The Common Good and Voter Polarization

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Abstract

Do voters see democracy entirely in spatial terms, as a tradeoff of conflicting interests, or do they also view it as a search for the "common good," as some democracy theorists have long conjectured? We develop a model in which voters have preferences over both common-good and spatial payoffs, and provide a novel method to disentangle the two. Estimating the model on California ballot propositions from 1986 to 2020, we find that 74 percent of voters placed significant weight on the common good and that partisan polarization roughly doubled over the time period, mainly due to Democrats drifting left.

1 Introduction

Democracy has its roots in two venerable traditions. One, going back at least to Aristotle, sees democracy as a search for the common good, policies that redound to the benefit of all. By involving the people in self-government, the dispersed information of the many can select the common good better than decisions made by a small group or single person.[1] A more recent tradition, called "pluralism," sees democracy instead as an arena for the resolution for inherently conflicting interests. Competition leads groups to check and balance each other, resulting in collective decisions that reflect compromise and a balancing of conflicting

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[1] The Condorcet Jury Theorem is in this tradition, as is the large theoretical literature on information aggregation (for a review, see Nitzan and Paroush, 2017). Ober (2008) applies theories of information aggregation to explain the political institutions of the most famous ancient democracy, classical Athens; he labels this form of government "epistemic democracy."

interests.[2] A tension has always existed between these two traditions, but it seems to have become acute recently with the metastasizing of partisan polarization.[3] In a world where the population seems to have divided into irreconcilable camps, one may wonder if voters perceive politics as having a common-good component or simply see it as an exercise in the division of rents.

While the idea of democracy as an epistemic search for a commonly-valued outcome has been a mainstay in the theoretical literature on information aggregation in voting, empirical research has emphasized spatial motives. For example, the foundational evidence on polarization, the NOMINATE scores of Poole and Rosenthal (1985, 1997), assumes purely spatial preferences. This paper develops an empirical strategy to determine whether voters consider the common-good in addition to their spatial preferences, and applies it to election returns from California ballot propositions over the last three decades.

Our approach can be motivated by a hypothetical example:

Ballot Measure #1. *To fund levee improvements for flood prevention through an increase in property taxes.*

In this example, voters can approach the issue by focusing on its common-good aspect – protecting the *community* from flooding. Alternatively, they can emphasize the spatial component – their *individual* tax burden and their *individual* flood risk.

In our framework, voters choose between two policy alternatives (vote for or against the ballot measure), each of which compounds a "common" payoff and an individualized "spatial" payoff. We model the spatial payoff as the distance from an ideal point, following the literature initiated by Poole and Rosenthal (1985, 1997), and refer to a voter's ideal point as his or her "ideology." We model the common good as a payoff that moves all voters' utilities in the same direction, but for which the optimal direction is uncertain, following the literature on common values associated with the Condorcet Jury Theorem. Voters receive informative signals about a policy's common-good payoff.

Citizens may vote differently because they have different information about the common-good payoff, because they have different ideologies, or because they put different weights on the two components. This creates an identification challenge: if many voters support a particular policy, it could be because it is closer to their ideological position than the alternative, or because it has a higher common-good payoff. One of the paper's contribu-

[2]This approach was embedded in the U. S. Constitution, as highlighted in Federalist Nos. 10 and 51. Other examples include Bentley (1908), Truman (1951), and Becker (1983).

[3]McCarty (2019) summarizes the literature.

tions is to show how these forces can be separated using only data on voter behavior and characteristics.

Both the common-good and spatial payoffs enter directly into the utility function, so are both "private" returns in some sense. The common-good payoff could nest other-regarding preferences such as altruism or fairness concerns (Fehr and Charness, 2024; Fisman et al., 2017; Kerschbamer and Muller, 2020; Enke et al., 2022), or could simply reflect direct ethical or moral preferences over what constitutes the well-being of the community. The essential feature of the common-good component, in our framework, is that one outcome provides a higher common-good payoff than the other for all voters; therefore, voters would agree on which policy most benefits the common good if they had full information. For example, all voters would agree that it is better to protect citizens from crime than not, but because of information differences, they might disagree on the policy that would best achieve that outcome.

Our strategy for separating the common-good and spatial effects is by observing how voters co-move across issues. Intuitively, we can empirically distinguish co-movements in their votes that are due to movements in the cutpoints between policies (that is, co-movement for spatial reasons) from those that are due to a common-good component (co-movement due to better information). As usual, identification relies on certain untestable assumptions about the economic environment; the key one for separating the different reasons for co-movement in votes is that the distribution of policies has more weight in the ideological center than the extremes.

We estimate the model on 168 California ballot propositions from 1986 to 2020. These propositions spanned a wide range of economic and social issues, including tax increases, tax cuts, primary elections, redistricting, same-sex marriage, capital punishment, and marijuana legalization. Their importance is indicated by the $4.2 billion spent on their campaigns compared to the $1.5 billion spent on legislative campaigns during the same period (Matsusaka, 2023). Despite offering a rich source of information, relatively few studies have used ballot measures to estimate voter preferences, and none that we know of have used them to study polarization.[4] Ballot propositions offer an especially clean link between votes and policy preferences: in contrast to candidate elections, where voters choose between two candidates that make promises on a bundle of issues that they may or may not keep, in

[4]Previous research that used ballot propositions to estimate preferences includes Deacon and Shapiro (1975), an early example; Snyder (1996), using a version of principal components analysis; and Gerber and Lewis (2004), using a purely spatial model. These studies do not investigate polarization, and apart from Deacon and Shapiro (1975) who proxy for the common good using observables, do not incorporate a common-good component.

proposition elections voters choose whether to adopt a single law that will go into effect exactly as proposed, or to retain the known status quo.

Our estimates indicate that most voters – 74 percent – placed a substantial weight on the common-good component of policies. In terms of magnitude, zeroing out the common-good payoff would have shifted the average voter's probability of supporting a proposal by the same amount as shifting the voter's ideological position 63 percent of the way between the median Democrat and median Republican.

Our spatial, or ideology, estimates indicate that voters were polarized, both in terms of divergence (the overall dispersion of preferences) and party polarization (the tendency of voters to sort ideologically by party), consistent with previous research using other data and methods. Polarization approximately doubled from 1986 to 2020, with most of the increase occurring after 2010. For the post-2012 period, where there is no existing evidence, we find that polarization grew largely because Democrats moved to the left, not because Republicans moved to the right, contrary to what has been found for members of Congress (e.g., McCarty, ~~(~~2019~~)~~).

