\text{own ideological shock}} . \quad (16)$$

where the parameter λ_{jt} captures candidates' cost of deviating from the party line.

There is an aggregate shock ζ_{jt} that creates some uncertainty around candidates' probability of winning (Persson and Tabellini, 2002). Assuming that ζ_{jt} follows a uniform distribution[7]: $\zeta_{jt} \sim U(-\frac{1}{\phi}, \frac{1}{\phi})$, I can write

$$\begin{aligned} P_j(\mathbf{x_{jt}}, \mathbf{x_{-jt}}) &= \mathbb{P}(s_j(\mathbf{x_{jt}}, \mathbf{x_{-jt}}) + \zeta_{jt} \geq 0.5) \\ &= 1 - \mathbb{P}(\zeta_{jt} \leq 0.5 - s_j(\mathbf{x_{jt}}, \mathbf{x_{-jt}})) \\ &= \frac{\phi}{2} s_j(\mathbf{x_{jt}}, \mathbf{x_{-jt}}) + \frac{1}{2} - \frac{\phi}{4} \end{aligned}$$

Taking the first order conditions with respect to each ideal point dimension gives the following equilibrium conditions:

$$(x_{jkt} - N_{jkt}) = \frac{1}{\widetilde{\lambda_{jt}}} \frac{\widehat{\partial s_{jt}}(\mathbf{x_{jt}}, \mathbf{x_{-jt}})}{\partial x_{jkt}} + \eta_{jkt}, \quad (17)$$

on each dimension k, and where $\frac{\widehat{\partial s_{jt}}(\mathbf{x_{jt}}, \mathbf{x_{-jt}})}{\partial x_{jkt}}$ is the derivative of the demand function with respect to candidates' position on dimension k, recovered from the demand estimation and $\widetilde{\lambda_{jt}} = \frac{4\lambda_{jt}}{\phi Q}$. I therefore only recover the strength of party discipline, relative to candidates' rent

[7] While not an uncommon assumption in political economy (see e.g., Acemoglu, Robinson, and Santos (2013)), uniform shocks lead to a linear relationship between vote shares and candidates' objective function. Supplemental Appendix H therefore shows that relative estimates of λ under an alternative distributional assumption for the shock, using a Logistic distribution, give very similar results.

if elected and the support of the shock. Intuitively, the larger the support of the shock and the greater the rent, the larger the actual level of party discipline will be for a given parameter $\widetilde{\lambda}$.

I use two different measures of leadership positions (N_{jt}): (i) the average across party leaders only (Majority/Minority leader, Speakers, Caucus and Conference Secretaries and Chairs), (ii) a simple average over all candidates.

5.2 Identification

Equation (17) cannot be estimated by OLS due to a simultaneity issue, where the demand-side derivative depends on the error term η_{jkt}. For instance, a candidate with a personal preference for progressive cultural positions ($\eta_{\text{cultural}} < 0$) may adopt a more progressive stance (lower x_{cultural}), which in turn influences the demand derivative the candidate faces, creating an endogeneity concern. The underlying hypothesis is that district demographics affect the ideology of candidates only through their impact on demand.

I therefore use the congressional district demographics as instrumental variables for the predicted vote share derivative, these instruments are relevant by construction and are exogenous under the assumption that candidates' idiosyncratic ideological shocks are not systematically correlated with district demographics.

The parameters are estimated by GMM with the following moment conditions:

$$\mathbb{E}[w_{jt} \cdot \eta_{jkt}] = 0 \tag{18}$$

where w_{jt} are the district-level demographics and η_{jkt} the candidate-specific shock on each topic k.

Figure A.14 in appendix presents Monte Carlo simulations demonstrating the proper identification of the supply-side parameters. Appendix Figure A.15 shows the intuition behind the supply-side estimation. I recover the strength of party discipline from the slope of the function linking candidate positions to the demand derivative in their congressional district. The larger the amount of party discipline the flatter the curve is; corresponding to situations in which candidates do not have a lot of leeway to adjust their positions to their local conditions.

5.3 Supply Estimates

Table 3 reports the estimated parameters, for each period and for each party. A higher λ indicates a higher cost, in terms of votes, for a candidate to deviate from the party line. I report results from three specifications, the first just uses a simple average as measure of party leadership position, the second uses a weighted average of party leaders and the third uses also a the weighted average of party leaders but excludes party leaders from the analysis. All specifications give similar estimates. The parameter λ in 2000 to 2010 is almost three times larger in the Republican Party than the Democratic Party indicating a stronger level of party discipline for Republican candidates. Party discipline has increased over time, with λ in 2012 to 2020 being almost three times larger than in 2000 to 2010, both in the Democratic and the Republican Party. This echoes previous findings documented in Congress by Canen et al. (2020) and Canen et al. (2021) or through campaign contributions from party PACs (Cox and Shapiro, 2024). Cox and Shapiro (2024) also find that the Republican leadership places a higher penalty on policy deviation than the Democratic leadership.

For a specific candidate in a district, increased party discipline results in electoral losses if they fail to sufficiently align their positions with those of their constituents. In practice, this trend also leads to a uniformization of candidates within each party across the country, and a sharper geographical divide between the two parties.

Note that the interpretation of λ in terms of party discipline here is in a broad sense. I do not observe the direct constraint exerted by the party leadership on candidates to adjust their positions. Rather, I am attributing any systematic deviation from the optimal candidate position to be a consequence of party discipline. This could include, for instance, changes in the selection of candidates towards candidates who are closer ideologically to the party leadership (any systematic deviation of $\boldsymbol{\eta_{jt}}$ towards $\mathbf{N_{jt}}$ will be attributed to party discipline), either through the primary process or candidates' decision to run for office. Overall, the objective of this supply model is to capture a trade-off between local and federal dimensions, where party discipline captures the strength of the federal over the local dimension.

	λ		
Dem 2000-2010	0.0267	0.0267	0.0147
	[0.0231, 0.0316]	[0.0231, 0.0316]	[0.0127, 0.0167]
Dem 2012-2020	0.1068	0.1075	0.0660
	[0.0845, 0.1450]	[0.0849, 0.1464]	[0.0412, 0.0909]
Rep 2000-2010	0.0900	0.0898	0.0507
	[0.0631, 0.1565]	[0.0630, 0.1564]	[0.0312, 0.0702]
Rep 2012-2020	0.3092	0.3024	0.1267
	[0.1569, 0.7534]	[0.1548, 0.4452]	[0.0105, 0.2423]
Leadership Measure	Simple Average	Party leaders only	Party leaders only
Sample	All	All	Excluding Party Leaders

Table 3: Estimated supply parameters

6 Political Realignment: Demand vs. Supply Factors

The previous two sections have recovered the factors determining voters' choice over candidates depending on their positions and candidates' choice of positions depending on the composition of their district and party dynamics. With these estimates at hand, I can simulate counterfactual equilibrium outcomes to understand what would have happened if any demand-side or supply-side factors had evolved differently. Each counterfactual scenario is characterized by a set of parameters that give a unique equilibrium defined by $(\mathbf{x}^*, \mathbf{s}^*) = f\left(\mathbf{m_t}, \boldsymbol{\beta_t}, \mathbf{N_t}, \boldsymbol{\lambda_t} \middle| F_t\left(\mathbf{w}; p\right), \boldsymbol{\alpha_t}, \boldsymbol{\xi_t}, \boldsymbol{\eta_t}\right)$ where $\mathbf{x}^*, \mathbf{s}^*$ are vectors of candidate positions and vote probabilities, $\mathbf{m_t} = (m_{p,d})_{\forall p,d}$ is a redistricting scenario, that is a map of precincts to districts. $F_t(\mathbf{w})$ is the distribution of demographics in each precinct, $\boldsymbol{\beta_t}$ are voters' ideological preferences, $\boldsymbol{\alpha_t}$ are voters' partisan preferences, $\boldsymbol{\xi_t}$ is a vector of precinct-level taste shocks, $\mathbf{N_t}$ is the vector of national level party positions, $\boldsymbol{\lambda_t}$ is the strength of party discipline, and $\boldsymbol{\eta_t}$ is a vector of candidate-level ideological shocks.

As emphasized above, this article is only able to study the impact of changes in leadership positions ($\mathbf{N_t}$) on vote shares through their subsequent influence on local House candidates. While leadership positions likely affect voters' overall perception of the party (α_i), this relationship cannot be causally estimated. For this reason, this section focuses exclusively on assessing the relative impacts of factors related to local candidates' ideology $(\mathbf{m}, \beta_\mathbf{t}, \mathbf{N_t}, \lambda_\mathbf{t})$, holding all other elements at their realized value in 2020.

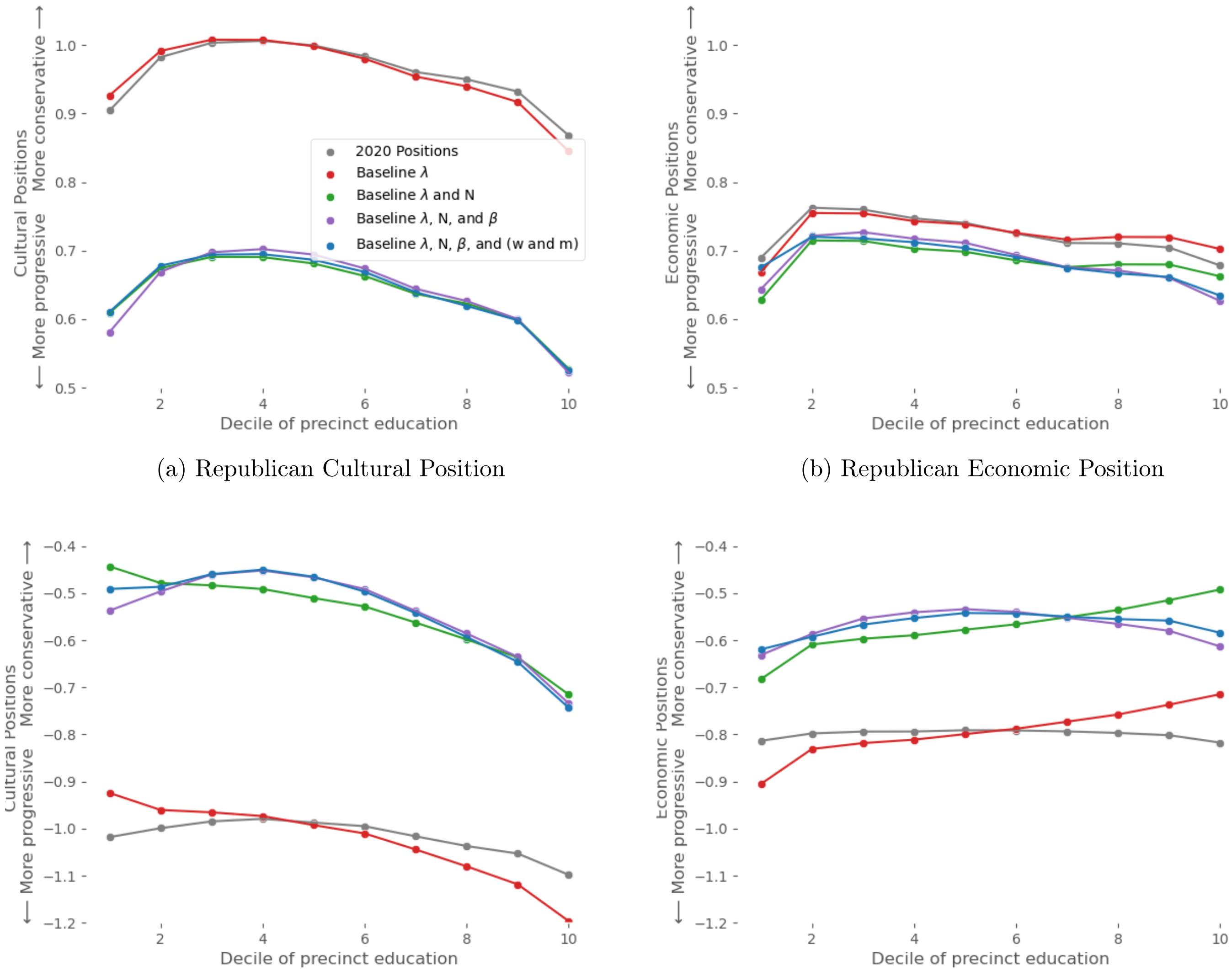
Changes in candidate positions Under each scenario, I obtain new equilibrium positions of candidates as the solution to a fixed point algorithm where each candidate plays their best response to the other's strategy. I solve for the fixed point by using an imitation game algorithm (McLennan and Tourky, 2005; Batista, Coleman, Furusawa, Hu, Lunagariya, Lyon, McKay, Oyama, Sargent, Shi, et al., 2024). Using these counterfactual candidate positions as inputs to the demand system, I generate counterfactual electoral outcomes.

Figure 9 visually depicts the impact of all four factors on candidate positions. Each subplot presents the average positions of candidates by decile of precinct education. Note that candidates choose their positions at the congressional district level, which encompasses multiple precincts. However, while districts may change, precincts[8] provide a basis for comparison as stable units. Analyzing precincts also enables me to assess the impact of redistricting — the reallocation of precincts to districts.

Starting with the realized distribution of candidate positions, I first examine the counterfactual positions if party discipline (λ) had not increased. This scenario results in a steeper

[8] Note that I am using the term "precinct" here to refer to the 2010 census block groups. Some precincts also change over time.

slope for each curve, as candidates have more flexibility to adapt to their local conditions. In addition to holding party discipline constant, I also analyze counterfactual positions while keeping party leadership positions unchanged. These leadership positions lead to a vertical shift in candidate positions: Democratic candidates adopt more progressive stances, while Republican candidates move toward more conservative ones. Changes in voter preferences similarly affect the steepness of each curve, reflecting shifts in the educational gradient of voter preferences. Finally, I reassign each precinct to its initial congressional district, holding the map $\mathbf{m}$ fixed, as well holding the demographic composition (w) of each precinct as fixed. Although the 2010 redistricting created more ideologically homogeneous districts (see Appendix Figure A.16), its overall impact on changes in candidate positions appears to be negligible.



(a) Republican Cultural Position

(b) Republican Economic Position

(c) Democratic Cultural Position

(d) Democratic Economic Position

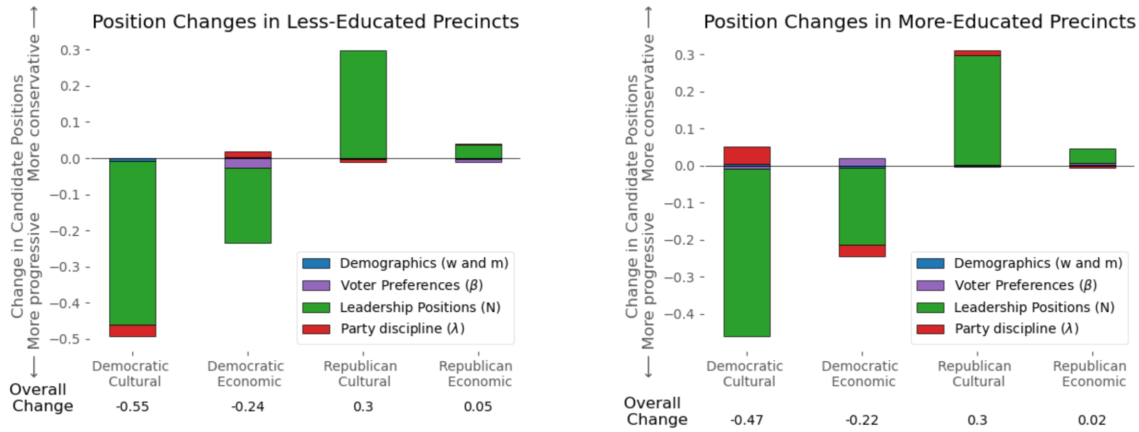
Figure 9: Counterfactual Candidate Positions.

Notes: The figure depicts candidates' predicted 2020 positions across various counterfactual scenarios, plotted against precinct education levels. Each line shows positions under a different counterfactual scenario. The grey line shows the realization of positions in 2020. The red line holds the party discipline parameters (λ) as fixed. The green line holds both λ and the leadership positions $\mathbf{N}$ as fixed, the purple line holds λ, $\mathbf{N}$, and voter preferences (β) as fixed, the blue line holds λ, $\mathbf{N}$, β, and voters' demographics (w) and redistricting $\mathbf{m}$ as fixed.

Given that the impact of each factor is non-linear, the order in which each parameter is changed affects their relative contributions to the overall change. I use a Shapley value decomposition (Shapley et al., 1953), as in Guriev, Henry, Marquis, and Zhuravskaya (2023), which compares the marginal impact of each factor across all possible combinations of the other factors. Appendix Table shows the marginal contribution of each variable separately.

Figure 10 shows the decomposition of changes in candidate positions, considering all driving factors separately for less-educated and more-educated voters. It compares the last election in the sample, 2020, with the average of the baseline period (2000 to 2010). Starting with Democratic candidates' positions on cultural questions, most of the shift toward more progressive positions can be explained by the change in the position of the leadership ($\mathbf{N_t}$). In less-educated precincts, increased party discipline has amplified this shift, preventing candidates from moderating their cultural positions to align with local constituent demands. Conversely, in more-educated precincts, party discipline has restrained candidates from adopting more progressive cultural stances. Note that party discipline moderates Democratic candidates' cultural positions more in more-educated precincts than in less-educated ones. This is due to the concentration of highly educated precincts in educated districts, as illustrated in Appendix Figure A.16. This concentration is primarily due to urban areas having their own districts, echoing some findings from Rodden (2019).

The change in Democratic candidates' economic positions is generally smaller and is also primarily driven by shifts in leadership. Party discipline plays an opposite role here compared to cultural positions. The rise in party discipline has prevented candidates from adopting more progressive stances in less-educated precincts and from becoming more conservative in more-educated precincts. The changes observed among Republicans, though smaller, follow a similar pattern. On the demand side, shifts in voter preferences account for only a small portion of the variation in candidate positions, with a tendency to push candidates toward more conservative economic positions in more-educated precincts and more progressive positions in less-educated precincts. Redistricting and the change in voter demographics only have a negligible impact.



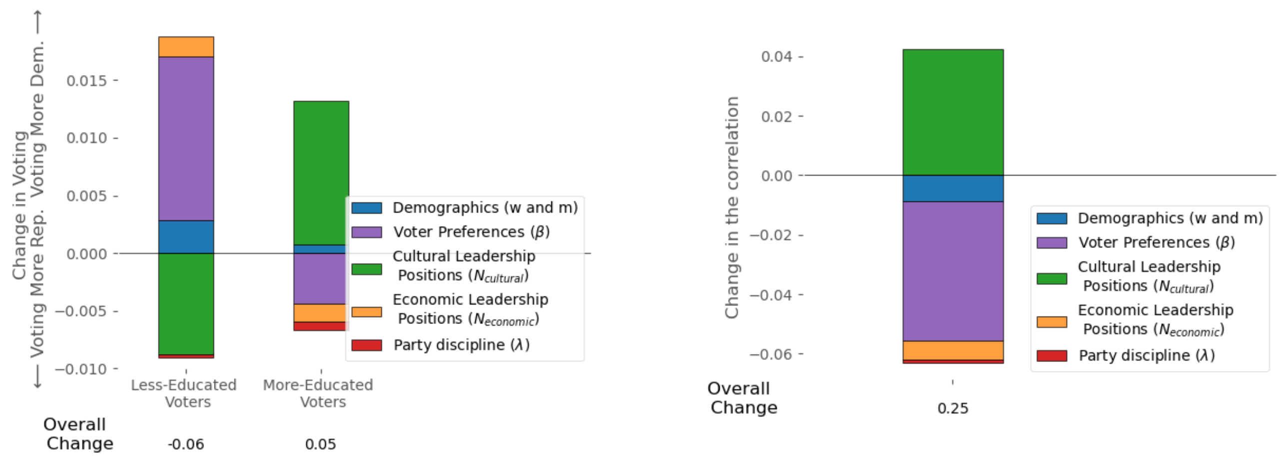
(a) Less-educated precincts

(b) High-educated precincts

Figure 10: Shapley Value Contributions to the Change in Candidate Positions, by Education

Notes: The figure shows the relative Shapley contributions of congressional redistricting $\mathbf{m}$, the change in voter preferences $\boldsymbol{\beta}$, the change in leadership positions $\mathbf{N}$, and the change in party discipline $\boldsymbol{\lambda}$ between 2020 and the average of the baseline period (2000 to 2010). Below each bar, the total changes in positions for that period, including unexplained elements, are reported.

Changes in voting behaviors Next, I assess the relative impact of supply-side and demand-side factors on voting behavior, focusing on educational divides in vote distribution. Panel (a) of Figure 11 presents the 2020 Shapley value contributions of demand-side and supply-side factors, separately for less-educated and more-educated voters. Beginning with voter ideological preferences, the change in β has resulted in Democratic candidates securing larger vote shares among less-educated voters and smaller vote shares among more-educated voters. This can be mostly explained by the rise of the educational gradient on economic question, leading to stronger preferences of less-educated voters for progressive economic policies. These changes counteract the overall pattern of political realignment. The shift in voter preferences has mitigated the broader voter realignment; without this change, the realignment would have been more pronounced. Changes in voter demographics and in redistricting have only a small impact. Overall, demographic changes benefited Democratic candidates among both less-educated and more-educated voters. This benefit can be explained by the population becoming more educated and less white, especially so among less-educated voters. In contrast, supply-side factors have driven less-educated voters toward the Republican Party and more-educated voters toward the Democratic Party. Specifically, the shift in leadership positions on cultural issues has caused Democratic candidates to lose support among less-educated voters while gaining votes from more-educated voters. This effect has been only partially offset by changes in positions on economic issues. The underlying dynamic can be summarized as follows: while parties were equally polarized on economic and cultural dimensions in the early 2000s, parties, especially the Democratic Party, have since diverged more on cultural issues than economic ones. Less-educated voters, who tend to prefer more progressive economic policies but more conservative cultural policies, now experience a lower utility from voting for Democratic candidates. Conversely, more-educated voters, who were previously deterred by the Democrats' progressive economic stance relative to Republicans, now enjoy a higher utility when voting for Democratic candidates as cultural issues have gained prominence.



(a) Democratic Voting, by Education

(b) Correlation between Education and Democratic Voting

Figure 11: Shapley Value Contributions to Changes in Voting Patterns.

Notes: The figure shows the relative Shapley contributions of demand- and supply- factors on voting behaviors. Panel (a) studies changes in votes, by education. Panel (b) studies the correlation between education and Democratic vote shares. Each panel shows the relative contributions congressional redistricting $\mathbf{m}$, the change in voter preferences $\boldsymbol{\beta}$, the change in leadership positions $\mathbf{N}$ on both the cultural and economic dimensions, and the change in party discipline $\boldsymbol{\lambda}$ between 2020 and the average of the baseline period (2000 to 2010). For each voter, I compare their probability of voting for the Democratic candidate under each counterfactual scenario. Below each bar, the total vote changes for that period (Panel (a)) and the total correlation changes (Panel (b)), including unexplained elements, are reported.

Lastly, Panel (b) of Figure 11 assesses the Shapley contributions of demand-side and supply-side factors to the change in the correlation between education and Democratic voting at the individual level. This correlation increased by 25 points between the 2000-2010 baseline average and 2020, the final year in the sample. Without the shift in voter preferences, this correlation would have increased by an additional 5 points. Similarly, without the change in demographics, the correlation would have increased by an extra point. In contrast, without the change in the leadership cultural positions, the correlation between education and Democratic vote would have been lower by about 4 points. The change in positions on the economic dimension has moderated that change on cultural positions. The change in party discipline has a net effect of almost zero, since it increases the losses among less-educated voters but reduces the losses among most-educated voters.

As already mentioned above, the framework developed in this paper focuses on district-level variation in ideology and thus does not explain the entirety of the variation in voter choices. A significant portion of the variation is captured by the parameters α_{it}, which reflect generic voter preferences for Democratic candidates, independent of ideology. These parameters are likely shaped by changes in leadership and the positions of upper-level candidates, highlighting the coattail effect (see, e.g., Calvert and Ferejohn (1983)). While the influence of such presidential and senatorial candidates, as well as party positions, on House candidate vote shares cannot be causally identified within the current framework, it is reasonable to conjecture that similar preferences apply to these upper-level candidates, suggesting that the results in this paper may represent a lower bound of the true effect.

It is important to note that the primary driver of realignment is not simply party polarization, but rather the divergence in polarization across different issue dimensions. Specifically, the greater polarization on cultural issues compared to economic issues has played a decisive role. If polarization on economic issues had increased in parallel with cultural issues, the observed realignment would have been less pronounced. The next section examines the political implications of this differential polarization, particularly for issues that encompass both economic and cultural dimensions, such as environmental policy.

7 Environmental Issues: Cultural or Economic?

As a final step in my analysis, I employ the model to assess the political consequences of the differential polarization discussed in previous sections on voters' support for environmental policies. Environmental issues offer a compelling case study not only because they have recently gained prominence in political discourse and public opinion (Dunlap et al., 2016; Egan et al., 2022), but also because they encompass both economic and cultural dimensions (Besley and Persson, 2023). Candidates can, for instance, advocate for environmentally progressive policies that emphasize cultural themes, such as climate education, climate justice, or 'believe in science' initiatives, or focus on policies with economic implications, like a "Green New Deal." The same applies to conservative stances on these issues. I begin by examining how parties balance cultural versus economic dimension within each topic.

Appendix Figure A.17 shows, for each political topic, the relative weighting of the cultural versus economic dimension, defined as the ratio of coefficients from a linear regression of candidate topic-specific positions on their cultural and economic ideal points; $\rho = \frac{\gamma_{cult}}{\gamma_{cult}+\gamma_{econ}}$.[9] Environmental issues stand out in the figure as the topic that is closest to both the economic and cultural dimensions, with a cultural weighting around 0.5. Additionally, there appears to be

[9] Since each topic is originally part of either the economic or cultural dimension, I re-estimate separately an ideal point on each topic and on each dimension, excluding that topic.

a significant difference between the two parties, with a much larger cultural weighting for Democratic candidates. In other words, Democratic candidates who are progressive on environmental issues tend to be progressive on cultural issues rather than economic ones. The reverse is true in the Republican Party, Republican candidates who are conservative on environmental issues tend to be conservative on economic issues rather than cultural ones. These differing weightings between parties suggest that parties may have some flexibility in how they position themselves on a topic, for a given level of progressiveness. To capture this idea of leadership weighting on one topic, I represent the environmental leadership position as a vector in a (economic, cultural) policy space with the environmental position as the norm and the weighting parameter ρ as the angle. The strength of the cultural and economic dimensions in the leadership position is then obtained by getting the polar coordinates of the vector:

$$N_l^{cult} = |N_l^{environment}| \cdot \sin \rho_l \tag{19}$$

$$N_l^{econ} = |N_l^{environment}| \cdot \cos \rho_l, \tag{20}$$

with $l \in \{D, R\}$.

There are multiple interpretations to ρ_l. The first is that there are various policy tools available to achieve the same goal (e.g., reducing carbon emissions), and politicians can choose a mix of economic or cultural policies to offer. The second interpretation is a framing one: to motivate a policy, politicians can appeal either to values or to material conditions. Since voters have heterogeneous preferences regarding values and material aspects, different framing strategies lead to different coalitions of support (Enke, 2020; Besley, 2023; Besley and Persson, 2023; Chong and Druckman, 2007).

Re-projecting the environmental positions in an (economic,cultural) policy space allows for the evaluation of voters' support for different ρ_l, using the demand estimates from section 4. For example, it is possible to evaluate a counterfactual scenario where Democratic environmental positions remain as left-wing as they currently are but adopt the same economic weighting as those of the Republican leadership, assessing how this shift would influence voter support.

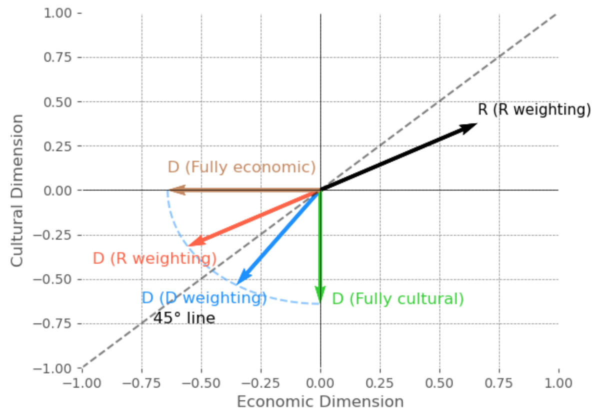
Previous sections have shown that voters who support progressive cultural policies do not necessarily support progressive economic policies, and vice versa. As a result, for an equally left-wing environmental policy, the type of voters who will back different policies depends on their cultural versus economic weighting. For each counterfactual leadership parameter ρ, I derive new optimal candidate positions using the supply estimates from Section 5, and projected vote shares among different voter groups, assuming the environment is the only issue on which candidates are campaigning.[10]

[10] Studying the environment in isolation is not meant to suggest that it will become the dominant issue but rather

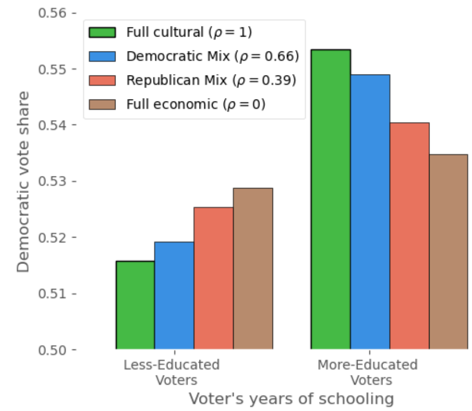
Panel (a) in Figure 12 presents the various counterfactual scenarios. The first scenario (D weighting) uses the current Democratic leadership weighting and positions. The second scenario applies the current Republican weighting ($\rho = 0.39$) to the Democratic leadership. The remaining scenarios explore leadership positions that are either fully cultural or fully economic .I derive equilibrium candidate positions for both Democratic and Republican candidates across various scenarios, with the Republican leadership position remaining fixed throughout. Although this assumption is an oversimplification, modeling the endogenous selection of leadership positions is beyond the scope of this paper.

Panel (b) in Figure 12 shows the resulting counterfactual levels of support. I find that using the current Democratic weighting ($\rho = 0.66$) leads to a larger vote share among more-educated than less-educated voters. Switching to a Republican weighting ($\rho = 0.39$) increases candidates' vote share among the less-educated by 1 point while it decreases the support from more-educated voters by almost 1.5 points. The figure also reports predicted vote shares for Democratic leadership positions that would be either fully cultural or fully economic. All in all, environmental policies offered by candidates that are framed as more economic, such as a "Green New Deal" tend to draw more support from less-educated voters, but less from more-educated voters. Interestingly, more cultural environmental policies receive higher overall support, as more-educated voters are more responsive to candidate policies, though such policies tend to deter less-educated voters. In a companion paper (Bombardini et al., 2024), we adapt the framework developed in this paper specifically to environmental issues, and precisely examine how demand and supply respond to changes in environmental conditions and employment opportunities in the environmental sector.

to understand the type of voter coalitions that would support different environmental policies. Measuring the relative importance that voters assign to the environment versus other issues is left for future research.



(a) Leadership Counterfactual Environmental Positions



(b) Counterfactual Vote Shares

Figure 12: Economically Oriented Progressive Environmental Positions Attract More Support from Low-Education Voters

Notes: For each cultural-economic mix, I compute counterfactual levels of support for a Democratic candidate who would campaign only on the environment, using their current position but varying the framing towards economic or cultural. I use the current weighting of Democrats and Republicans as well as a full cultural and a full economic framing. For example, for a Democratic candidate campaigning only on the environment with a leadership weighting of $\rho = 0.66$ (current Democratic mix) would get 51.5% support from less-educated voters and 55% support from more-educated voters.

8 Conclusion

Separating supply and demand is a major challenge in the study of economic markets, and the political arena is no exception. It is arguably the "market" where demand and supply are most intertwined. Without clear costs on the supply side, the policies offered by politicians could be seen as purely endogenous to voter preferences. As a result, the observed equilibrium outcomes, such as electoral results, cannot be simply understood as voter choices among political proposals. Moreover, many determinants of voter choices, like candidate positions, are unobserved or difficult to measure. These challenges have hindered scholars from fully estimating a political equilibrium model. To better understand recent political shifts, such as increased polarization and realignment, it is crucial to disentangle the contributing demand-side and supply-side factors.

Multiple pieces of evidence have shown that on the one hand parties have moved away from each other (Hare and Poole, 2014; Gentzkow et al., 2019) and that on the other hand voters are no longer voting for whom they were voting for twenty years ago (Kitschelt and Rehm, 2019; Gethin et al., 2022). This paper connects these two facts and tries to remedy the measurement and endogeneity issues aforementioned by building and estimating a multidimensional political equilibrium model of joint candidates' choice of positions and voters' choice of candidates.

I show that less-educated voters prefer more conservative cultural policies but more progressive economic policies, and increasingly so over time. In parallel, political parties have increasingly polarized on cultural issues rather than on economic ones, and rising party discipline has constrained local candidates from adapting to their local conditions. By combining these phenomena, I demonstrate through counterfactual scenarios that most of the shifts in candidate positions and changes in voter choices can be attributed to supply-side factors. In contrast, concurrent changes in voter preferences among less-educated voters have favored the Democratic Party, suggesting that the political realignment would have been even more pronounced without these changes in preferences.

Finally, I employ the empirical framework developed in this paper to assess counterfactual levels of support for environmental policies. I show that more economically-oriented environmental policies would draw more support from less-educated voters than the equivalent culturally-oriented policies. However, Democratic candidates' positions on the environment in the last two decades have been much more cultural than economic, compared to Republicans' positions.

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Appendix

Contents

A Notation

Symbol	Description
p	index of precinct (block-group)
t	index of election year
j	index of candidate
k	index of topic, with K the total number of topics
i	index of voter
$g(p)$	precinct "pair"
$d(p)$	district of precinct p
x_{jkt}	position of candidate j on topic k in election t
x_{kt}	difference in position between the Democrat and the Republican on topic k in election t
v_{ikt}	ideology of voter i on topic k in election t
ξ_{jpt}	precinct p unobserved taste shock for candidate j at election t
ξ_{jt}	Common district-level taste shock for candidate j at election t
$\Delta\xi_{jpt}$	Precinct p specific deviation from the district-level taste shock for candidate j at election t
ξ_p	precinct p' unobserved constant taste shock for Democratic candidates
$\Delta\xi_{g(p)t}$	Precinct pair unobserved taste shock for Democratic candidates at election t
ϵ_{ijt}	Voter i's unobserved taste shock for candidate j at election t
β_{ikt}	Voter i's preference over candidate's positions on dimension k at election t
α_{it}	Voter i's "non-ideological" partisanship at election t
η_{jkt}	Candidate j's unobserved preference for topic k
D_{it} (resp. D_{pt})	Demographics of voter i (resp. precinct p) at election t
$s_{jpt}(.)$	Candidate j's vote share in election t in precinct p
ν_{it}	Unobserved voter i heterogeneity in preferences at time t
Π_{jt}	Candidate j objective function at time t
λ_{jt}	Parameter of party discipline at election t in candidate j's party
N_{jkt}	Position of party P's leadership on dimensions k at time t
$P_{D,t}$	Joint distribution of voters' demographics at time t
$\mathbf{m}$	Mapping of precincts p to districts d: $\mathbf{m} = (m_{pd})_{\forall p,d}$

B Additional Tables and Figures not shown in the main paper

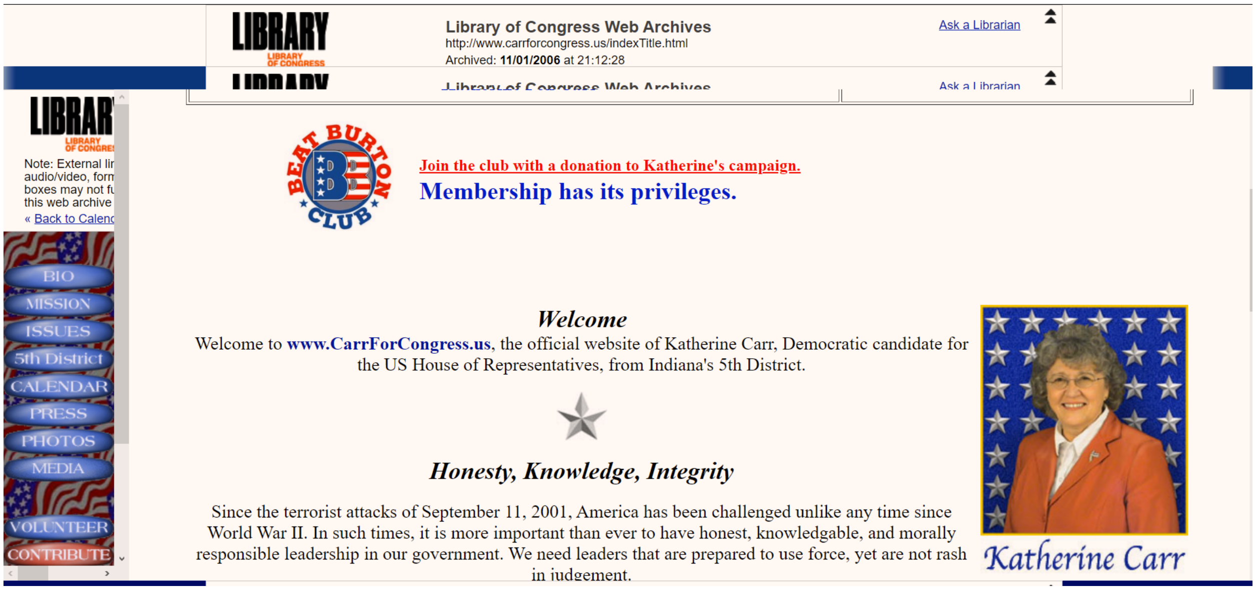
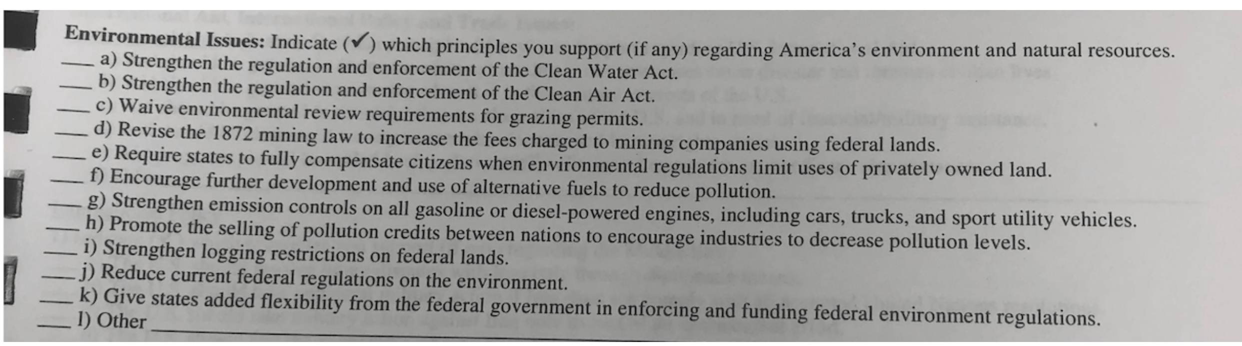


Figure A.1: Example of a website for a U.S. House candidate in Indiana in 2006



Environmental Issues: Indicate (✓) which principles you support (if any) regarding America's environment and natural resources.