After establishing baseline results, we conduct a series of robustness checks, both to stress-test key assumptions, and to test if our common-good estimates are spuriously capturing other effects. First, we allow voters to receive signals that are correlated within members of a party. Second, we restrict the model to economic issues to explore whether a second spatial dimension is driving our results. Third, we test for the possibility that a common shock unrelated to information about the common good, such as emotional responses triggered by campaign messaging, causes votes to move in the same direction. Fourth, we probe several assumptions of our policy-setting model. In all of our robustness specifications, we continue to find statistically and economically significant common-good preferences, and find no evidence that other potential sources of common 'shocks' are driving the results. Finally, as a rough proof of concept, we also report common-good estimates for specific issue types to show that the common-good estimates square with intuition.

Our empirical model draws from several streams in the literature. It nests a pure spatial model at one extreme, and a pure common-good model at the other. The idea that voters have fixed spatial preferences that can be inferred from variation in votes across individual issues is in the tradition of the literature following Poole and Rosenthal (1985, 1997). In terms of common-good payoffs, Iaryczower and Shum (2012) and Iaryczower and Katz (2016) model judges with spatial preferences and private information about a common payoff (the legally "correct" decision). In their settings, variation in "policies" can be captured by case characteristics, whereas in ours it would be difficult to assume that all policies have the same cutpoints (e.g., even narrowly defined policies such as taxes on cigarettes may differ in their position due to differences in the tax rate). From Londregan (1999, 2000), we draw the idea of solving the identification problem by imposing structure on the policy proposal process.

In terms of political polarization, the literature has focused on political elites, with the well-known finding that elite polarization has increased since the 1970s (McCarty et al., 2016). There is much less evidence on polarization among voters. Our reading of the evidence, especially Hill and Tausanovitch (2015), is that voters have not become more extreme – at least through about 2010 – but have been sorting by party (Gentzkow, 2016; McCarty, 2019). We contribute evidence from the largely unexploited data on ballot proposition votes, and extend the evidentiary base on voter ideology into the most recent decade – existing estimates end in 2012 – leading to a new finding that polarization has grown significantly since 2010. These results suggest that voters have been following, not leading, their elected representatives in polarizing.

Our paper is also related to the literature that estimates the quality or "valence" of candidates for office. Kendall et al. (2015) and Cruz et al. (2019) conduct field experiments to estimate voters' weights on the unobserved valence of candidates, using beliefs elicited from survey data to identify the valence component. Buttice and Stone (2012), Beath et al. (2016), and Iaryczower et al. (2020) estimate candidate valence assuming that it can be proxied by observable characteristics such as education, sex, etc.[5] Formally, valence is similar to a common-good payoff in that it affects the utility of all voters in the same way; however, while valence can be captured with candidate characteristics, the common-good payoff is embedded in voter preferences or the policies themselves and must be recovered in a different way. One of our contributions is to provide estimates of the amount of common-good considerations associated with policy issues. We also hope to advance the literature in terms of methods by identifying an assumption on the issue space that allows preferences to be inferred without having an observable empirical proxy or elicited beliefs, potentially widening the scope of problems that can be studied.

[5] Iaryczower et al. (2020) allow for unobservable candidate valence by estimating candidate policy locations using contributions data. Although campaign contribution data are available for ballot propositions, we do not use contribution data to identify ideology because contributions could have been made for both ideological and common-good reasons.

2 Empirical Model

We develop a two-stage model in which each citizen, $i = 1, 2, \ldots, N$, votes on a series of ballot measures or issues, $j = 1, \ldots, J$. In the first stage, for each issue j, a randomly selected voter proposes a new policy, x_j, to replace a randomly selected status quo policy, q_j. In the second stage, voters choose between the two policies.

2.1 Second Stage: Voting

Voter i's utility from voting for $k_j \in \{q_j, x_j\}$ is

$$u(k_j) = -\underbrace{\left(k_j - \tilde{\theta}_{ij}\right)^2}_{spatial} + w_i \cdot \underbrace{\tilde{V}(k_j)}_{common}. \tag{1}$$

Voters derive expressive utility from a spatial component and a stochastic common-good component.[6] The spatial payoff is determined by the quadratic distance between the policy and the voter's ideal point or "ideology", $\tilde{\theta}_{ij}$, in a one-dimensional policy space.[7] The common-good payoff, $\tilde{V}(k_j)$, moves the utility of all voters in the same direction, but they may place different weights w_i on it. A voter with a positive weight, w_i, is willing to sacrifice some of their spatial benefit for the common good.

The common-good payoff is a binary random variable normalized to be drawn from $\{0, 1\}$ independent of x_j and q_j.[8] In the levee example, voters receive a common-good payoff associated with the general or collective value they place on flood protection for the community, independent of their private benefits from protection or their property taxes (which would be captured by the spatial component). Because the common good payoff is binary, the difference in the common-good payoff between the proposed and status quo policy can take one of three values, $\tilde{\psi}_j \in \Psi \equiv \{-1, 0, -1\}$. Common-good considerations matter for issue j if $\tilde{\psi}_j \in \{-1, 1\}$, and do not matter if $\tilde{\psi}_j = 0$. We assume that the two

[6] Expressive utility is a standard assumption in ideal point estimation and is plausible in settings with a large number of voter, where the probability of casting a pivotal vote is minuscule.

[7] Quadratic utility is common in spatial models (e.g., Clinton et al., ~~(~~ 2004; ~~) and~~ Heckman and Snyder, ~~(~~ 1997~~)~~). In Appendix B, we show that the likelihood function for a linear utility function is the same up to a scaling parameter, apart from some exceptions in the parameter space. We prefer the quadratic specification to avoid having to deal with these exceptions in estimation.