___ a) Strengthen the regulation and enforcement of the Clean Water Act.
___ b) Strengthen the regulation and enforcement of the Clean Air Act.
___ c) Waive environmental review requirements for grazing permits.
___ d) Revise the 1872 mining law to increase the fees charged to mining companies using federal lands.
___ e) Require states to fully compensate citizens when environmental regulations limit uses of privately owned land.
___ f) Encourage further development and use of alternative fuels to reduce pollution.
___ g) Strengthen emission controls on all gasoline or diesel-powered engines, including cars, trucks, and sport utility vehicles.
___ h) Promote the selling of pollution credits between nations to encourage industries to decrease pollution levels.
___ i) Strengthen logging restrictions on federal lands.
___ j) Reduce current federal regulations on the environment.
___ k) Give states added flexibility from the federal government in enforcing and funding federal environment regulations.
___ l) Other ___

Figure A.2: Example of candidate survey (environment section in 2002)

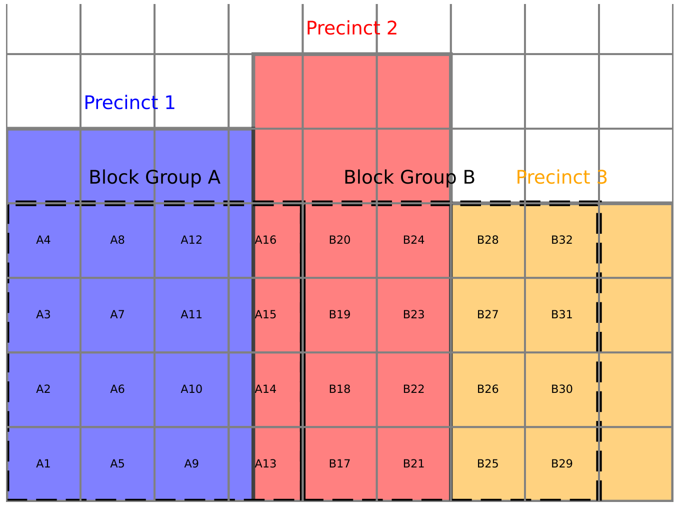


Figure A.3: Precinct votes allocation

Notes: This Figure describes the strategy to allocate votes from the precinct to the block-group-level. Each square of the grid shows a census block. Block groups are shown in green and precincts are shown in blue, red, and yellow.

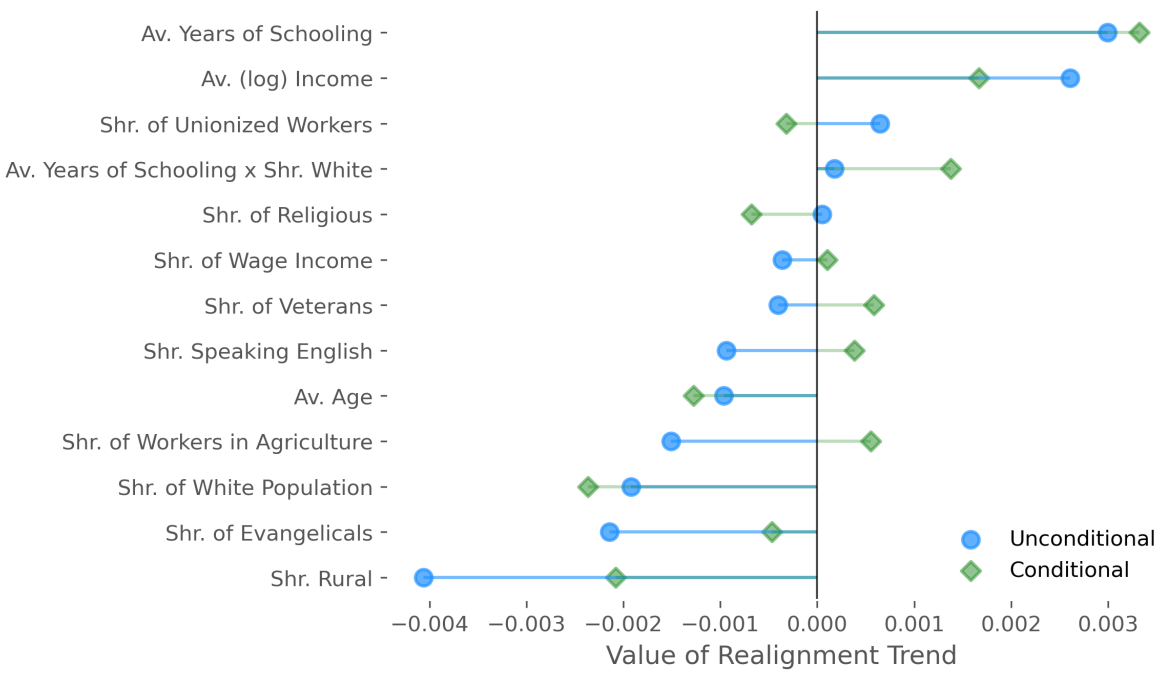


Figure A.4: "Horse race" of demographics in political realignment with unconditional regressions

Notes: The Figure shows the impact of z-score of precinct-level demographic variables on Democratic vote shares. The unconditional regression (shown with a round blue marker) tests for the trend separately for each variable, showing β_2^w from the following linear regression: $S_{dem,p,t} = \sum_w \beta_1^w w_{p,t} + \beta_2^w w_{p,t} \times year_t + \mu_t + \epsilon_{p,t}$ where $S_{dem,p,t}$ is the share of vote obtained by Democratic candidates in precinct p at time t, w_{pt} is the normalized value of the demographic in that precinct at time t, $year_t$ is the year of the election, and μ_t are election fixed-effects. Conditional coefficients are as in figure 2, unconditional coefficients show the results from a regression of each demographic variable separately.

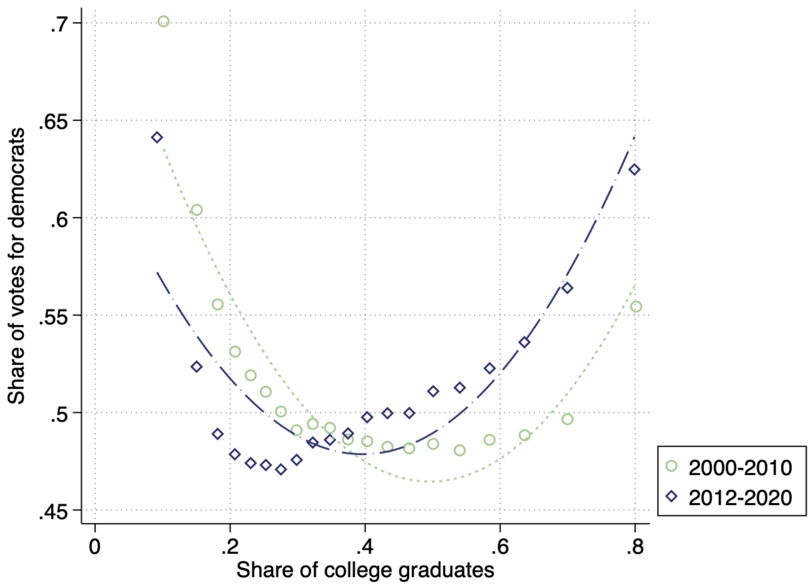
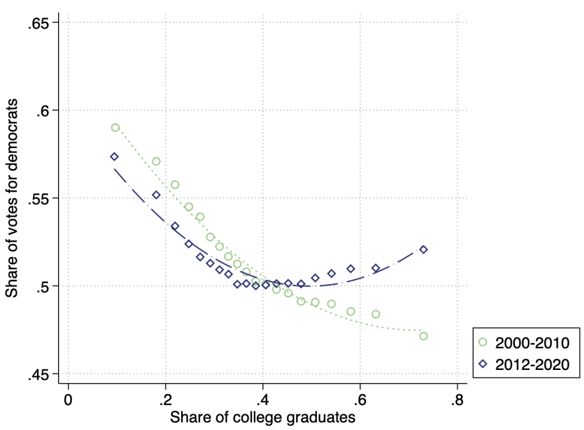
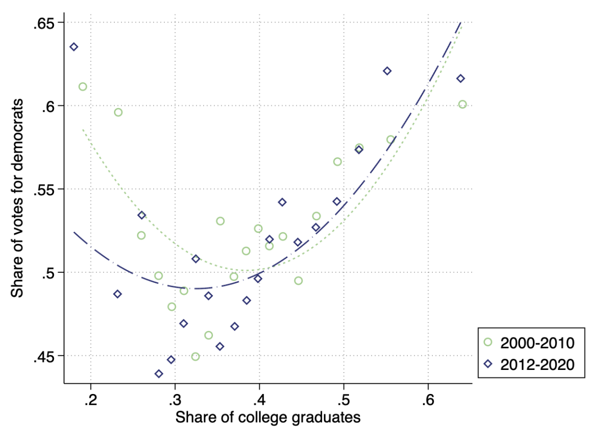


Figure A.5: Relationship between education and Democratic vote.

Notes: Each dot represents 5% of the population. The curve is a quadratic fit of the data. Equal weights is given to each year within each period. Appendix Figure A.7 shows the same relationship separately for each election.



(a) Within-district



(b) Between-district

Figure A.6: Evolution of the within and between congressional district education gradient

Notes: The two Figures show the quantiles of the distribution of education and Democratic votes. Each dot represents 5% of the population. The curve is a quadratic fit of the data. Equal weights is given to each year within each period. The first panel shows the relationship within-district, conditional on congressional district by election fixed effects. The second panel shows the relationship between districts.

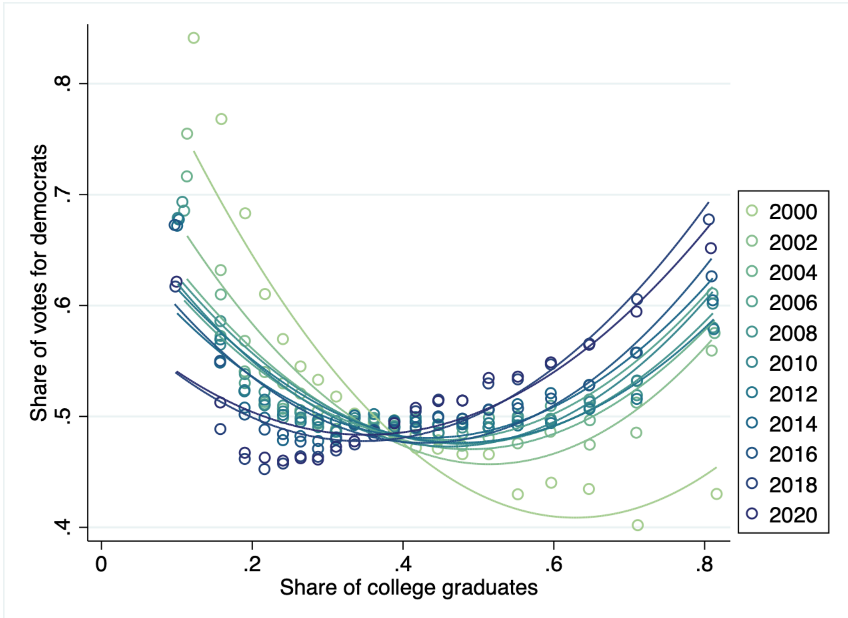
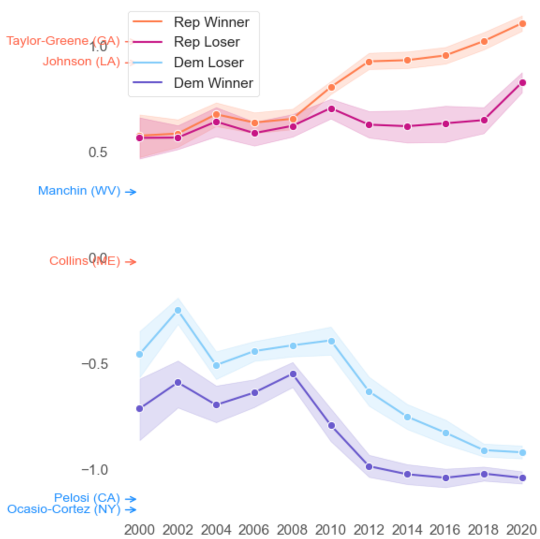
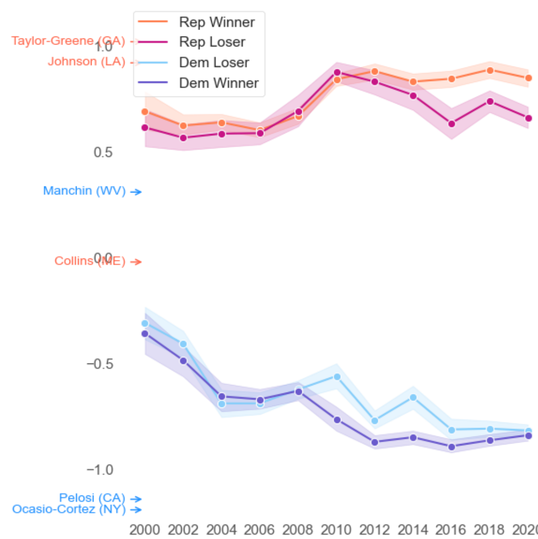


Figure A.7: Relationship between education and Democratic vote, separately for each elections.

Notes: Each dot represents 5% of the population. The curve is a quadratic fit of the data. Equal weights is given to each year within each period.



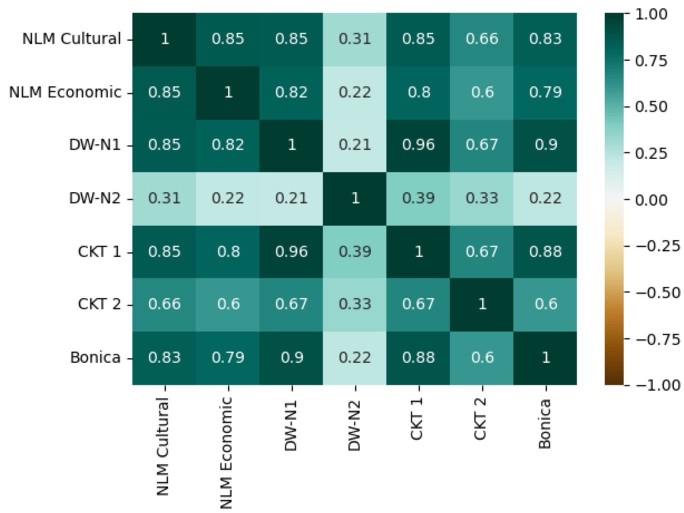
(a) Cultural Positions



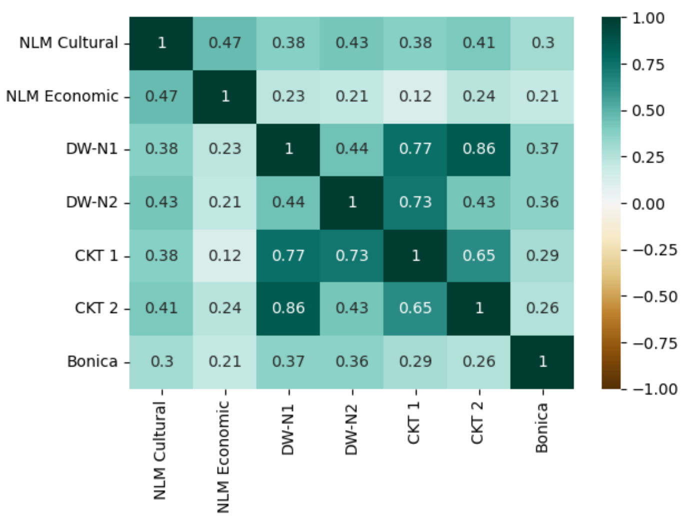
(b) Economic Positions

Figure A.10: Evolution of candidate positions on economic and cultural questions, separated by election winner and losers

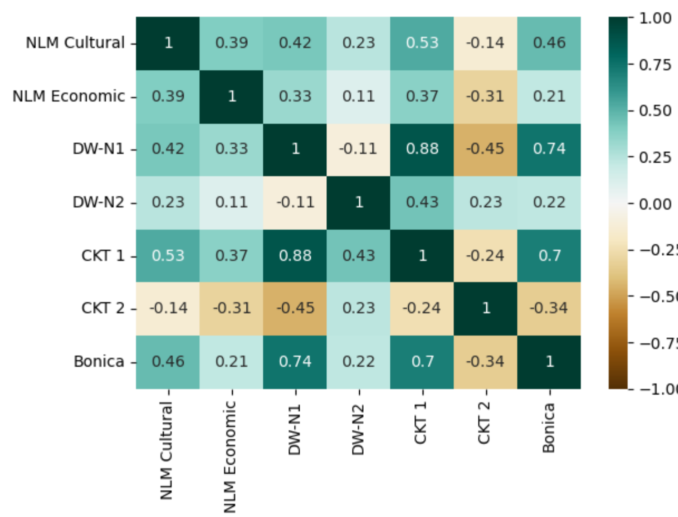
Notes: The figure shows the evolution of the average position of candidates in each party on each dimension, separately for Congressional candidates who have win and those who have lost the election.