[8] The payoff $\tilde{V}(k_j)$ must be normalized because an unbounded common-good component cannot be separately identified from the weight, w_i. Furthermore, because we allow $\tilde{V}(k_j)$ to differ across issues, we cannot allow the weights to differ across issues. In our formulation, weights are allowed to be heterogeneous across voters, but the results can alternatively be interpreted as heterogeneous benefits from the common good. Even if the benefits are heterogeneous, however, the common good moves votes in the same direction for all voters, and thus differs from heterogeneity in the spatial dimension.

common-good payoffs are equally likely, which for the differences implies that the prior on $\tilde{\psi}_j = 0$ is 1/2, and the prior on the other values is 1/4. Voters learn about the common-good payoff by receiving an informative signal $\tilde{s}_{ij} \in S \equiv \{-1, 0, 1\}$ that indicates the true state with probability π_i, and one of the other two states with probability $\frac{1-\pi_i}{2}$. In our main specification, $\tilde{s}_{ij}$ is distributed independently conditional on $\tilde{\psi}_j$. Signals are therefore correlated only through $\tilde{\psi}_j$; we allow for conditional correlation in signals in a robustness check.[9]

For the spatial component, instead of focusing on the policy options, it is convenient to assume that voters know the midpoint between policies, $m_j \equiv \frac{x_j + q_j}{2}$, but not the locations of the policies themselves; know the "direction" of the proposed alternative, $\mathcal{D}_j \equiv I(x_t > q_t)$; and know the distribution of $x_j - q_j$ (conditional on m_j and $\mathcal{D}_j$). Focusing on the midpoint follows Canen et al. (2020, 2022) and has the important advantage that one can prove identification.[10]

Voter i chooses x_j if it provides higher expected utility than q_j (the tie-breaking rule is inconsequential) conditional on his or her information, $\mathcal{I}_{ij} = \{m_j, \mathcal{D}_j, \tilde{s}_{ij}\}$:

$$E\left[-\left(x_j - \tilde{\theta}_{ij}\right)^2 + \left(q_j - \tilde{\theta}_{ij}\right)^2 + w_i\tilde{V}(x_j) - w_i\tilde{V}(q_j)|\mathcal{I}_{ij}\right] \quad \geq \quad 0;$$

which simplifies to

$$\alpha_j^d(\tilde{\theta}_{ij} - m_j) + w_i E\left[\tilde{\psi}_{ij}|\mathcal{I}_{ij}\right] \quad \geq \quad 0 \qquad (2)$$

where $\alpha_j^d \equiv E\left[(x_j - q_j)|m_j, \mathcal{D}_j = d\right]$ is the expected distance between policies.

We assume that voter i's ideology is subject to an idiosyncratic shock for each issue j, $\tilde{\theta}_{ij} = \theta_i + \varepsilon_{ij}$, where ε_{ij} is drawn from a standard normal distribution Φ. Ideological shocks are independent across voters and independent of $\tilde{\psi}_j$, $\tilde{s}_{ij}$, q_j, and the proposer's identity.[11] Denote the probability that citizen i votes for x_j conditional on $\tilde{\psi}_j$ and direction $\mathcal{D}_j$ as $\gamma_{ij}^{\psi d} \equiv Pr(Y_{ij} = 1|\tilde{\psi}_j = \psi, \mathcal{D}_j = d)$. Then, assuming $\alpha_j^1 \neq 0$, which will be true for almost

[9] Using a discrete number of states and signals allows us to apply identification results for finite mixture models. We assume fixed priors because the model cannot be identified for arbitrary priors. See Appendix A for further details.

[10] While we believe it is plausible, as we assume, that voters understand the election in terms of a change ("increase the sales tax by 1 percent"), it would also be plausible to assume that they understand the two policy options directly ("sales tax of 4 percent" versus "sales tax of 5%"). If we were to assume that x_j and q_j are known by voters, both of these would become parameters that must be separately identified and estimated. This would be a more difficult problem and we are unaware of any work that estimates these two parameters in an identified model.

[11] The specification would be similar if we assumed shocks to utility instead of shocks to ideology, but ideology shocks simplify the estimation process (Canen et al., 2020, 2022).

all parametrizations,

$$
\begin{aligned}
\gamma_{ij}^{\psi 1} &= \sum_{s\in S} Pr\left(\tilde{s}_{ij}=s|\psi\right) Pr\left(\alpha_j^1\left(\theta_i+\varepsilon_{ij}-m_j\right)+w_i E\left[\tilde{\psi}_j|\tilde{s}_{ij}=s\right]\geq 0\right) \\
&= \sum_{s\in S} Pr\left(\tilde{s}_{ij}=s|\psi\right)\Phi\left(\theta_i-m_j+\frac{w_i}{\alpha_j^1}E\left[\tilde{\psi}_j|\tilde{s}_{ij}=s\right]\right); \qquad (3)
\end{aligned}
$$

and

$$
\gamma_{ij}^{\psi 0}=\sum_{s\in S} Pr\left(\tilde{s}_{ij}=s|\psi\right)\left(1-\Phi\left(\theta_i-m_j+\frac{w_i}{\alpha_j^0}E\left[\tilde{\psi}_j|\tilde{s}_{ij}=s\right]\right)\right). \qquad (4)
$$

These vote probabilities nest a standard spatial model ($w_i = 0$) as well as a purely common-value model akin to Condorcet's Jury Model ($w_i \to \infty$). With $w_i = 0$, the idiosyncratic ideology shocks absorb all variation in votes not predicted by ideologies. At the other extreme, all variation is attributed to differences in signals across voters. Note that inclusion of idiosyncratic ideology shocks ensures that a common-good component does not exist simply by assumption: policies that simply align private interests such that no voter faces a tradeoff will be fit by a purely spatial model with all $w_i = 0$.

2.2 First Stage: Choice of Policy Proposal

For each issue j, a status quo policy q_j is drawn from the distribution $Q(q)$. The new proposed policy is selected by a voter $i = p$ drawn from the (estimated) distribution of ideologies $T(\theta)$. The proposer simply chooses his or her ideal point, which implies that $x_j = \theta_p$. The proposer does not choose the common-good component – in terms of the levee example, we have in mind that the value of improving the levy is inherent in the issue, but the proposer has discretion to formulate a tax scheme. The policy-setting model produces a distribution over x which, together with the assumed distribution for q, determines the distributions over policy midpoints and differences, which we denote as $f^d(m|\boldsymbol{\theta}, \mathcal{D}_j = d)$ and $g^d(x - q|\boldsymbol{\theta}, \mathcal{D}_j = d, m_j)$, respectively, where $\boldsymbol{\theta}$ indicates the set of all voter ideologies.

2.3 Identification: Intuition and Key Assumptions

Appendix A provides a formal proof of identification of the model parameters. Here we provide a sketch of the proof.

Ideologies are identified as usual in spatial models – through the difference in how voters with different ideologies vote on the same issue.[12] The direction of each proposed alternative, $\mathcal{D}_j$, is then identified by whether voters towards one end of the spectrum tend to favor the alternative or the status quo.

To identify the signal precision, we leverage the fact that the vote probabilities in (4) are given by a finite mixture model. In such a model, the mixing probabilities (which map to the signal precision) are identified provided an ordering constraint is satisfied.[13] Intuitively, the signal precision is governed by the *co-movement* in votes, not explained by ideology. With low signal precision, votes would be uncorrelated across voters conditional on ideology – the ideology shocks would capture all residual variance. With high signal precision, votes would instead be correlated as many voters receive the same signal.

To identify the midpoints and common-good weights, we require the policy-setting information. To understand how it is crucial for identification, imagine a landslide election. Theoretically, a landslide could happen for two reasons: (i) the proposal or status quo (and therefore policy midpoint) was ideologically extreme, or (ii) the common-good payoff was large. It might seem that we cannot distinguish the two possibilities without independent information on the location of the policy midpoint or the value of the common-good component. However, note that if extreme midpoints are less likely than centrist midpoints, then it is more likely that voters were swayed by a high common-good payoff than an ideologically extreme policy. A key part of our identification comes from the assumption that centrist midpoints are more likely than extreme midpoints. The policy-setting assumption that assumes proposers are randomly drawn from the population offers a way to microfound such an assumption. Centrist midpoints are a feature of agenda-setting models – in those models even an extreme proposer chooses a proposal with a midpoint centered on the median voter, whether the proposer is the sitting government (Romer and Rosenthal, 1979) or a citizen (Gerber, 1996; Matsusaka and McCarty, 2001). Intuitively, extreme midpoints are unlikely: if the status quo were extreme, it would more likely attract a group that wanted to move policy toward the middle or the other extreme (creating a centrist midpoint) than a group that wanted an even more extreme policy (creating an extreme midpoint).

With the policy-setting information, we can identify the common-good weight by looking at the average difference in votes across signal realizations for a given voter. As with the signal precision, a voter with a low common-good weight will vote as in a spatial model, but a voter with a high common-good weight will change as a function of the signal. The

[12] For this, we require two voters with the same common-good weight but different ideologies, a restriction which we impose in the empirical specification (see Section 4).

[13] The probabilities being mixed over must map to signal realizations in the same way for any set of parameters, something which we establish in Appendix A.

policy-setting information is key because it pins down the average midpoint without having to first identify the individual midpoints. Once the common-good weight is known, the individual midpoints are identified issue by issue.

While the assumption that policy midpoints are more likely to be centrist than extreme is important, other assumptions about the proposal process are not. In our baseline model, a policy's common-good component is exogenous (not chosen by the proposer) and orthogonal to the spatial dimension. Another possibility is that the common-good component is inherently correlated with its spatial location. For example, if a proposer chooses a highly redistributive tax scheme (left on the the spatial dimension) it may imply a high deadweight loss (low common-good payoff). In this case, the proposer faces a tradeoff between policies closer to his or her ideal point and the common-good value of the proposal. In Appendix B, we develop and estimate a model with this tradeoff. The findings of this model are similar to our baseline model.[14] An additional assumption is that the proposer does not account for the possibility that the policy may fail, as would be implied by strategic models of the proposal process (Matsusaka and McCarty, 2001). In Section 5.4, we estimate a model in which the proposer is strategic. Other assumptions are discussed in the robustness section below.

Because estimation of the common-good weight is the paper's core empirical innovation, it is worthwhile to say a few more words about what exactly our estimate does and does not capture. There is an active stream of literature that explores the sources of what we call common-good payoffs (Charness and Fehr forthcoming). They could arise, for example, from altruistic or distributional preferences. They could also be freestanding ethical preferences that are not connected to the utility of others, such as views on whether capital punishment ought to be employed or not. In the levee example, we would detect a common-good component if all voters happened to have equal exposure to flood risks, or if voters had different exposure but consider flood protection a generalized benefit to the community. Our estimate cannot distinguish these different sources of common-good payoffs. What our estimates do capture is the extent to which voters view policy choices partially in terms of an underlying payoff that they have in common. We are able to identify this payoff by explicitly estimating, and therefore controlling for, the spatial consequences of policies.

[14] We present the version of the model in the main text because it fits the data better. A Vuong test rejects the null of equal fit with ~~(~~$p < 0.001$.

3 Data

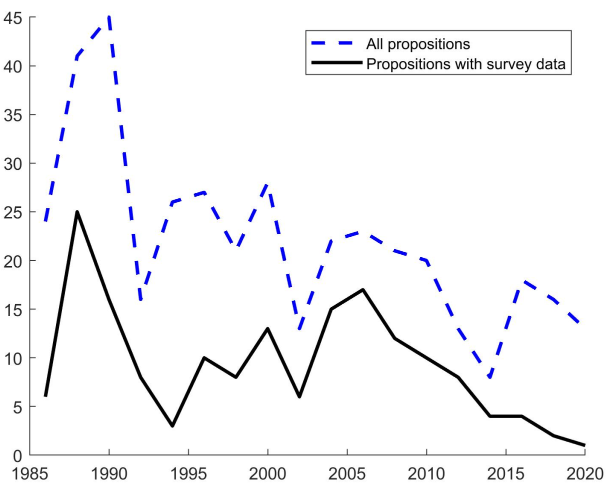
Our data cover California propositions during 1986-2020. The 168 propositions for which we have survey data (out of 395 total) were statutes or constitutional amendments that voters could approve or reject by majority vote. Of these, 116 propositions were new laws proposed by citizens and three were proposals to repeal existing laws, all of which qualified for the ballot by collecting signatures. With slight abuse of terminology we refer to these together as "initiatives", even though the latter three are more correctly referred to as "veto referendums." The remaining 49 propositions were placed on the ballot by the legislature ("legislative proposals"). The range of issues was wide, including tax increases and tax cuts; regulation of insurance companies, farmers, and health providers; social issues such as abortion, same-sex marriage, marijuana legalization, and the death penalty; elections and voting; and government processes, among other things. The propositions spanned the ideological spectrum: some were backed by Democrats, some by Republicans, and some were opposed or supported by both parties.

Figure 1 shows the number of propositions that went to a vote each year, and the number of propositions in our sample. Californians have been voting on issues since the state entered the union in the 19th century; initiatives and veto referendums have been available since 1912. Although California was not the first state to use direct democracy, it has become the leader in using initiatives, and some of its most consequential laws have been the result of citizen initiatives. The number of propositions varies by year, with an average of 22 per two-year electoral cycle. As a result of historical experience, Californians are quite familiar with voting on issues, and can tap a rich array of information sources when deciding how to vote: an official ballot pamphlet containing a nonpartisan analysis from the office of the legislative analyst as well as arguments from proponents and opponents; endorsements and recommendations from politicians, interests groups, and media; and in many cases extensive campaign advertising. As such, we expect voters to be fairly well informed about most issues, and their votes to reflect their preferences (Lupia, 1994, Lupia and McCubbins, 1998).