(a) All Sample



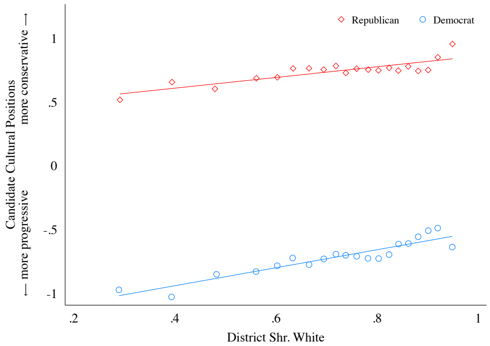
(b) Democrats only



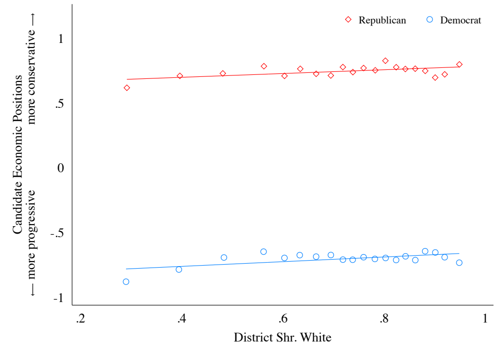
(c) Republicans only

Figure A.8: Comparison between own measures and common measure of ideology

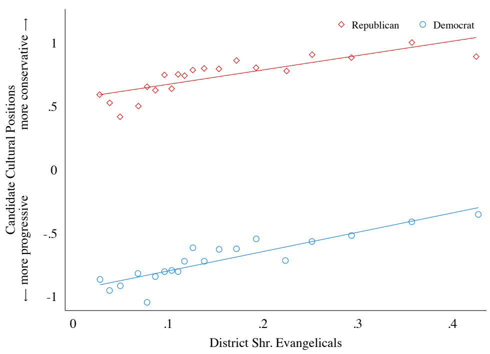
Notes: The first panel shows the pairwise Spearman (rank) correlation between measures computed for this paper (denoted as NLM) and other commonly used measures of ideology. The correlations with DW-Nominate first and second dimensions (DW-N1 and DW-N2) are only for House and Senate winners. The pairwise correlations with Canen, Kendall, and Trebbi (2021) use only Senate election winners. The pairwise correlations with (Bonica, 2014) uses all candidates. The second and third panel show the within-party correlations for Democrats and Republicans, respectively.



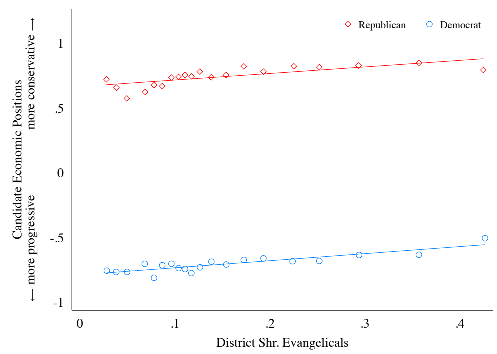
(a) Share of White and Cultural Issues



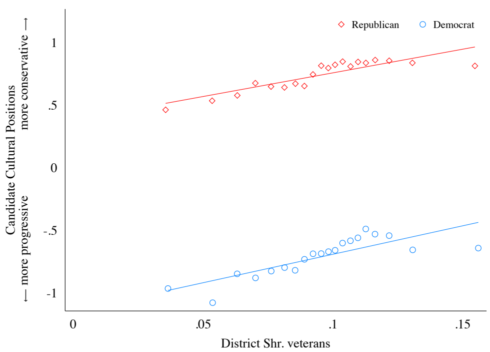
(b) Share of White and Economic Issues



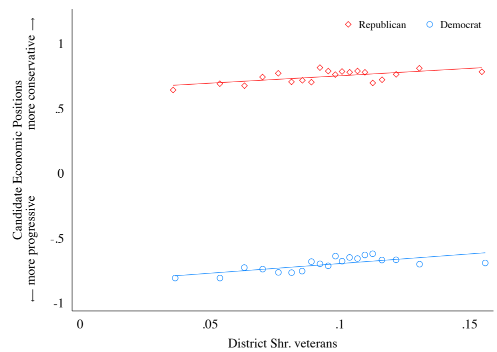
(c) Share of Evangelicals and Cultural Issues



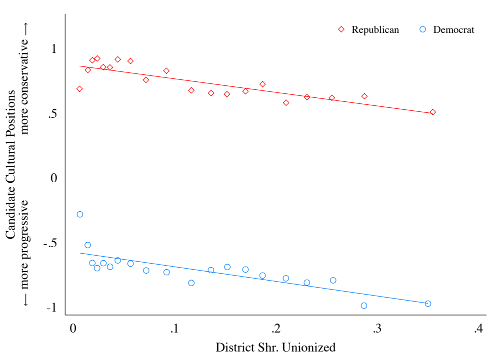
(d) Share of Evangelicals and Economic Issues



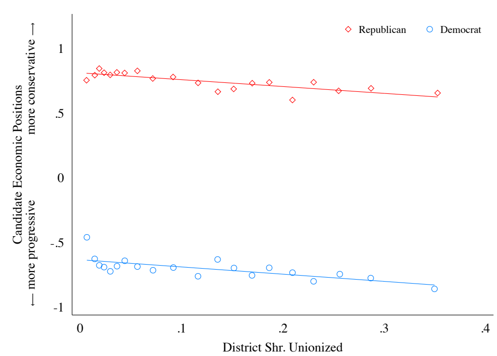
(e) Share of Veterans and Cultural Issues



(f) Share of Veterans and Economic Issues



(g) Share of Unionized and Cultural Issues



(h) Share of Unionized and Economic Issues

Figure A.9: Candidate positions and congressional district composition

Notes: As in Figure 6, each panel shows the relationship between candidate positions and district demographics. Each dot represents 5% of the distribution and shows the average position of candidates, separately for Democrats and Republicans.

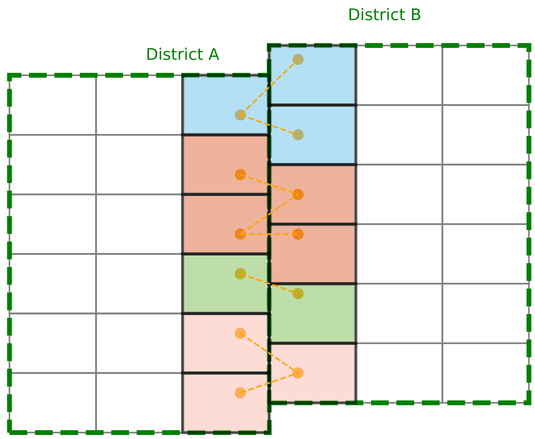


Figure A.11: Construction of precinct *pairs*

Notes: The Figure describes the method adopted to match contiguous precincts with each other. Each square represents a precinct. Each precinct's population-weighted centroid is represented by a dot in the precinct. Each precinct is matched to the precinct to the closest precinct on the other side of the border. Each color represents a precinct "pair".

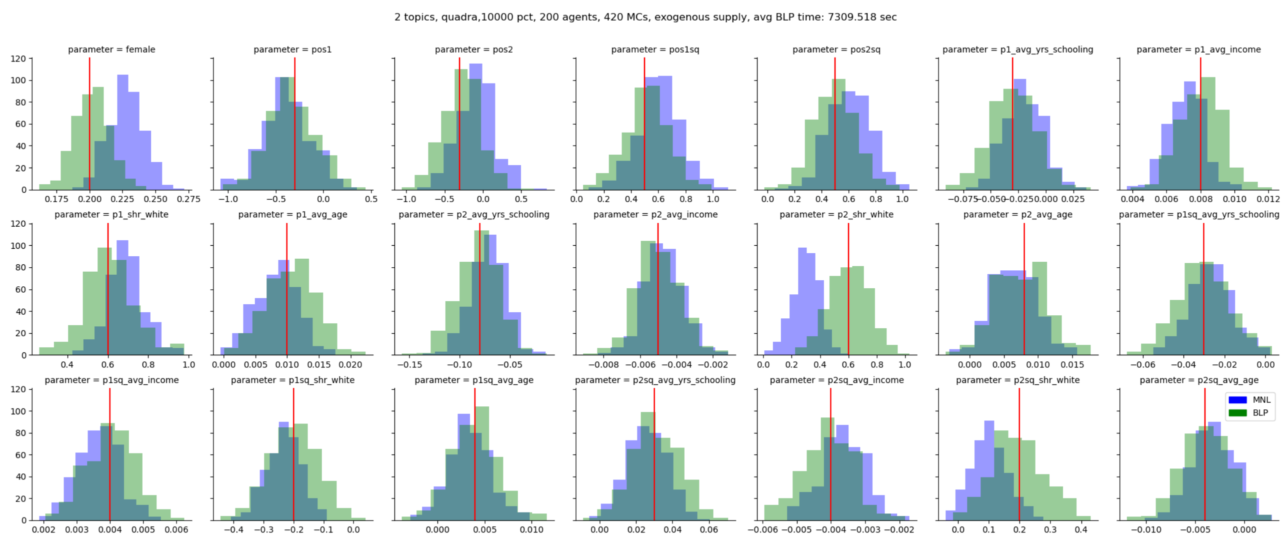


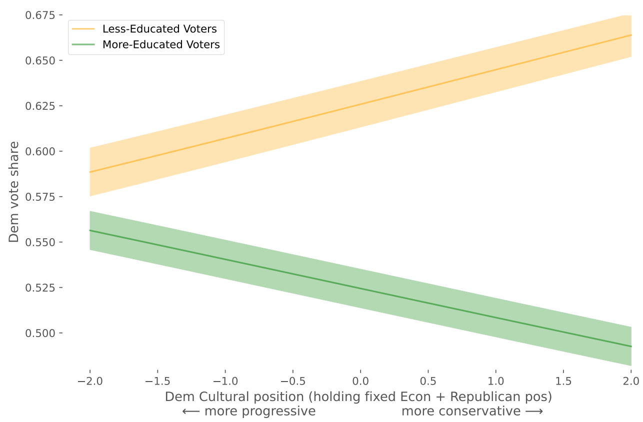
Figure A.12: Distribution of demand-side parameters from 420 monte carlo simulations using 100 ,000 precincts

Notes: Each histogram shows the distribution of parameters, in blue using the multinomial logit (NLLS) and in green using the numerical integration (BLP). The red lines show the true parameters.

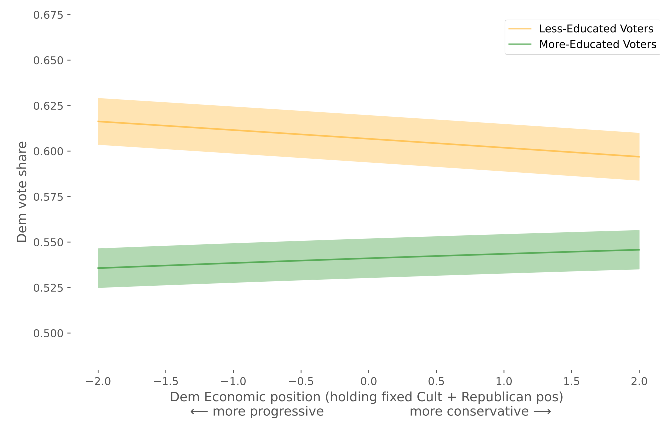
Parameter	MNL (Homogenous voters)				BLP (Heterogenous voters)			
	Bias	MSE	Coverage Proba	Power	Bias	MSE	Coverage Proba	Power
x_1	0.158	0.087	0.933	0.933	0.032	0.089	0.981	0.894
x_2	0.103	0.024	0.837	1.000	0.010	0.019	0.942	1.000
x_1 × yrs schooling	0.320	0.253	0.875	0.394	0.007	0.218	0.971	0.929
x_1 × yrs schooling × race	0.113	0.019	0.779	1.000	0.005	0.008	0.962	1.000
x_1 × race	0.141	0.034	0.740	1.000	0.003	0.027	0.952	1.000
x_1 × age	0.202	0.098	0.885	0.913	0.004	0.076	0.962	0.962
x_2 × yrs schooling	0.130	0.035	0.894	1.000	0.011	0.026	0.971	1.000
x_2 × yrs schooling × race	0.067	0.020	0.933	1.000	0.006	0.019	0.952	1.000
x_2 × race	0.496	0.261	0.010	0.990	0.004	0.031	0.913	1.000
x_2 × age	0.142	0.126	0.904	0.788	0.006	0.139	0.923	0.817
yrs schooling	0.191	0.097	0.885	0.865	0.034	0.086	0.942	0.885
yrs schooling × race	0.105	0.025	0.817	1.000	0.002	0.017	0.952	1.000
race	0.458	0.258	0.433	0.740	0.043	0.102	0.923	0.942
age	0.134	0.160	0.952	0.625	0.058	0.190	0.962	0.712

Table A.1: Statistics on simulated parameters

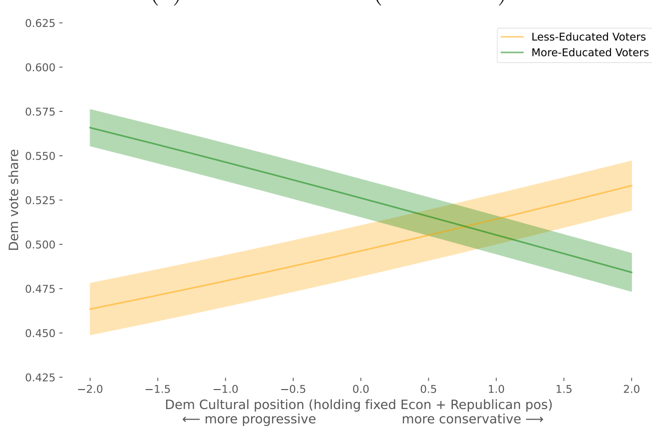
Notes: The table reports statistics of simulations of parameter identifications. For both the model with homogeneous voters: Multinomial Logit (MNL) and the model with heterogeneous voters (BLP), it gives the bias of the estimates, the mean squared error (MSE), the coverage probability, and the power.



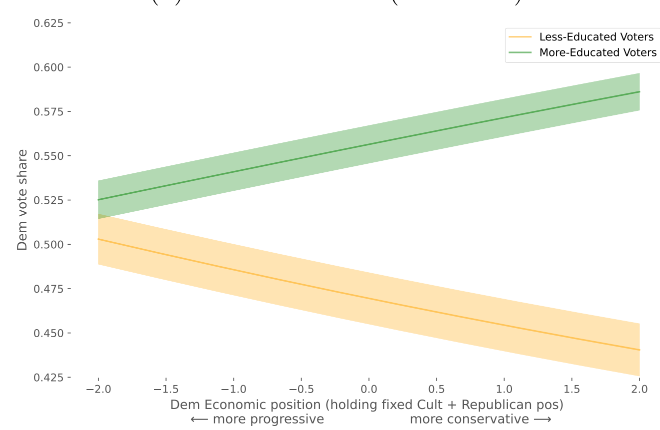
(a) Cultural issues (2000-2010)



(b) Economic issues (2000-2010)



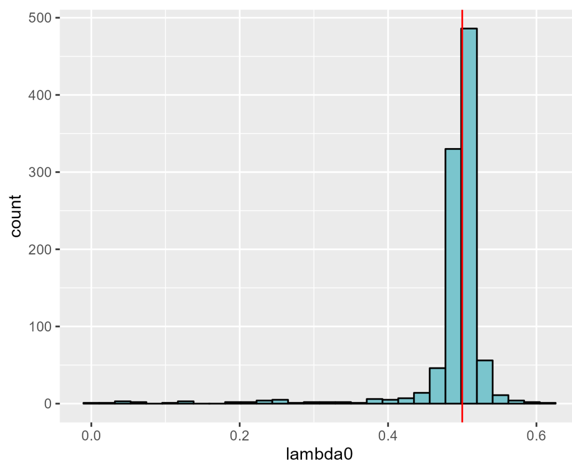
(c) Cultural issues (2012-2020)



(d) Economic issues (2012-2020)

Figure A.13: Deviations from candidate positions and vote shares

Notes: fhe Figure shows the predicted vote shares of Democratic candidates as a function of their position on cultural topic (upper panel) and the economic topic (lower panel), using estimates from the second period with precinct pair by election and precinct fixed effects. Negative values indicate more progressive positions. Each panel holds fixed the position on the other topic and the position of the Republican candidate. 95% Confidence Intervals are reported.



(a) λ_0

Figure A.14: Distribution of supply-side parameters from 420 monte carlo simulations using 435 districts.

Notes: Each histogram shows the distribution of parameters, estimated by GMM. The red line shows the true parameters.

	Outcome: ln(s/(1-s))	
	(1)	(2)
	2000-2010	2012-2020
CultDem - CultRep	0.014	0.015
	(0.032)	(0.016)
EconDem - EconRep	-0.011	-0.029
	(0.028)	(0.017)
CultDem - CultRep × Av. Edu	-0.032***	-0.027***
	(0.010)	(0.005)
CultDem - CultRep × Shr. White	0.077	-0.042
	(0.076)	(0.049)
CultDem - CultRep × Av. Edu × Shr. White	-0.050*	-0.042**
	(0.030)	(0.019)
CultDem - CultRep × Av. Age	0.000	0.000
	(0.002)	(0.001)
EconDem - EconRep × Av. Edu	0.004	0.027***
	(0.009)	(0.006)
EconDem - EconRep × Shr. White	0.110	-0.048
	(0.072)	(0.068)
EconDem - EconRep × Av. Edu × Shr. White	0.035	0.000
	(0.031)	(0.022)
EconDem - EconRep × Av. Age	-0.001	0.003**
	(0.002)	(0.001)
Precinct-pair x Year FE	X	X
Precinct FE	X	X
Observations	82,847	124,075

Table A.2: Estimation of Voter Preferences with Homogeneous Voters (Equation (11))

Notes: This table shows the coefficient from Equation (11): a regression of candidates' log odds ratio on interactions of precinct-level demographics and candidate positions, by period. Each column control for precinct fixed effects and precinct-pair by election fixed effects. Standard errors clustered two ways, by congressional district by year, and by precinct, are reported in parentheses.

	Outcome: ln(s/(1-s))	
	(1) 2000-2010	(2) 2012-2020
Av. Edu	-0.006	0.153***
	(0.011)	(0.010)
Shr. White	-2.500***	-3.088***
	(0.116)	(0.073)
Av. Edu × Shr. White	0.256***	0.387***
	(0.037)	(0.026)
Av. Age	0.008***	-0.005***
	(0.002)	(0.002)
Observations	82,847	124,075

Table A.3: Coefficients from second step (Equation (11))

Notes: This table shows the estimated coefficients from the second step, with homogeneous voters, regressing the fixed effects on voter demographics. Standard errors clustered two ways, by congressional district by year, and by precinct, are reported in parentheses.

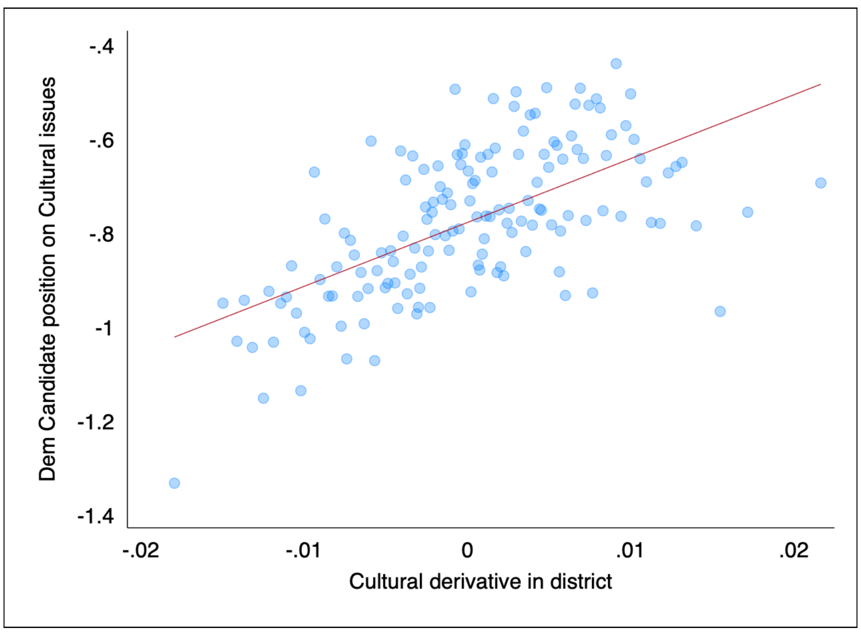


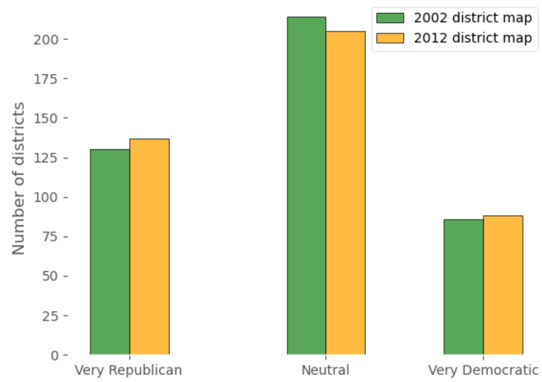
Figure A.15: Demand derivative and candidate ideological positions.

Notes: The Figure shows the relationship between the district-level demand derivative for cultural issues and the positions adopted by Democratic candidates. The figure illustrates that Democratic candidates who adopt more progressive stances on cultural issues tend to run in districts where a marginal shift toward more progressive positions on such issues would give them larger vote shares.

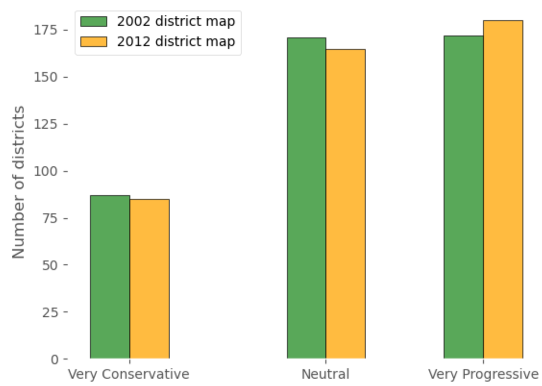
	Republican Party		Democratic Party	
	Cultural	Economic	Cultural	Economic
Welfare	0.02	0.837	0.007	0.799
Trade	0.006	0.532	0.03	0.503
Labor	0.006	0.883	0.003	0.839
Social Security	0.019	0.373	0.007	0.515
Health care	0.056	0.42	0.043	0.444
Taxes	0.045	0.397	0.037	0.423
Environment	0.094	0.156	0.189	0.099
Campaign Finance	0.038	0.028	0.039	0.017
Education	0.071	0.036	0.035	0.018
Gun regulation	0.12	0.05	0.205	0.037
Abortion	0.101	0.027	0.181	0.034
Immigration	0.116	0.022	0.178	0.024
Diversity Issues	0.159	0.009	0.286	0.022
International	0.064	0.002	0.056	0.022
Crime	0.089	0.002	0.105	0.037

Table A.4: Partial R-squared of Cultural and Economic dimensions in Explaining Candidate Topic-specific Positions

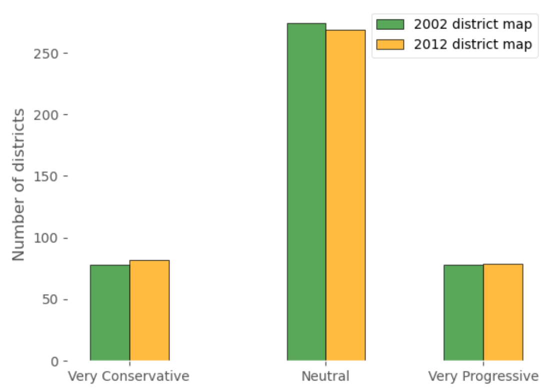
Notes: The table reports the partial R-squared of the cultural and economic dimensions in explaining candidate topic-specific positions. For example, the cultural dimension explains only 2% of the variation in Republican Welfare positions that is left unexplained by the economic dimension while the the economic dimension explain 84%.



(a) Average Democratic Partisanship



(b) Average Cultural Preferences



(c) Average Economic Preferences

Figure A.16: Number of politically biased districts following the 2010 Congressional redistricting.

Notes: The Figure shows the number of congressional district that can be considered as very politically biased, either in terms of partisanship (a) or ideology (b and c). For each graph, I compute the district level average partisanship or ideological coefficient with the 2002 or 2012 district maps. Districts are classified as neutral if they fall between the 25^{th} and 75^{th} percentiles of the precinct distribution. For example, following the 2010 redistricting, there are 7 fewer districts that can be considered as neutral in terms of partisanship.

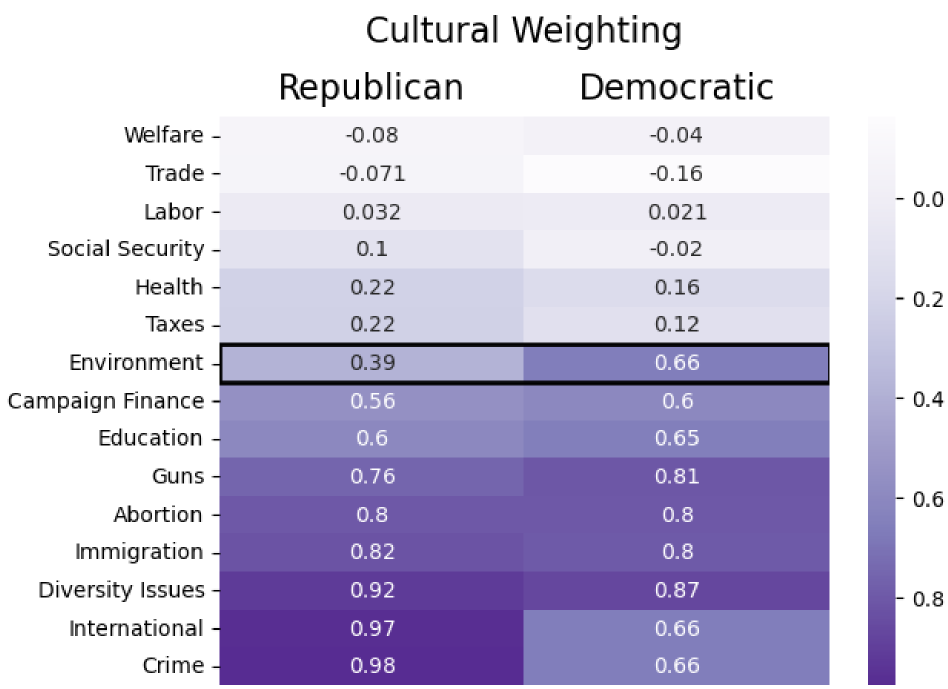


Figure A.17: Party Cultural Weights on each Topic

Notes: For each topic, I re-estimate the ideal point model to get a position specifically on that topic and a cultural and economic dimensions, excluding that topic. I then project the topic ideal points on the cultural and economic dimensions and plot the relative weighting coefficients $\rho = \frac{\beta_{cult}}{\beta_{cult}+\beta_{econ}}$.

C Electoral results and precinct boundaries

This section describes the methods and sources used to build the panel of electoral precincts. Since boundaries of electoral precincts change over time, I have interpolated all the precinct results to the census block-group level, which have approximately the same population (1,875 for precincts vs. 1,375 for block-groups). Table A.5 show the distribution of state-years included in the sample. Table A.6 show the distribution of state-years collected and cleaned for the project but not included in the sample, either because of important unbalanceness or states with a single congressional district.

I first describe the sources used for the electoral results and the precinct shapefiles. I then explain the interpolation strategy to obtain results at the block-group level. Third, I explain how I treat absentee ballots. Finally, I describe the mechanisms implemented to check the quality of the data.

C.1 Data sources

For each election year and each state, I started by collecting all the data that was already available from previous data collection initiatives. Specifically, I collected the data available from the following five initiatives: the Harvard Election Data Archive (Ansolabehere, Ban, and Morse (2018), Ansolabehere, Palmer, and Lee (2014)), data from the MIT Election Data and Science Lab (Baltz, Agadjanian, Chin, Curiel, DeLuca, Dunham, Miranda, Phillips, Uhlman, Wimpy, et al., 2022), data from the Voting and Election Science Team at the University of Florida, data from the *OpenElections* initiative, and data from the *Redistricting Data Hub*.

I also collected the U.S. Census Voting Districts (VTD) boundary shapefiles for 2000, 2010, and 2020.

If the results and/or the boundaries were missing from these sources or if the matching rate was too low I collected the results and the boundaries myself from Secretary of States of each state and some counties for some. I provide below the list of alternative sources when election results or precinct shapefiles were not provided by any of the above-listed initiatives.

The list of state-years included in the final dataset is provided in Appendix Table A.5, together with a description of the various sources.

Since most of the precinct-level election results and precinct shapefiles do not come from the same sources, I match precinct-level results to their shapefiles using fuzzy-string matching within county, keeping the most likely pairs that have a normalized Levenshtein similarity above 0.70. Also, since I do not have shapefiles for every single year in the period for each state, I match the precinct-level election results with their closest shapefiles from the same decennial period. Since precinct boundaries can change while keeping the same name, I conduct some tests on the number of votes between the election data and the precinct data. I exclude all precincts that have a difference in the total number of votes between election for the same offices of more than 25%.

- For Arkansas, precinct shapefiles come from the Arkansas GIS Office.
- For California, all the election results and precinct boundaries come from the Statewide Database at the University of California, Berkeley.
- For Colorado, 2000 and 2002 election results from the Colorado Secretary of State.
- For Florida, election results from 2012 onward come from the state-level Division of Elections.
- For Massachusetts, precinct shapefiles come from the Metric Geometry and Gerrymandering Group (MGGG).
- For Minnesota, election results were obtained from the Office of the Secretary of State and precinct boundaries from the Legislative Coordinating Commission of the Minnesota legislature.
- For New Mexico, 2006 and 2010, I digitized the electoral results from PDF reports from each county.
- For North Carolina, electoral results and precinct shapefiles were obtained from the North Carolina State Board of Elections.
- For Virginia, precinct boundaries come from Erika Lopresti's Github
- For Washington State, King County results for 2012 and 2014 come from the county election commission.
- For Wisconsin, all the results and precinct boundaries come directly from the State Legislature.

I systematically used the congressional district information included in the electoral results, if the district was not mentioned for each precinct, I assign them using the shapefile of congressional districts compared with the precinct boundaries.

C.2 Panel of electoral precincts

To assign votes to each block group I implement the following strategy, illustrated on Figure A.3 in Appendix. First, I use geospatial analysis to compare the precinct shape with each census block and create spatial crosswalks. Second, I compute the total precinct population that belongs to the block group by using the block-level population. When a block is divided into several precincts, I assign only the share of the population that is covered by the precinct.

The total number of votes for candidate j in block group bg can be written as:

$$Votes_{j,bg} = \sum_{p:\{p \cap bg\} \neq \emptyset} \sum_{b \in \{p \cap bg\}} Votes_{j,p} \cdot w_{b,p} \cdot \frac{Pop_b}{Pop_p}$$

where $w_{b,p}$ is the share of block's b area that falls within precinct p's boundaries, Pop_b and Pop_p the population of the block and precinct population, respectively.

For example, taking the situation described in Appendix Figure A.3; where there are three precincts. In order to allocate the votes to block group A and block group B, I first compute the share that intersects with each block within these block groups. Blocks are shown as grey squares of the grid. Assuming that the population of each block is equal: 80% of the population in precinct 1 belongs to block group A (block A1 to A12 and one third of A13, A14, A15, and A16 ($w_{b,p} = \frac{1}{3}$)). Similarly, 16.7% of precinct 2 belongs to block group A, while 50% belongs to block group B. 66% of precinct 3's population belongs to block group B. The total votes of each candidates in block group A, is therefore obtained by taking 80% of the votes from precinct 1 and 16.7% of the votes from precinct 2.

This strategy makes the following underlying assumption: (1) the population is uniformly distributed within each block, (2) the share of votes for each candidate is uniformly distributed across precincts. Importantly, I do not need to assume that the population is uniformly distributed within precincts or within block groups across blocks.

C.3 Absentee Ballots

Each state and sometimes each county reports absentee ballots differently. There are three main types of reporting of absentee votes. First, some counties directly assign absentee votes to each candidate results, without distinction with the election-day votes. Second, some counties record absentee ballots separately for each precinct, providing a separate estimate of number of votes for each candidate in each precinct. Third, some counties report absentee votes at a more aggregate level than the precinct level. The rule applied in the election results has been to assign absentee ballots to specific precincts when possible and only when they were reported at a more disaggregated level than the county. For example, Michigan counties usually reports absentee ballots at the ward level, which is more aggreagated level than the precinct (about 3 precincts per ward on average). I therefore allocate the absentee votes to each precinct proportionally. If the Democratic candidate obtained 40% of their in-person votes from precinct A in ward 1, I allocate 40% of the absentee ballots from ward 1 to precinct A.

State	2000	2002	2004	2006	2008	2010	2012	2014	2016	2018	2020
Alabama	x	x	x	x	x	x	x	x	x	x	x
Arizona		x	x	x	x	x	x	x	x	x	x
Arkansas	x	x	x	x	x	x	x	x	x	x	x
California	x	x	x	x	x	x	x	x	x	x	x
Colorado			x	x	x	x	x	x	x	x	x
Connecticut	x	x	x	x	x	x	x	x	x	x	x
Florida				x	x	x	x	x	x	x	x
Idaho	x	x	x	x	x	x	x	x	x	x	x
Illinois							x	x	x	x	x
Iowa	x	x	x	x	x	x	x	x	x	x	x
Kansas	x	x	x	x	x	x	x		x	x	x
Maine	x	x	x	x	x	x	x	x	x	x	x
Maryland		x	x	x	x	x	x	x	x	x	x
Massachusetts	x	x	x	x	x	x	x	x	x	x	x
Michigan	x	x	x	x	x	x	x	x	x	x	x
Minnesota	x	x	x	x	x	x	x	x		x	x
Mississippi			x	x	x	x	x		x	x	x
Missouri	x	x	x	x	x	x		x	x	x	x
Nebraska		x		x		x		x		x	x
New Hampshire	x	x	x	x	x	x	x	x		x	x
New Jersey	x	x	x	x	x				x	x	x
New Mexico	x		x	x	x	x	x	x	x	x	x
New York				x	x	x	x	x	x	x	x
North Carolina	x	x	x	x	x	x	x	x	x	x	x
Oklahoma	x	x	x	x	x	x		x		x	x
Ohio				x	x	x		x	x	x	x
Oregon	x	x	x	x	x	x		x	x	x	x
Pennsylvania	x	x	x	x	x	x	x	x	x	x	x
Rhode Island	x	x	x	x	x		x	x	x	x	x
South Carolina			x	x	x	x	x	x		x	x
Tennessee		x	x	x	x	x	x	x	x	x	x
Texas	x	x	x	x	x	x	x	x	x	x	x
Virginia	x	x	x	x	x	x	x	x	x	x	x
Washington				x	x	x	x	x	x	x	x
Wisconsin		x	x	x	x	x	x	x	x	x	x

Table A.5: States with Electoral Results Included in the Sample

State	2000	2002	2004	2006	2008	2010	2012	2014	2016	2018	2020
Alaska		x	x	x	x	x	x	x	x	x	x
Delaware		x	x	x	x	x	x		x	x	x
Georgia							x	x	x	x	x
Hawaii				x	x	x	x	x	x	x	x
Indiana							x	x	x	x	x
Kentucky									x	x	x
Louisiana	x	x	x	x	x	x	x	x	x	x	x
Montana										x	x
Nebraska					x					x	x
Nevada					x	x				x	x
North Dakota			x	x	x	x	x	x	x	x	x
South Dakota				x	x	x	x	x	x	x	x
Utah									x	x	x
Vermont		x	x	x	x	x	x	x	x	x	x
West Virginia										x	x
Wyoming	x	x	x	x	x	x	x	x	x	x	x

Table A.6: Electoral Results for States Not Included in the Sample

Notes: States are excluded from the sample either because their coverage is too low (e.g., Indiana or Michigan), because they are At Large seats (e.g., Delaware or Wyoming) or because they do not belong to the continental U.S. (Alaska and Hawaii).