For voter preferences on individual propositions we use pre-election survey data from the Field Poll (1986-2012) and Public Policy Institute of California (PPIC) (2010-2020), both well-regarded pollsters in the state.[15] The surveys asked voters how they intended to

[15] Field Poll data are available at https://dlab.berkeley.edu/data-resources/california-polls. PPIC data are available at https://www.ppic.org/data-depot/. We use the Field Poll for the 2010 and 2012 general elections and PPIC for the 2010 and 2012 primary elections (the Field Poll did not survey the 2010 and 2012 primaries). We did not go back before 1986 because the demographic questions are not readily comparable

Figure 1. Number of Propositions by Two-year Electoral Cycle



vote on select ballot propositions, their party identification, and demographic information. If there was more than one wave of polling before an election, we use the survey nearest to the election, typically a week or two before election day. We use each survey's recommended sample weights when constructing distributions over policy midpoints and when reporting aggregate results.

The available demographic variables are: categorical dummies for age, education, income, race, and county of residence.[16] For party identification, we use a respondent's self-reported party registration, which in California is simply a designation of which party's primary the person preferred to participate in. After dropping observations with missing data, 96,213 responses remain from 31,007 respondents.

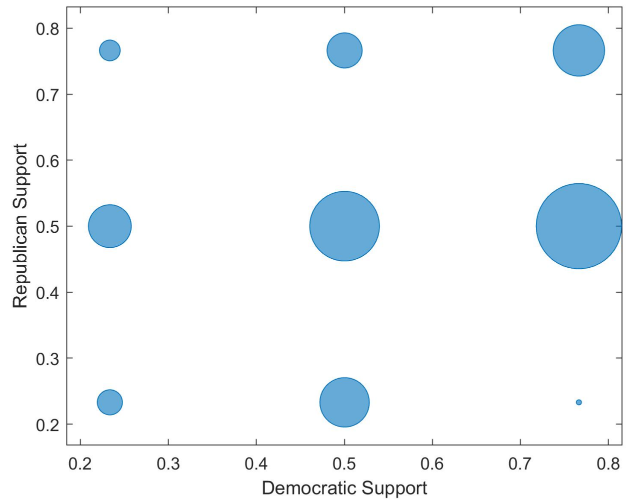
The propositions in our sample were typically the higher-profile issues, both in terms of media coverage and campaign spending. For the years in which we have campaign finance data (1998-2016), spending per proposition averaged \$21.5 million for issues that were polled, compared to \$11.7 million for issues that were not polled.

Survey respondents indicated whether they intended to vote for (47 percent) or against

in the pre- and post-1986 surveys. Data for the 1994 elections, the primary elections in 2014, 2016, and 2018, and the general election in 2020 are unavailable. An advantage of survey data is that they do not depend on the turnout decision; turnout shocks, if correlated across voters in particular ways, could potentially bias estimates of the common-good weights.

[16]When response categories varied from survey to survey, we collapsed them into a common set of categories. We do not consider gender because it was not collected for 2002. Counties with fewer than 50 observations were omitted. We exclude the roughly 3 percent of voters that did not identify as White, Black, Asian, or Hispanic, and the 0.4 percent of voters that identified as more than one race.

Figure 2. Support by Party



Note. Fraction of Republican voters supporting the proposition (y-axis) versus fraction of Democrats supporting the proposition (x-axis). The fractions of support are binned and plotted at the midpoint of the bin. The size of the dot indicates the number of propositions in the data with the given support by each party..

(41 percent); the undecided (12 percent) were omitted.[17] An alternative approach would be to treat undecided respondents as indifferent between voting for and against, as in Deacon and Shapiro (1975); we drop them because more than half indicated that they had not even heard of the proposition – meaning they were uninformed, not indifferent. We use the information on whether respondents knew about the proposition in a later part of the analysis.

There is considerable variation in the support across propositions and across voters identifying with each party. Figure 2 shows the number of propositions in the data with given support by voters of either party (binned by fraction of support). In the upper right, for example, 20 propositions have broad appeal, while in the lower left, 10 have little support among either party. In the upper left and lower right, support comes almost exclusively from partisans of one type. As discussed in the previous section, a key goal of the estimation exercise is to determine when bipartisan support (or lack of support) is driven by common-good considerations. It is therefore reassuring that support across parties is not concentrated in any one particular place in the distribution.

Information on the subject matter of propositions was taken from a database maintained

[17]Support for ballot propositions tends to be higher in surveys than in the final vote (6 percent higher in our data among decided voters), in part because of the well-known phenomenon of support dropping during the course of a campaign (de Figueiredo, Ji, and Kousser, 2011; Matsusaka, 2018).

by the Initiative and Referendum Institute (www.iandrinstitute.org). Propositions were classified into general categories – taxes, regulation, social issues, elections and voting, government processes, and other – by three coders working independently, as described in Appendix C.[18]

4 Empirical Specification

Because the data include only a handful of votes for each respondent, we construct voter types from respondent characteristics. In particular, we assume $\theta_i = X_i\beta$ where X_i consists of the set of observable characteristics, county fixed effects, and time dummies for each four-year period along with their interactions with a voter's party registration. We include select interaction terms to limit the number of parameters to be estimated. A consequence of this specification is that the marginal effects of demographics (age, education, etc.) are constant over time.

Absolute ideological movements over time are identified using issues that came to a vote in different years. For example, proposals to require parental notification and a 48-hour waiting period before a minor had an abortion were on the ballot in 2005, 2006, and 2008. There are enough repeat issues to establish links across the entire period except from 2014 onward, which we therefore treat as a single period (see Appendix D).[19]

To identify the common-good weights separately from ideologies requires a form of exclusion restriction in which some observable is a determinant of ideology but not of the weight. We therefore specify $w_i = \exp(W_i\delta)$, where W_i includes only demographic observables, excluding party registration, its interactions with time dummies, and county fixed effects.[20] This imposes that ideology, but not common good preferences, vary by party and county. We assume a homogeneous signal precision; in the robustness section we allow the signal precision to vary for voters that were and were not previously aware of the issue.