D Recovering precinct-level full distribution of demographics

In order to recover the distribution of voter preferences in each precinct, I need the joint distribution of voter demographics, however, only the marginal distributions are available from US Census data. I therefore implement a multi-level demographic model to recover the joint distribution. I consider two types of demographics: binary (white vs. non white) and continuous (education, income and age). The objective is to recover the joint distribution of the three continuous variables for both white and non-white voters.

Census data from IPUMS (Manson et al., 2021) provide count variables that give the total number of people in some education, income, and, age brackets, by race. This data allows me to obtain the average and the variance of each of these variables by race. Note that the estimated variance is probably under-estimated since the census data only provides brackets. There are two additional challenges. First, while IPUMS provides the marginal distribution of education by race, income by race, and age by race from block-group-level data, the data does not contain the joint distribution along these three dimensions. I therefore use PUMA-level individual data from the ACS from IPUMS to obtain correlations between education, income, and age for each year. Second, since the marginal distribution by race for education and income for 2010 and 2020 are only available at the tract level, I use tract-level marginal distribution by race and block-group level distribution for the whole population to extend each block group's 2000 marginal distribution by race.

The overall approach is described below in more detail:

In each block-group, for each decennial year, I need to estimate four matrices:

$$\boldsymbol{\mu^{white}} = (\mu_{edu}^{white}, \mu_{income}^{white}, \mu_{age}^{white}) \tag{21}$$

$$\boldsymbol{\mu^{NW}} = (\mu_{edu}^{NW}, \mu_{income}^{NW}, \mu_{age}^{NW}) \tag{22}$$

$$\boldsymbol{\sigma^{white}} = \begin{pmatrix} \sigma_{edu}^{white} & \sigma_{edu,income}^{white} & \sigma_{edu,race}^{white} \\ \sigma_{edu,income}^{white} & \sigma_{income,income}^{white} & \sigma_{income,age}^{white} \\ \sigma_{edu,age}^{white} & \sigma_{income,age}^{white} & \sigma_{age,age}^{white} \end{pmatrix} \tag{23}$$

$$\boldsymbol{\sigma^{NW}} = \begin{pmatrix} \sigma_{edu}^{NW} & \sigma_{edu,income}^{NW} & \sigma_{edu,race}^{NW} \\ \sigma_{edu,income}^{NW} & \sigma_{income,income}^{NW} & \sigma_{income,age}^{NW} \\ \sigma_{edu,age}^{NW} & \sigma_{income,age}^{NW} & \sigma_{age,age}^{NW} \end{pmatrix} \tag{24}$$

1. I use census individual level data to get the covariance of the continuous demographics by white/non-white by PUMA (about 1,000 census block-groups by PUMA). This gives me the non-diagonal terms of $\boldsymbol{\sigma^{W}}$ and $\boldsymbol{\sigma^{NW}}$

2. $\boldsymbol{\mu^{white}}$ and $\boldsymbol{\mu^{NW}}$ are fully observed observed in 2000 at the block-group level but only partially in 2010 and 2020, for which μ_{edu}^{white} and μ_{edu}^{NW} are only reported at the tract-level.

3. For μ_{edu}^{white} and μ_{edu}^{NW} in 2010 and 2020, I estimate them by using a combination of the overall education distribution in the block-group (BG) in these years, the initial distribution of education by race in 2000 and the distribution of education by race in 2010 at the tract-level. I recover $\mu_{edu,2010,BG}^{white}$ by making the following assumption:

$$\frac{\frac{\mu_{edu,t,BG}^{white}}{\mu_{edu,t,BG}^{all}}}{\frac{\mu_{edu,2000,\text{tract}}^{white}}{\mu_{edu,2000,\text{tract}}^{all}}} = \frac{\frac{\mu_{edu,2010,BG}^{white}}{\mu_{edu,2010,BG}^{all}}}{\frac{\mu_{edu,2010,\text{tract}}^{white}}{\mu_{edu,2010,\text{tract}}^{all}}} \tag{25}$$

Everything is observed except $\mu_{edu,2010,BG}^{white}$, the underlying hypothesis is that the ratio of education of white to non white in the block group versus in the tract has stayed constant between 2000 and 2010. I recover the distributions for non-white and for 2020 in the same way.

4. The diagonal terms of $\sigma^{\mathbf{NW}}$ and $\sigma^{\mathbf{white}}$ are only observed in 2000. In the other years I just observe the diagonal terms of an aggregated matrix for all races. I therefore use the same as strategy as above:

$$\frac{\frac{\sigma_{edu,2000,BG}^{white}}{\sigma_{edu,2000,BG}^{all}}}{\frac{\sigma_{edu,2000,\text{tract}}^{white}}{\sigma_{edu,2000,\text{tract}}^{all}}} = \frac{\frac{\sigma_{edu,2010,BG}^{white}}{\sigma_{edu,2010,BG}^{all}}}{\frac{\sigma_{edu,2010,\text{tract}}^{white}}{\sigma_{edu,2010,\text{tract}}^{all}}} \tag{26}$$

I recover the distributions for non-white, for 2020, and for age and income in the same way.

E Multimodal Text-and-Survey Ideal Point Model

For each election, I want to recover the underlying position x_j of candidate j. For simplicity, I write the ideal point with $k = 1$. For each candidate j, I observe the patterns of responses to the Votesmart survey questions $\mathbf{y_j} = (y_{j1}, y_{j2}, ..., y_{jQ})$ with Q the number of questions answered by that candidate at this election. Note that each question re-ordered so that $y_{jq} = 1$ corresponds to a conservative position.

I can write the probability that candidate j would have adopted this specific response pattern as:

$$L(x_j|\mathbf{y}_j) = \prod_{q=1}^{Q} \Pr(y_{jq}|x_j)$$

with $\Pr(y_{jq}|x_j)$ the probability of responding y_{jq} to question q.

$$\Pr(y_{jq} = 1|x_j) = \frac{1}{1 + e^{-a_q(x_j - b_q)}}$$

where y_{jq} denotes the response of candidate j to question q, x_j is the underlying position of candidate j, a_q is the discrimination (polarization) parameter for question q, b_q is the political orientation parameter for question q. In the specific context of political questions, a_q can be understood as the level of polarization of the question. An apolitical question where responses would be essentially uncorrelated with the underlying political dimension would get a very low a_q. b_q captures the political location of the question; it gives the threshold above which I expect a candidate to answer *yes* to the question. For high b_q, only very conservative candidates are expected to answer *yes*, for low b_q, most candidates are expected to answer *yes*. Note that I do not use a quadratic utility model as in Shor and Rogowski (2018) since most question ask more about a direction (e.g., increase social security contributions) than about a specific location of a policy

The model is estimated using Marginal Maximum Likelihood: I maximize the marginal likelihood of the observed data, integrating over the distribution of the latent trait:

$$\mathcal{L} = \prod_{j=1}^{N} \int_{-\infty}^{+\infty} L(x_j|\mathbf{y}_j) f(x_j) dx_j \tag{27}$$

where N is the number of candidates and $f(x_j)$ is the probability density function of the latent trait in the population that I assume is a Normal distribution with mean 0 and variance 1.

I also obtain the standard errors of the prediction as:

$$se(x_j) \quad = \quad \frac{1}{\sqrt{\sum_{q=1}^{Q} I_q(x_j)}} \tag{28}$$

with $I(x_j) = a_q^2 p_q(x_j)(1 - p_q(x_j))$ the total information.

where $p_q(x_j)$ is the probability of candidate j answering *yes* to question q, $p_q(x_j) = \frac{1}{1+e^{-a_q(\theta_{x_j} - b_q)}}$ where b_q is the difficulty parameter of that question (level at which has 50% chance of answering positively). Intuitively, I get more information from answers to questions with unpredictable answers (around 50%).

I estimate one ideal point model per issue (cultural, economic, environment, and cultural without environment) using Girth (Sanchez, 2021) on Python. The survey includes two main types of questions: questions asking whether a given candidate supports a policy (binary answer, such as: "Strengthening the regulation and enforcement of the Clean Water Act") or questions asking about the desired level of spending or taxes on a specific dimension, such as "Do you think inheritance taxes should be greatly increased/slightly increased/maintain status/slightly decreased/eliminated". For each of these ordered questions, I build a set of new dummy variables equals to one if the answer is lower than each threshold. This gives me a set of binary questions for each election cycle. Appendix Table A.7 summarizes the number of raw question by sub-topic and their classification in issues.

Subtopic	Main Topic	Number of distinct raw questions
Abortion	Cultural	7
Crime	Cultural	11
Education	Cultural	7
Environment	Cultural[a]	17
Labor and Employment	Economic	9
Gun regulations	Cultural	8
International Trade	Economic	6
Campaign Finance	Cultural	4
Immigration	Cultural	8
Diversity Questions	Cultural	3
Health Care	Economic	9
Taxes and Spending	Economic	19
Security and International Policy	Cultural	7
Social Security	Economic	13
Welfare	Economic	4

Table A.7: Summary of topic classifications

[a]For the analysis in section 7, I re-compute the cultural ideal points, excluding environment from the classification.

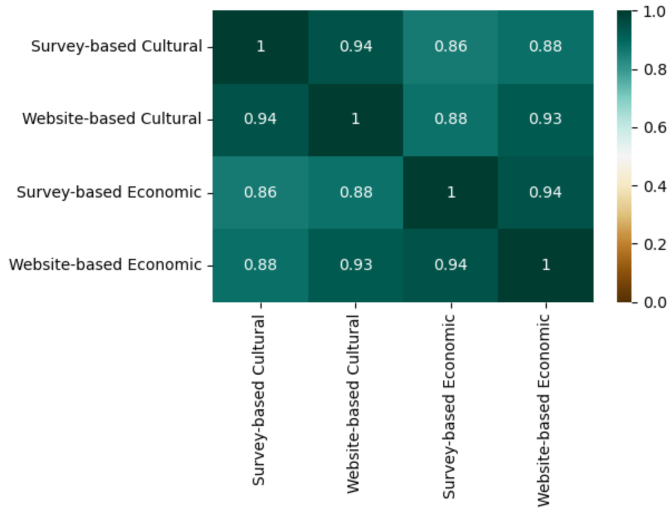
Once I have obtained an ideal point and a standard error for each candidate that has answered the survey, I train and apply a machine learning regressor (Extreme Gradient Boosting) using features extracted from their website. I scrape the website in the following way: I collect all the text available on the first page, all the text available on any page listed on the first page and iterate once again by taking all the text available on any page listed on these second pages. I only collect text that is on the website (i.e., I do not scrape external websites even if they are referenced on the candidate's website). Starting from the raw text data scraped from candidate websites, I clean the text in regular ways by removing all words that are a consequence of the data being displayed on a website (e.g., "contact me", "send an email", "access photos", etc.), removing names of candidates, state names and region names. I then construct unigrams, bigrams and trigrams (sequences of 1, 2 or 3 words) and I remove words that are too infrequent (used in less than 0.05% of the documents), this gives me a large matrix of occurences of tokens for each candidate. In addition, I also compute document embeddings (Dai et al., 2015) which give a vector representation of each document.

The mean squared error (MSE) for the economic prediction is 0.17 (R-squared of the prediction is at 0.91) and 0.21 for the cultural dimension (R-squared of 0.89). For candidates for whom I only have the website (26%) of the sample, I only assign the website ideal point, for those with only the survey (18%), I only assign the survey ideal points and for all those with both survey and website ideal points (46%), I take a weighted average of the two measures using the following formula:

$$x_j = w_j x_j^{survey} + (1 - w_j) x_j^{\widehat{website}} \tag{29}$$

with $w_j = \frac{MSE(x^{website})}{se(x_j^{survey})^2 + MSE(x^{website})}$.

Figure A.18 shows the correlation between the survey-based and website-based measures.



(a) All Sample

(b) Democrats only

(c) Republicans only

Figure A.18: Comparison between survey-based and website-based measures

Notes: The first panel shows the pairwise correlation between survey-based and website-based measures. The first panel look at the overall correlation. The second and third panel show the within-party correlations for Democrats and Republicans, respectively.

F Theory Appendix

This section studies the existence and uniqueness of an equilibrium in the framework estimated in this paper where two candidates compete in a two-dimensional space. I remind the reader that such an equilibrium, in each congressional district, is defined by a collection of positions $(\mathbf{x_D}, \mathbf{x_R})$ and vote shares (s_D, s_R) such that (i) $\mathbf{x_D}$ maximizes $\Pi_j(\mathbf{x_D}, \mathbf{x_R})$ when $\mathbf{x_R}$ is fixed, (ii) $\mathbf{x_R}$ maximizes $\Pi_j(\mathbf{x_D}, \mathbf{x_R})$ when $\mathbf{x_D}$ is fixed, and (iii) $s_j = \int_{\mathbf{w}} s_{ijt}\,(\mathbf{x_D}, \mathbf{x_R}; \mathbf{w_i})\, dF_t(\mathbf{w_i})$ for $j \in \{D, R\}$, where Π_j are candidates' objective functions defined in section 2, omitting the election subscripts t for clarity.

As explained in section 5, I assume that there is a shock to candidates' probability of wining that follows a uniform distribution $\zeta_{jt} \sim U[-\frac{1}{\phi}, \frac{1}{\phi}]$, I therefore re-write the probability of winning as:

$$\begin{aligned}
P_j(\mathbf{x_j}, \mathbf{x_{-j}}) &= \mathbb{P}(s_j(\mathbf{x_j}, \mathbf{x_{-j}}) + \zeta_{jt} \geq 0.5) \\
&= 1 - \mathbb{P}(\zeta_{jt} \leq 0.5 - s_j(\mathbf{x_j}, \mathbf{x_{-j}})) \\
&= \frac{\phi}{2} s_j(\mathbf{x_j}, \mathbf{x_{-j}}) + \frac{1}{2} - \frac{\phi}{4}
\end{aligned}$$

which allows the express candidates' objective as a function of their vote share.

- **Existence:**

  I follow Ozdaglar (2013) to demonstrate the existence of the equilibrium. I denote by $S := [-10, 10] \times [-10, 10]$ candidates' strategy space, which is convex and compact. Π_j is continuous in candidate $-j$'s strategy. In order to apply the Theorem 2 of *op. cit.*, I need to show that Π_j is concave in each candidate's strategy. This is equivalent to showing that the following inequalities hold:

$$\begin{aligned}
\frac{\partial^2 s_j(\mathbf{x})}{\partial x_{1,D}^2} &\leq 2\lambda_D \\
\frac{\partial^2 s_j(\mathbf{x})}{\partial x_{2,D}^2} &\leq 2\lambda_D \\
\frac{\partial^2 s_j(\mathbf{x})}{\partial x_{1,R}^2} &\leq 2\lambda_R \\
\frac{\partial^2 s_j(\mathbf{x})}{\partial x_{2,R}^2} &\leq 2\lambda_R
\end{aligned}$$

  where λ_j has been re-normalized by $\frac{2\lambda_j}{\phi Q}$. The threshold for which these conditions are true depends on the exact structure of voter preferences. Using the demand-side and supply-side parameters estimates in the paper, whose estimation does not rely on the existence of an equilibrium, I get that

$$\min(\widehat{\lambda}_j) = 0.025 \quad \text{and} \quad \max(\widehat{\frac{\partial^2 s_j(\mathbf{x})}{\partial x_{k,j}^2}}) = 0.001,$$

for $j \in \{D, R\}$ and $k \in \{\text{cultural}, \text{economic}\}$, across all elections.

The previous inqualities hold, then implying that Π_j is concave in each candidate's strategy which concludes the proof of the existence of the equilibrium.

- **Uniqueness:**

  I follow Rosen (1965) and Ozdaglar (2013) to study the uniqueness of the equilibrium. Rosen shows that if the objective functions are diagonally strictly concave then the game has a unique pure-strategy Nash Equilibrium. Rosen also shows that if the symmetric matrix $U(\mathbf{x}) + U^T(\mathbf{x})$ is negative definite for all $x \in S$, then the objective functions are diagonally strictly concave, where $U(\mathbf{x})$ is the Jacobian of the gradient vector of the objective functions.