For policy setting, we assume that the status quos are drawn from a generalized error distribution, a generalization of the normal distribution, with mean and scale of $\frac{\theta_{max}+\theta_{min}}{2}$ and $\frac{\theta_{max}-\theta_{min}}{2}$, respectively, where $\theta_{max} = \max(\boldsymbol{\theta})$ and $\theta_{min} = \min(\boldsymbol{\theta})$. We set the shape

[18] By law, propositions are required to embrace only a single subject. This may be partly aspirational (Matsusaka and Hasen, 2010), but omnibus proposals are rare.

[19] With unbounded shocks and sufficient data, the probability that a voter votes Yes or No uniquely determines θ_i, independent of m_j, so that even though the issues change over time, we obtain unbiased estimates of polarization (see Canen et al., ~~(~~2022~~)~~).

[20] Specifically, we require multiple ideologies for the same weight in order to identify the directions of each issue. See the proof in Appendix A. The reason we omit many possible determinants rather than only one is that we found that when we try to include more determinants, the coefficients become very unstable across specifications - there does not appear to be enough variation in the data to produce consistent estimates.

parameter to 2, implying a normal distribution; the findings are similar with other values.

The final parameter vector to be estimated is then $\Theta = \left\{ \{m_j, \mathcal{D}_j\}_{j=1}^J, \beta, \delta, \pi \right\}$. We construct the likelihood of observing a midpoint and a series of votes conditional on this midpoint. Because the distribution of θ can vary from election to election due to both changes in the distribution of likely voters (represented by the sample weights) and changes in preferences over time, the policy midpoint and difference distributions are election specific: $f_e^d(m|\boldsymbol{\theta}, \mathcal{D}_j = d)$ and $g_e^d(x - q|\boldsymbol{\theta}, \mathcal{D}_j = d, m_j)$, for elections $e = 1, \ldots, E$. We write $j = 1, \ldots, J_e$ for the propositions in election e where $J_1 + J_2 + \ldots + J_E = J$. The distributions $g_e^d(x - q|\boldsymbol{\theta}, \mathcal{D}_j = d, m_j)$ determine α_j^d for a given election, m_j, and $\mathcal{D}_j$, so that α_j^d does not need to be separately estimated.

We construct the joint log-likelihood of observing a set of midpoints and their associated votes. Because we do not know $\mathcal{D}_j$, it must be estimated. Instead of estimating a binary parameter, we calculate the likelihood for each value of $\mathcal{D}_j$ on each issue, j, and then choose the maximum of the two.[21] The likelihood is then

$$\mathcal{L}\left(\left\{\{\,Y_{ij}\}_{i=1}^{N}\right\}_{j=1}^{J};\Theta\right) = \max_{\{D_j\in\{0,1\}\}_{j=1}^J} \left\{ \sum_{e=1}^{E}\sum_{j=1}^{J_e} \log\left[\sum_{\psi\in\Psi} Pr(\psi)\left[f_e^1(m_j|\boldsymbol{\theta},\mathcal{D}_j=1)^{\mathcal{D}_j} f_e^0(m_j|\boldsymbol{\theta},\mathcal{D}_j=0)^{1-\mathcal{D}_j}\right.\right.\right.$$
$$\left.\left.\left.\prod_{i=1}^{N}\left(\gamma_{ij}^{\psi 1}\right)^{Y_{ij}\mathcal{D}_j}\left(1-\gamma_{ij}^{\psi 1}\right)^{(1-Y_{ij})\mathcal{D}_j}\left(\gamma_{ij}^{\psi 0}\right)^{Y_{ij}(1-\mathcal{D}_j)}\left(1-\gamma_{ij}^{\psi 0}\right)^{(1-Y_{ij})(1-\mathcal{D}_j)}\right]\right]\right\}. \tag{5}$$

The likelihood takes the form of a finite mixture model because voters' signals are independent conditional on ψ, and the joint probability of observing each m_j and a set of votes is the product of the marginal probability of observing m_j and the marginal probability of observing the votes conditional on m_j. We estimate (5) via maximum likelihood using the custom optimization algorithm described in Appendix E. The estimates are consistent for large N and T (e.g., Arellano and Hahn, 2007).

[21]See Canen et al. (2022) for another application of this technique in a similar setting.

5 Results

5.1 Voter Estimates

5.1.1 Common-Good Parameters

Our first finding is that voters do in fact perceive a common-good component in policy issues. Figure 3 plots the distribution of the estimated common-good weights, w_i, across the entire sample. The mean is 0.68, with standard error 0.17 ($p < 0.001$) and 73 percent of voters have weights that can be differentiated from zero at the 5 percent significance level. A likelihood ratio test rejects a purely spatial model ($p < 0.001$).[22]

To assess the economic significance of common-good considerations, we calculate the voting probabilities given by (3) and (4), using the estimated signal precision of $\pi = 0.65$ (standard error of 0.02). We then calculate how much the voting probability would change if the common-good component vanished, and how much ideology would have to change to produce an equivalent shift in voting probability. This "equivalent ideological shift" is 0.39 on average, meaning that a common-good voter with a signal would have the same voting probability as a voter 0.39 ideological units away with no weight on the common good. This magnitude seems nontrivial – 63 percent of the distance between the average distance between the median Republican and median Democrat.

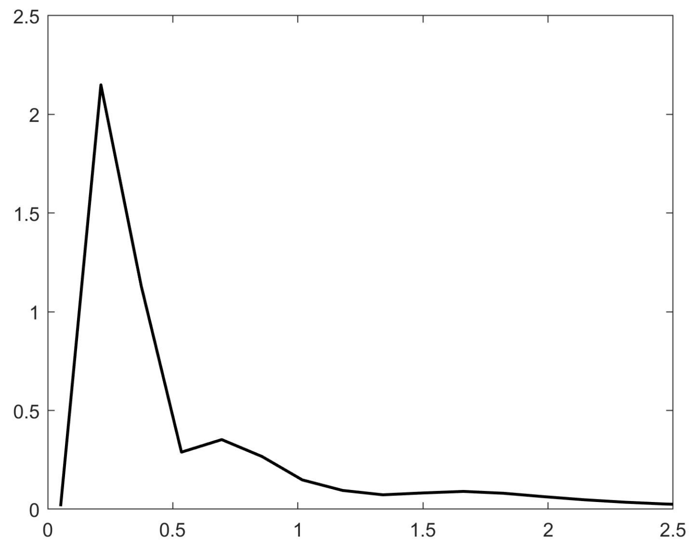
Table 1 reports the relations between voter characteristics and (in the left panel) common-good weights and (in the right panel) ideologies. The estimates indicate that common-good weights are lower for older than younger voters, lower for wealthier than poorer voters, and higher for non-white voters (holding constant other attributes); education is not significantly correlated with common good weights. These results are broadly consistent with survey evidence in Enke et al. (2022, 2023a) (summarized in and Enke, ~~(~~2023b~~)~~) that white, older, and richer voters are less morally universalistic — care less about out-group members — which could translate into placing less weight on the common good.