  In the framework of this paper, the gradient of the objective functions can be written as:

$$\begin{aligned}
\nabla\Pi(\mathbf{x}) &= \big(\nabla\Pi_D(\mathbf{x}), \nabla\Pi_R(\mathbf{x})\big)^T \\
&= \big(\frac{\partial \Pi_D(\mathbf{x})}{\partial x_{1,D}}, \frac{\partial \Pi_D(\mathbf{x})}{\partial x_{2,D}}, \frac{\partial \Pi_R(\mathbf{x})}{\partial x_{1,R}}, \frac{\partial \Pi_{re}(\mathbf{x})}{\partial x_{2,R}}\big)^T \\
&= \big(\frac{\partial s_D(\mathbf{x})}{\partial x_{1,D}} - 2\lambda_D(x_{1,D} - N_{1,D}), \frac{\partial s_D(\mathbf{x})}{\partial x_{2,D}} - 2\lambda_D(x_{2,D} - N_{2,D}), \\
&\quad -\frac{\partial s_D(\mathbf{x})}{\partial x_{1,R}} - 2\lambda_R(x_{1,R} - N_{1,R}), -\frac{\partial s_D(\mathbf{x})}{\partial x_{2,R}} - 2\lambda_R(x_{2,R} - N_{2,R})\big)^T
\end{aligned}$$

  The Jacobian of the gradient $U(\mathbf{x})$ can be written as:

$$U(\mathbf{x}) = \begin{bmatrix}
\frac{\partial^2 \Pi_D(\mathbf{x})}{\partial x_{1,D}^2} & \frac{\partial^2 \Pi_D(\mathbf{x})}{\partial x_{1,D}\partial x_{2,D}} & \frac{\partial^2 \Pi_D(\mathbf{x})}{\partial x_{1,D}\partial x_{1,R}} & \frac{\partial^2 \Pi_D(\mathbf{x})}{\partial x_{1,D}\partial x_{2,R}} \\
\frac{\partial^2 \Pi_D(\mathbf{x})}{\partial x_{1,D}\partial x_{2,D}} & \frac{\partial^2 \Pi_D(\mathbf{x})}{\partial^2 x_{2,D}} & \frac{\partial^2 \Pi_D(\mathbf{x})}{\partial x_{2,D}\partial x_{1,R}} & \frac{\partial^2 \Pi_D(\mathbf{x})}{\partial x_{2,D}\partial x_{2,R}} \\
\frac{\partial^2 \Pi_R(\mathbf{x})}{\partial x_{1,D}\partial x_{1,R}} & \frac{\partial^2 \Pi_R(\mathbf{x})}{\partial x_{2,D}\partial x_{1,R}} & \frac{\partial^2 \Pi_R(\mathbf{x})}{\partial x_{1,R}^2} & \frac{\partial^2 \Pi_R(\mathbf{x})}{\partial x_{1,R}\partial x_{2,R}} \\
\frac{\partial^2 \Pi_R(\mathbf{x})}{\partial x_{1,D}\partial x_{2,R}} & \frac{\partial^2 \Pi_R(\mathbf{x})}{\partial x_{2,D}\partial x_{2,R}} & \frac{\partial^2 \Pi_R(\mathbf{x})}{\partial x_{1,R}\partial x_{2,R}} & \frac{\partial^2 \Pi_R(\mathbf{x})}{\partial x_{2,R}^2}
\end{bmatrix}$$

  and

$$U(\mathbf{x}) + U^T(\mathbf{x}) = \begin{bmatrix} 2(A-2\lambda_D) & 2B & 0 & 0 \\ 2B & 2(C-2\lambda_D) & 0 & 0 \\ 0 & 0 & -2(A+2\lambda_R) & -2B \\ 0 & 0 & -2B & -2(C+2\lambda_R) \end{bmatrix}$$

where

$$\begin{aligned} A &= \frac{\partial^2 s_D(\mathbf{x})}{\partial x_{1,D}^2} \\ B &= \frac{\partial^2 s_D(\mathbf{x})}{\partial x_{1,D}\partial x_{2,D}} \\ C &= \frac{\partial^2 s_D(\mathbf{x})}{\partial x_{2,D}^2} \end{aligned}$$

I denote by Δ_1, Δ_2, Δ_3, and Δ_4 the leading principal minors. $U(\mathbf{x}) + U^T(\mathbf{x})$ is negative definite if $\Delta_1 < 0$, $\Delta_2 > 0$, $\Delta_3 < 0$, and $\Delta_4 > 0$. The leading principal minors can be expressed as:

$$\begin{aligned} \Delta_1 &= A - 2\lambda_D \\ \Delta_2 &= (A-2\lambda_D)(C-2\lambda_D) - B^2 \\ \Delta_3 &= -2(A-2\lambda_D)(C-2\lambda_D)(A+2\lambda_R) - (A+2\lambda_R)\big[(A-2\lambda_D)(C-2\lambda_D) - B^2\big] \\ \Delta_4 &= 8(A-2\lambda_D)(C-2\lambda_D)(A+2\lambda_R)(C+2\lambda_R) + \\ &\quad 2(A-2\lambda_D)(C-2\lambda_D)\big[(A+2\lambda_R)(C+2\lambda_D) - B^2\big] + \\ &\quad 2(A+2\lambda_R)(C+2\lambda_R)\big[(A-2\lambda_D)(C-2\lambda_D) - B^2\big] \end{aligned}$$

In the framework estimated in the paper, I get the following minimum and maximum values across all elections:

$$\max(\Delta_1) = -0.0396, \quad \min(\Delta_2) = 0.0015 \ , \max(\Delta_3) = -0.0092, \ \text{ and } \ \min(\Delta_4) = 0.0018,$$

which implies that $U(\mathbf{x}) + U^T(\mathbf{x})$ is negative definite, leading to the uniqueness of the equilibrium.

It should be noted that the logic behind these conditions is pretty intuitive. Indeed, it imposes that the potential convexity in the vote share is compensated by the concavity of the party discipline component.

G Additional Demand Results

This section first provides an exhaustive list of the moments used for estimation and then explores the robustness of the demand results in three dimensions: (1) using an alternative identification strategy, (2) adding additional candidate observable characteristics, (3) recovering voters' endogenous turnout decision.

G.1 List of Moments used for Demand Estimation

I use both aggregate moments from precinct-level election results and micro-moments from survey data.

The vector of aggregate moments is denoted by $g_A(\theta)$ while the vector of micro moments is denoted $g_M(\theta)$.

I write for each topic $k = \{cultural, economic\}$, for each demographic characteristic $w_{pt} = \{education_{pt}, race_{pt}, education_{pt} \times race_{pt}, age_{pt}\}$

$$g(\theta) = \begin{pmatrix} \left.\begin{matrix} \mathbb{E}[x_{d(p)kt} \cdot \xi_{pt} | \xi_{g(p)t}, \xi_p] \\ \mathbb{E}[\big(x_{d(p)kt} \cdot w_{pt}\big) \cdot \xi_{pt} | \xi_{g(p)t}, \xi_p] \\ \mathbb{E}[w_{pt} \cdot \xi_{pt} | \xi_{g(p)t}, \xi_p] \\ \mathbb{E}[x^2_{d(p)kt} \cdot \xi_{pt} | \xi_{g(p)t}, \xi_p] \\ \mathbb{E}[\big(x^2_{d(p)kt} \cdot w_{pt}\big) \cdot \xi_{pt} | \xi_{g(p)t}, \xi_p] \end{matrix}\right\} g_A(\theta) \\ \left.\begin{matrix} \mathbb{C}[w_{pt}, x_{d(p)kt}] - \widehat{\mathbb{C}}[w_{pt}, x_{d(p)kt}] \\ \mathbb{E}[w_{pt}] - \widehat{\mathbb{E}}[w_{pt}] \end{matrix}\right\} g_M(\theta) \end{pmatrix},$$

where $\widehat{\mathbb{C}}$ and $\widehat{\mathbb{E}}$ are the empirical counterparts of the observed moments in the survey data, for each value of the parameters θ.

$\mathbb{C}[w_{pt}, x_{d(p)kt}]$ captures the covariance between voters' demographic heterogeneity and the ideology of the candidates they vote for and $\mathbb{E}[w_{pt}]$ the average demographic of voters who chose Democratic candidates.

G.2 Alternative identification strategy

As a robustness check, I test an alternative set of fixed effects, using congressional district by election fixed effects instead of precinct pair fixed effects. If I assume that candidates choose their positions based solely on aggregate district-level taste shocks, this approach allows me to accurately identify within-district heterogeneity in ideological preferences. Essentially, this alternative strategy compares how precincts, facing the same choice set but differing in demographic composition, voted differently. This strategy would leave the average level of preferences unidentified since it is captured by the district by election fixed effects. Formally, if I re-write the unobserved taste shock as:

$$\xi_{pt} \quad = \quad \xi_p + \xi_{d(p)t} + \widetilde{\Delta\xi_{pt}},$$

where $\xi_{d(p)t} = \frac{1}{P} \sum_{p' \in d(p)} \xi_{pt}$ is the taste shock common to the whole congressional district and $\widetilde{\Delta\xi_{pt}}$ is the precinct-specific deviation in taste shock.

This gives the following moment conditions: $\mathbb{E}[x_{d(p)kt} \cdot \widetilde{\Delta\xi_{pt}}] = 0$, which require that precinct temporary deviations in taste shocks are not correlated with differences in candidate positions.

Note that congressional district by election fixed effects exploit a source of variation that is very different to the variation used with precinct-pair by election fixed effects. With precinct-pair by election fixed effects, I am compare arguably similar precincts that were facing a choice between different candidates. In contrast, with district by election fixed effects, I compare different precincts facing a choice between the same candidates. Table A.9 presents the results with congressional-district-by-election fixed effects, note that the average preferences for ideology gets absorbed by the fixed effects.

	Outcome: ln(s/(1-s))	
	(1)	(2)
	2000-2010	2012-2020
CultDem - CultRep	0.000	0.000
	(.)	(.)
EconDem - EconRep	0.000	0.000
	(.)	(.)
CultDem - CultRep × Mean Edu	-0.012***	-0.059***
	(0.004)	(0.005)
CultDem - CultRep × Shr White	0.044	0.092**
	(0.064)	(0.036)
CultDem - CultRep × Mean Edu × Shr White	-0.038***	-0.069***
	(0.014)	(0.013)
CultDem - CultRep × (mean) age_num	-0.000	0.001**
	(0.001)	(0.001)
EconDem - EconRep × Mean Edu	-0.007*	0.033***
	(0.004)	(0.006)
EconDem - EconRep × Shr White	0.194***	0.066
	(0.068)	(0.045)
EconDem - EconRep × Mean Edu × Shr White	-0.028*	0.006
	(0.017)	(0.015)
EconDem - EconRep × (mean) age_num	0.001	-0.000
	(0.001)	(0.001)
District x Year FE	X	X
Precinct FE	X	X
Observations	417,277	657,999

Table A.8: Estimation of Voter Preferences with Homogeneous Voters (Equation (11))

Notes: This table shows the coefficient from Equation (11): a regression of candidates' log odds ratio on interactions of precinct-level demographics and candidate positions, by period. Each column control for precinct fixed effects and precinct-pair by election fixed effects. Standard errors clustered two ways, by congressional district by year, and by precinct, are reported in parentheses.

G.3 Additional candidate observable characteristics

While the identification strategy handles any unobservable voters' taste shocks that would span across the congressional district border, one might wonder whether voter preferences for ideology might capture instead preferences of voters for candidate characteristics that vary would with ideology. This section tests the sensitivity of the demand results to the addition of three candidate observable characteristics: incumbency, gender, and race. I obtain candidate gender using name classification algorithms and candidate race and ethnicity from Bouton, Cagé, Dewitte, and Pons (2022), which contain candidate's race and ethnicity for House elections after 2006. All elections were either candidates' gender or race and ethnicity are undetermined are excluded, except elections pre-2006 for which the race variables, defined below, are set to zero. While other dimensions such as age likely play a role as well, they are rarely observed for non-incumbents. For each additional observable characteristics, I recover heterogeneity across demographic variables by estimating the following voter random utility model:

$$
\begin{aligned}
u_{it} = \quad & \sum_k \beta_{ikt} x_{d(i)kt} + \alpha_{it} + \gamma_{it}^1 (Inc_{Dd(i)t} - Inc_{Rd(i)t}) + \gamma_{it}^2 (Fem_{Dd(i)t} - Fem_{Rd(i)t}) \\
& + \gamma_{it}^3 (NonWhite_{Dd(i)t} - NonWhite_{Rd(i)t}) + \xi_{p(i)t} + \epsilon_{it}
\end{aligned}
\tag{30}
$$

where $Inc_{jd(i)t}$ is a dummy equal to one if candidate j is the incumbent, $(Inc_{Dd(i)t} - Inc_{Rd(i)t})$ is therefore the difference between Democratic and Republican candidates incumbent status, which can take values $\{-1, 0, 1\}$, $Fem_{jd(i)t}$ is a dummy equal to one if candidate j is a women, $NonWhite_{jd(i)t}$) if candidate j is non-white, and all the other parameters as defined in equation (7).

I estimate the specification with homogeneous voters within precincts as in equation 11, both with and without the inclusion of additional controls and their interaction with demographic variables. The coefficients on ideology in specifications (2) and (4), which include the extra controls, are only marginally reduced in magnitude and are not statistically different from those in specifications (1) and (3). There is a significant incumbent advantage, which is lower in the second period than in the first. More-educated and white voters are less responsive to this incumbency advantage. Non-white candidates tend to perform better on average than white candidates, and especially so in precincts that have a larger share of non-white voters.

	2000-2010		2012-2020	
	(1)	(2)	(3)	(4)
CultDem - CultRep	0.013	0.002	0.015	0.021
	(0.032)	(0.027)	(0.016)	(0.018)
EconDem - EconRep	-0.011	0.068**	-0.029	-0.045**
	(0.028)	(0.027)	(0.017)	(0.019)
Female Cand. Dem - Rep		0.016		-0.013
		(0.022)		(0.012)
Incumbent Dem - Rep		0.378***		0.212***
		(0.028)		(0.017)
NonWhite Cand. Dem - Rep		0.069		0.047***
		(0.049)		(0.017)
CultDem - CultRep × Av. Edu	-0.032***	-0.030***	-0.027***	-0.015**
	(0.010)	(0.009)	(0.005)	(0.006)
CultDem - CultRep × Shr. White	0.077	-0.033	-0.042	0.007
	(0.076)	(0.094)	(0.049)	(0.067)
CultDem - CultRep × Av. Edu × Shr. White	-0.050*	-0.026	-0.042**	-0.041
	(0.030)	(0.035)	(0.019)	(0.025)
CultDem - CultRep × Av. Age	0.000	-0.000	0.000	-0.001
	(0.002)	(0.002)	(0.001)	(0.001)
EconDem - EconRep × Av. Edu	0.004	-0.006	0.027***	0.022***
	(0.009)	(0.008)	(0.006)	(0.008)
EconDem - EconRep × Shr. White	0.110	0.080	-0.048	-0.002
	(0.072)	(0.097)	(0.068)	(0.084)
EconDem - EconRep × Av. Edu × Shr. White	0.035	-0.020	0.000	-0.024
	(0.031)	(0.038)	(0.022)	(0.027)
EconDem - EconRep × Av. Age	-0.001	0.003	0.003**	0.001
	(0.002)	(0.002)	(0.001)	(0.001)
Female Cand. Dem - Rep × Av. Edu		-0.010		0.009*
		(0.009)		(0.005)
Female Cand. Dem - Rep × Shr. White		-0.048		-0.122*
		(0.085)		(0.065)
Female Cand. Dem - Rep × Av. Edu × Shr. White		0.067*		-0.011
		(0.039)		(0.021)
Female Cand. Dem - Rep × Av. Age		-0.002		0.000
		(0.002)		(0.001)
Incumbent Dem - Rep × Av. Edu		-0.007		-0.003
		(0.007)		(0.005)
Incumbent Dem - Rep × Shr. White		-0.404***		-0.207***
		(0.121)		(0.068)
Incumbent Dem - Rep × Av. Edu × Shr. White		-0.031		0.002
		(0.032)		(0.021)
Incumbent Dem - Rep × Av. Age		0.005***		0.001
		(0.002)		(0.001)
NonWhite Cand. Dem - Rep × Shr. White		-0.362***		-0.205***
		(0.138)		(0.058)
NonWhite Cand. Dem - Rep × Av. Edu × Shr. White		-0.017		0.028
		(0.056)		(0.024)
NonWhite Cand. Dem - Rep × Av. Age		0.003		-0.001
		(0.003)		(0.001)
Precinct-pair x Year FE	X	X	X	X
Precinct FE	X	X	X	X
Observations	82,847	62,814	124,075	88,948

Table A.9: Robustness to the Inclusion of Candidate Observable Characteristics

Notes: This table reproduced table A.2 including additional candidate observable characteristics. Specification (1) and (3) are identical to the specifications in the main paper.

G.4 Voters' turnout decision

While the model estimated in the main paper abstracts from voters' turnout decisions, candidates' positions are likely to influence whether voters choose to vote or not, making it an interesting margin to study. The model presented in Section 4 can be easily generalized to a model with turnout decision, where voter's utility to vote for candidate j is written as:

$$u_{ijt} = \sum_k \beta_{ikt} x_{jd(i)kt} + \alpha_{iDt} \mathbb{1}_{j=D} + \alpha_{iRt} \mathbb{1}_{j=R} + \omega_{it} + \xi_{jp(i)t} + \epsilon_{ijt}, \tag{31}$$

where $x_{jd(i)kt}$ is the position of candidate $j = \{0, D, R\}$ on topic k in congressional district $d(i)$ in election t. The parameter β_{ikt} captures the preferences of voter i on dimension k. Further, α_{iDt} (resp. α_{iRt}) is voter i's utility when voting for a Democratic (resp. Republican) candidate independently of their positions, ω_{it} is voter's utility of turning out, independently of the candidate chosen, $\xi_{jp(i)t}$ is a precinct-level taste shock for candidate j in election t, and ϵ_{ijt} is an individual-level taste shock in favor of candidate j in election t, which I assume follows a type-I extreme value distribution. I normalize the utility of not voting to $u_{i0t} = \epsilon_{i0t}$, which gives the following specification, assuming voters are homogeneous within precincts:

$$\ln\left(\frac{\widetilde{S_{jpt}}}{1 - S_{0pt}}\right) = \mathbf{w}'_{\mathbf{pt}} \mathbb{1}_{j=D} \boldsymbol{\alpha}^{\mathbf{w}}_{\boldsymbol{Dt}} + \mathbf{w}'_{\mathbf{pt}} \mathbb{1}_{j=R} \boldsymbol{\alpha}^{\mathbf{w}}_{\boldsymbol{Rt}} + \sum_k \beta_{kt} x_{jd(p)kt} + \mathbf{w}'_{\mathbf{pt}} \boldsymbol{\beta}^{\mathbf{w}}_{\boldsymbol{kt}} x_{jd(p)kt} + \xi_{jpt}, \tag{32}$$

where $\widetilde{S_{jpt}}$ denote observed overall vote shares and $1 - S_{0pt}$ the turnout in precinct p at election t.

I estimate equation (32) using the same identification strategy as in the main paper, with precinct-pair fixed effects. Since there are two candidates, I include precinct-pair by party by election fixed effects, as well as precinct by party fixed effects. The corresponding estimates are reported in Table A.10. The estimates on the effect of ideology are smaller but lead to the same conclusions as the specification without turnout: educated voters prefer more progressive cultural policies but more conservative economic policies, especially in the second period. The gradients are generally larger for white voters. The coefficients on the demographic variables indicate voters' average utility of voting, independent of candidates' party. In both periods, educated, white, and older voters have a higher turnout.

	Outcome: $\ln(\widetilde{S_j}/(1\text{-}S_0))$	
	(1) 2000-2010	(2) 2012-2020
Cultural Position	-0.005	0.004
	(0.016)	(0.012)
Economic Position	0.007	-0.012
	(0.016)	(0.012)
Dem=1 × Av. Edu	-0.029**	-0.025**
	(0.011)	(0.010)
Dem=1 × Shr. White	-0.449***	-0.667***
	(0.128)	(0.173)
Dem=1 × Av. Edu × Shr. White	0.032	-0.151***
	(0.038)	(0.036)
Dem=1 × Av. Age	-0.004	-0.002
	(0.003)	(0.002)
Av. Edu	0.017**	0.019***
	(0.008)	(0.007)
Shr. White	0.386***	1.333***
	(0.100)	(0.177)
Av. Edu × Shr. White	0.021	0.098***
	(0.027)	(0.024)
Av. Age	0.011***	0.004***
	(0.003)	(0.001)
Cultural Position × Av. Edu	-0.020***	-0.013***
	(0.006)	(0.005)
Cultural Position × Shr. White	0.001	0.015
	(0.047)	(0.032)
Cultural Position × Av. Edu × Shr. White	-0.014	-0.046**
	(0.018)	(0.018)
Cultural Position × Av. Age	-0.001	-0.001
	(0.001)	(0.001)
Economic Position × Av. Edu	0.000	0.010**
	(0.006)	(0.005)
Economic Position × Shr. White	0.038	-0.134***
	(0.044)	(0.039)
Economic Position × Av. Edu × Shr. White	0.030	0.009
	(0.020)	(0.019)
Economic Position × Av. Age	-0.001	0.003**
	(0.001)	(0.001)
Precinct-pair x Party x Year FE	X	X
Precinct x Party FE	X	X
Observations	215,988	259,176

Table A.10: Robustness to the Estimation of Turnout Decision.

Notes: This table reproduced table presents the estimated coefficients from equation 32.

H Alternative supply specification

While Section 5 has estimated a supply model where candidates maximize their vote shares while complying with party discipline, this section explores the robustness of this section to having instead candidates maximizing their probability of winning the election.

I write each candidate's objective function as Π_{jt}, which depends on the candidate's share of votes, the distance between their chosen position and the party leadership, and their own ideological shock.

$$\Pi_{jt}(\mathbf{x_{jt}}) = \underbrace{P_j(\mathbf{x_{jt}}, \mathbf{x_{-jt}})}_{\text{probability of winning}} - \underbrace{\lambda_{jt}||\mathbf{x_{jt}} - \mathbf{N_{jt}}||^2}_{\text{distance from national party platform}} + \underbrace{\boldsymbol{\eta}'_{jt}\mathbf{x_{jt}}}_{\text{own ideological shock}} . \quad (33)$$

where the parameter λ_{jt} captures candidates' cost of deviating from the party line.

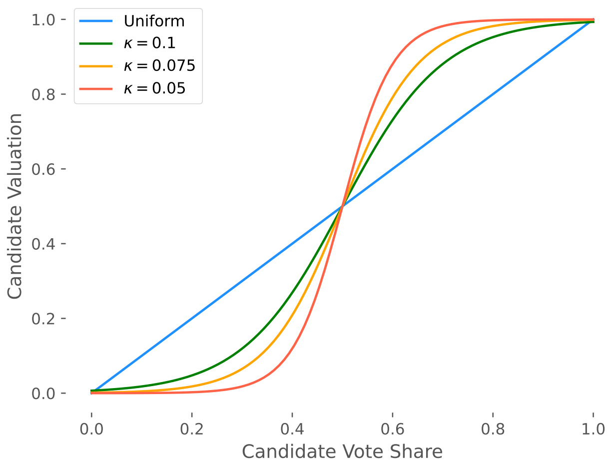
There is an aggregate shock ζ_j that creates some uncertainty around candidates' probability of winning.

If, instead of a uniform distribution as used in the main paper, ζ follows a Logistic distribution, which allows the probability of winning to be a non-linear function of the vote share, the probability of winning can be re-written as:

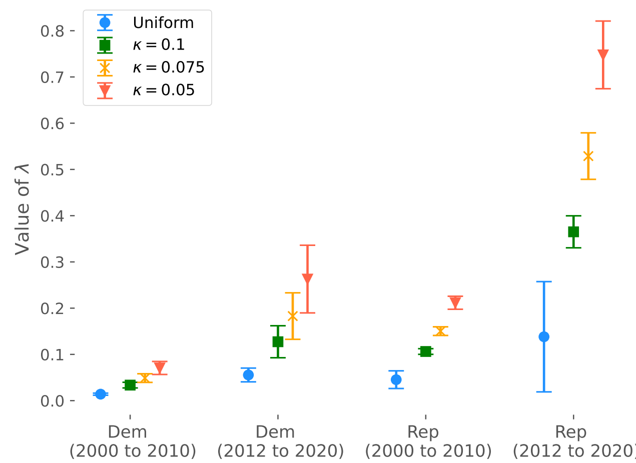
$$\begin{aligned} P_j(\mathbf{x_{jt}}, \mathbf{x_{-jt}}) &= \mathbb{P}(s_j(\mathbf{x_{jt}}, \mathbf{x_{-jt}}) + \zeta_j \geq 0.5) \\ &= 1 - \mathbf{P}(\zeta_j \leq 0.5 - s_j(\mathbf{x_{jt}}, \mathbf{x_{-jt}})) \\ &= \frac{1}{1 + \exp\left(-\frac{s_j - 0.5}{\kappa}\right)} \end{aligned}$$

where κ is the scale of the Logistic distribution.

Figure A.19 reports different measures of the estimate of party discipline λ for different values of the scale of the Logistic distribution (κ). The findings are quantitatively similar for each value of κ and the ratio between λ for a given value of κ is almost identical. Overall, lower values of κ lead to larger estimates of party discipline since, for most candidates, the slope of candidates' valuation becomes steeper.



(a) Candidate valuation for different κ



(b) Estimated λ

Figure A.19: Estimated λ for different values of κ.

Notes: The Figure shows estimated levels of party discipline when relaxing the linearity assumption of the candidate valuation of their vote share. I re-estimate λ where the voting aggregate shock follows a Logistic distribution instead of a uniform distribution. The Figure reports different estimates of λ for different scale parameters of the Logistic distribution κ with location 0.5. Panel (a) shows different shape of their valuation for different values of κ. Panel (b) shows the corresponding estimates of party discipline.

I Alternative candidate ideology model

I estimate an ideal point for each candidate for each political topic. I adapted the framework of Vafa et al. (2020) who set up an unsupervised topic model (*Text-Based Ideal Point*). The original model consists in estimating one single ideal point for each candidate across topics. I estimate the ideal point x_{jkt} of each candidate j, in period t on topic k. These ideal points are jointly estimated with the following additional latent variables:

- θ_{dkt}, the per-document d topic k intensity at period t;
- β_{ktv} , the neutral topics k in period t for term v ;
- η_{ktv} , the ideology associated to each term v with respect to topics k in period t.

I place Gamma priors on θ and β and normal priors on η as well as the ideal points x.

All these latent variables interact together to draw the observed count of each term v in document d, authored by $j = a_d$ in period t that I assume follows a Poisson distribution.

$$y_{dv} \sim \text{Pois}\big(\sum_k \theta_{dk}\ \beta_{kv}\ \exp(x_{k,a_d}\eta_{kv})\big)$$

Let's take a politician with an ideal point of $x_{jk} = 0$, meaning that candidate j is completely "neutral" on topic k. To talk about topic k, candidate j will only use words depending on the extent to which they belong to topic k (β_{kv}), independently of their polarization (η_{kv}). However, if candidate j is located on the very right of the political spectrum and has a very positive $x_{j,k}$, they will be more likely to use words which are polarized in the same direction. For instance, on the reproductive rights topic, words "pro-choice" will have a very negative η_{kv} whereas words like "pro-life" will have a very positive η_{kv}, leading right-wing candidates (with positive x_j) to be more likely to use words like "pro-life" and less likely to use words like "pro-choice" to talk about reproductive rights questions.

The four latent variables are estimated by variational inference, fitting an approximate posterior distribution.

I estimate a model with $K = 30$ topics. Out of the 30 topics, 12 have relevant political content. The 18 others are either not directly political (e.g., about contributions, contact information or campaign events) or are not interpretable. I show on Figure A.20 the words associated with the 12 selected topics and the labels I assigned to them. The list of words for the 30 topics is provided in the Appendix.

The central column shows neutral words for each topic (ideal point of 0). The left (resp. right) column shows words with the highest probability for each topic for an ideal point of -1 (resp 1). Note that the signs have been adjusted in order that the average score for Democrats across time is always lower than the average score of Republicans.

Figure A.20: Neutral and polarized words

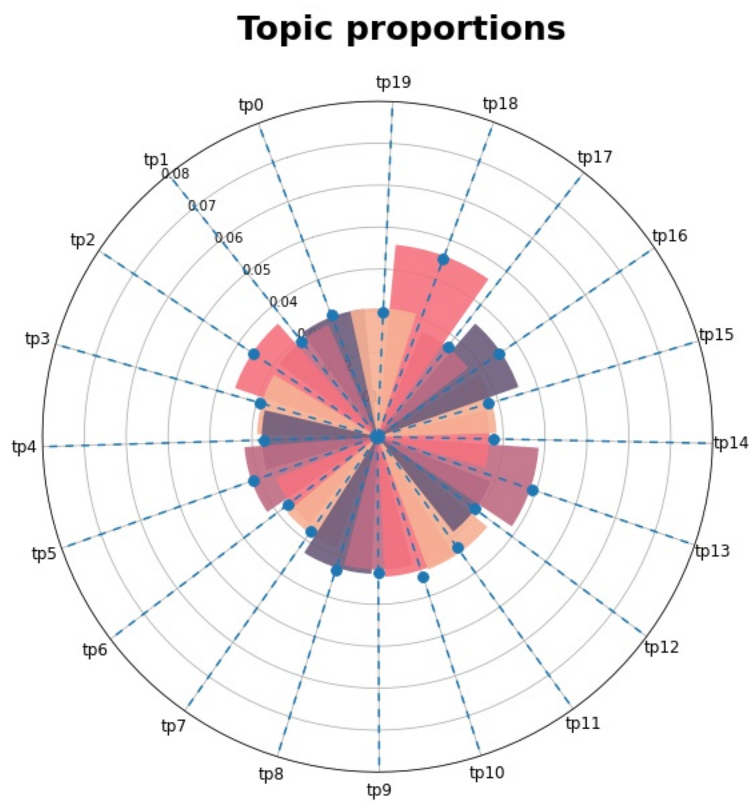


Figure A.21: Topic proportions

Figure A.21 shows the topic proportions for each of the principal topics. The blue dots indicates the average across parties and the bar shows the proportion for the Democratic candidates in particular. Democratic candidates tend to talk more than other candidates about veterans, health care, industry and donations but less about the economy, finance, war and security.

Figures A.22 to A.25 show the distribution of ideal points on different topics. Interestingly, ideal points are not all on a straight line, meaning that candidates differentiate themselves from one topic to another. In other words, the position of the candidate on the economy doesn't pinpoint the position of the candidate on healthcare. The party lines remain, however, clearly defined for most political topics. In particular, reproductive rights, health care, economic topics or education have a very distinct ideal points distribution for the Democratic Party than for the Republican party. That being said, there is no single topic where the most conservative Democrat is less conservative than the most liberal Republican. In other words, on all topics, the distribution of both parties overlap.

Figure A.26 shows the correlation between the ideal points obtained from TBIP and from model developed in the main paper, using both candidate survey and candidate website to recover their ideology. The correlation is 0.45 for the cultural topic and 0.49 for the economic topic.

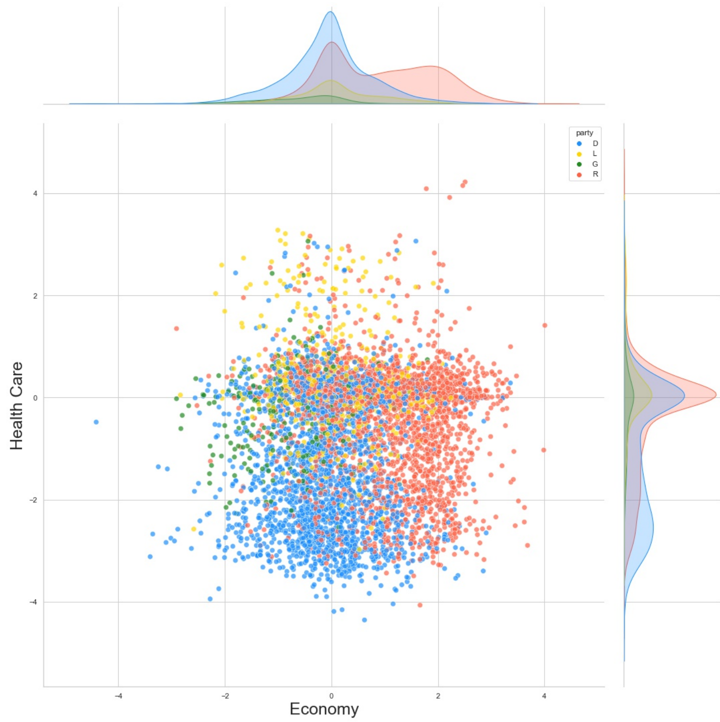


Figure A.22: Ideal point distributions (economy and healthcare)

Figure A.23: Ideal point distributions (education and abortion)

Figure A.24: Ideal point distributions (war and veterans)

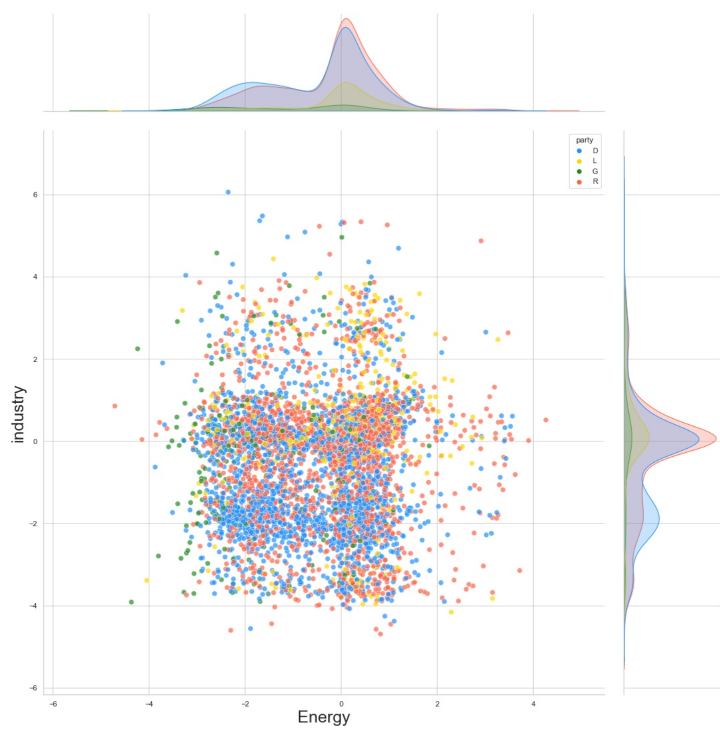
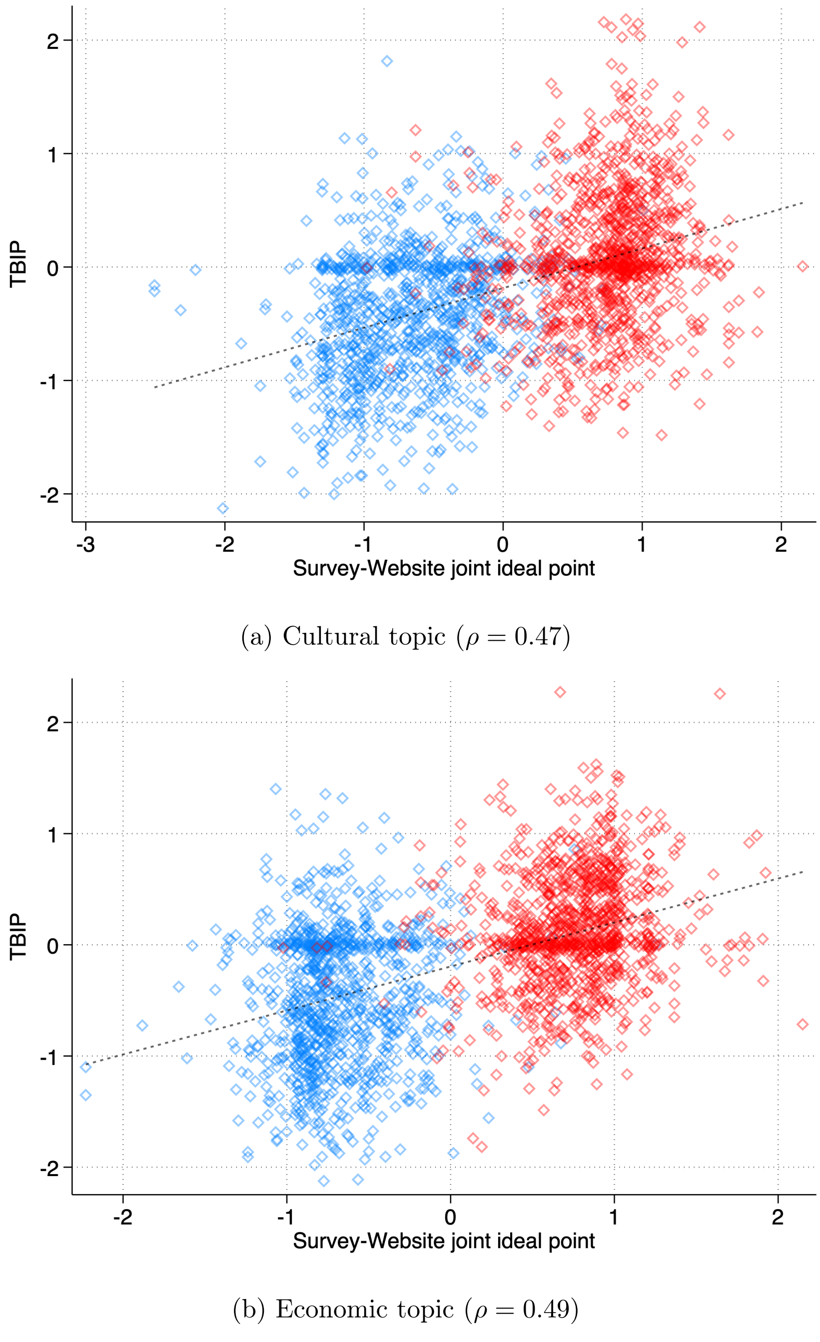


Figure A.25: Ideal point distributions (industry and energy)



(a) Cultural topic ($\rho = 0.47$)

(b) Economic topic ($\rho = 0.49$)

Figure A.26: Correlation between survey-website joint ideal point and TBIP