In terms of ideology, where positive values indicate an ideologically conservative position, the estimates imply that older voters are more conservative than younger voters, and highly educated voters are more liberal than less-educated voters, holding constant other attributes; we do not find significant ideological differences associated with income or race/ethnicity.[23]

[22] We estimate a purely spatial model by forcing $w_i = 0$ while still using the policy-setting model to provide additional information about the midpoint locations.

[23] One might conjecture that voters with extreme ideologies place less weight on the common good. Figure F1 of Appendix F illustrates some evidence consistent with this conjecture.

Figure 3. Estimated Distribution of Common-Good Weights



Note. Kernel density estimates of estimated common-good weights.

Table 1. Common Good Weights, Ideology, and Voter Characteristics

	Variable	Estimate		Variable	Estimate
Common good (δ)	Age:40-64	-0.50 (0.27)	Ideology (β)	Age: 40-64	**0.12 (0.03)**
	Age: 65+	**-0.73 (0.36)**		Age: 65+	**0.20 (0.03)**
	College	-0.70 (0.36)		College	**-0.09 (0.03)**
	College+	-0.75 (0.51)		College+	**-0.23 (0.04)**
	Income: 20-60k	-0.74 (0.40)		Income: 20-60k	0.03 (0.04)
	Income: >60k	**-1.46 (0.45)**		Income: >60k	0.07 (0.05)
	Asian	**1.93 (0.62)**		Asian	-0.00 (0.10)
	Black	**1.63 (0.54)**		Black	0.03 (0.09)
	Hispanic	**1.57 (0.40)**		Hispanic	0.05 (0.04)
	Constant	0.41 (0.47)			
Common good (π)		**0.65 (0.02)**			

Note. We do not report the time fixed effects, party coefficients, or their interactions. The omitted categories are voters with a high school education or less, voters with annual incomes below \$20,000, voters under the age of 40, whites, and voters not identifying as Republicans or Democrats (β only). Asymptotic standard errors are in parentheses. Bold coefficients for δ, β, and π indicate significance at the 5 percent level or less. For π, we test the one-sided hypothesis that the coefficient is greater than one-third.

5.1.2 Ideological Parameters and Polarization

Estimates of polarization among the general public – as opposed to among politicians – are rare (see Hill and Tausanovitch, ~~(~~2015,~~)~~ for estimates and references), and to the best of our knowledge no estimates based on referendum elections exist. Allowing preferences to have a common-good component, we are able to extract spatial preferences that are less at risk of spuriously incorporating common-good effects.

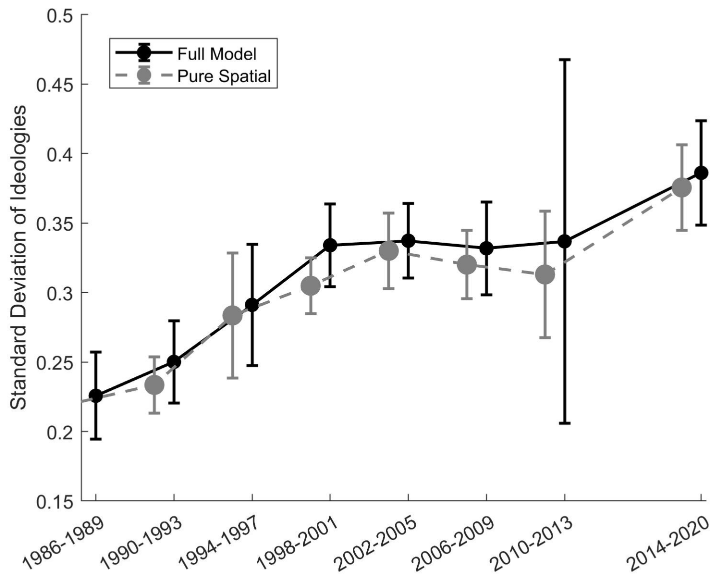
The literature uses two concepts of polarization. The first, which we call "divergence" following Hill and Tausanovitch (2015), is simply the dispersion of ideologies, θ_i. An increase in divergence reflects the replacement of moderate voters by more extreme voters, independent of their party identification. Figure 4 plots the standard deviation of ideologies over time along with estimates from a purely spatial model. The point estimates suggest that the variance of preferences grew from the start of our study period in 1986 until about 2001, remained unchanged for ten years, then diverged sharply in the last decade. Our estimates are somewhat noisy; the standard errors are large enough to preclude confident statements about the details of the time trend, but a tendency toward greater dispersion from the start to the end of the period seems apparent. Comparing across models, it does not seem that omitting the common-good component significantly biases the estimates.

Hill and Tausanovitch (2015) compute voter ideology over the period 1956-2012, using a purely spatial model with data from survey responses to policy questions. Their main conclusion is an absence of a detectable trend in divergence. Examination of their divergence figures suggests there may have been an elevated divergence period from 1956 to 1974, a relatively low period from 1976 to 1996, and a "moderate" period from 1998 to 2012. During the years our samples overlap (1986-2012), they report somewhat noisy evidence of a modest increase in divergence; our findings for this period are fairly similar, giving some reassurance that the two studies are tapping the same things. For the period after their study (2013-2020), we find evidence of a pronounced jump in divergence. If we append our evidence to theirs, the picture for the entire 1956-2020 period can be described as: yearly fluctuations with no evidence of a trend from 1956 until around 1990; a gradual increase in divergence from then on – albeit with annual fluctuations – with a clear increase by 2020.[24]

The second measure of polarization, called "sorting," is the extent to which ideological preferences are correlated with partisan identity. Figure 5 plots the distribution of ideologies at five points in time, distinguishing between voters that identify as Democrats, Republicans, or neither of the two major parties. As one would expect, the figure shows substantial

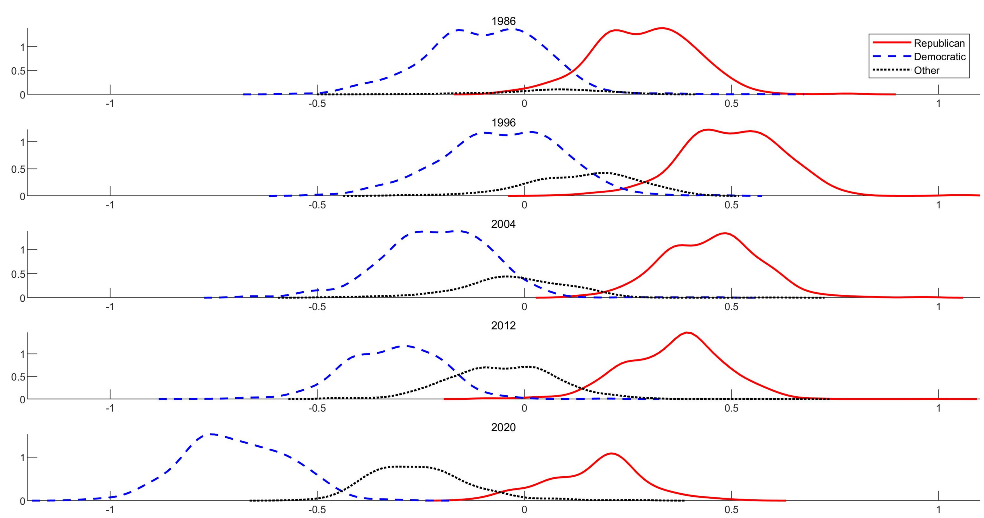
[24] We should note that the post-2012 jump appears prior to the 2016 election, so appears to be more than a Trump phenomenon.

Figure 4. Standard Deviation of Ideologies θ_i Over Time



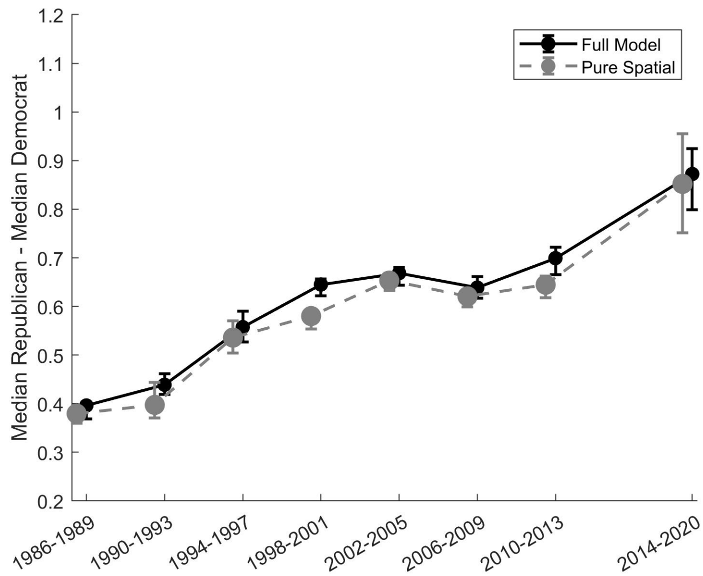
Note. Error bars indicate 95 percent confidence intervals with asymptotic standard errors.

Figure 5. Distribution of Ideologies by Party



Notes: Kernel density estimates of estimated ideologies, broken down by party identification and scaled according to the fraction each type makes up in the population (as obtained from the survey sample weights).

Figure 6. Ideological Distance between Median Republican and Median Democrat Over Time



Note. Errors bars indicate 95 percent confidence intervals with bootstrapped standard errors (200 samples of ideologies drawn from their asymptotic distributions).

sorting by party in all years. Less obviously, we see that sorting has increased over time and reached an extreme level recently: in 1986, moderate Democrats and Republicans substantially overlapped in ideology, but this overlap had completely vanished by 2020.[25] Furthermore, in contrast to existing evidence on elite polarization in which polarization is mainly attributed to Republicans moving right over time[26], our results suggest that the most recent jump in sorting is due to Democrats moving to the left.

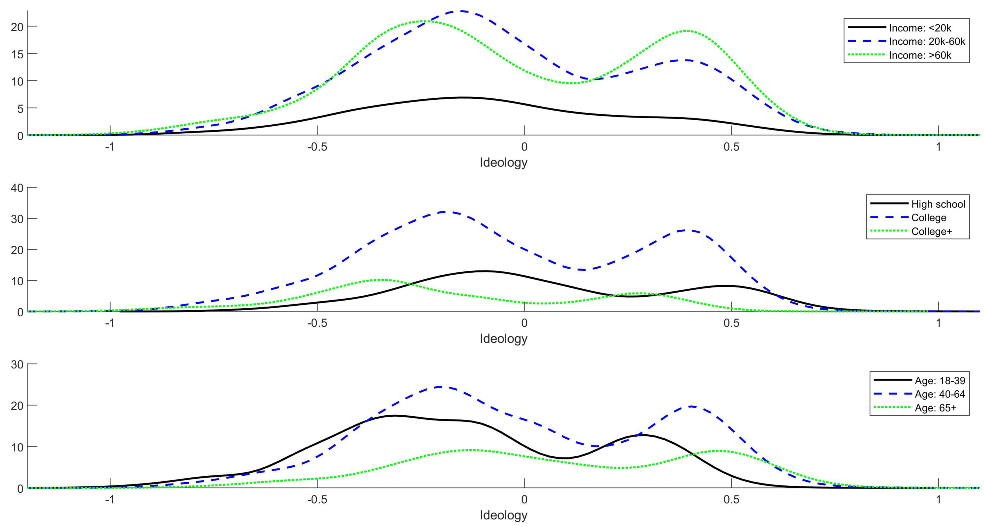
A simple measure of party sorting is the distance between the ideology of the median Democrat and the median Republican, shown in Figure 6. As with divergence, we observe an increase from the start of our period until about 2001, a relatively stable period over the next ten years, and then a large jump in recent years. From 1986 to 2020, polarization by this measure grew by 125 percent. Hill and Tausanovitch (2015, 2018) report a gradual increase in party sorting beginning in the mid-1980s and running through 2012.

The broad conclusion is that polarization among voters appears to have grown during our period of study, both in terms of divergence and party sorting, with a noticeable jump in the last few years. Our findings thus reinforce some existing evidence on polarization,

[25]Figure 5 also illustrates an increase in voters that are do not identify as Democrats or Republicans – mainly because of a decline in self-identified Republicans.

[26]See Canen et al. (2022), for results that dispute this standard view.

Figure 7. Distribution of Ideologies by Income, Education, and Age



Note. Kernel density estimates of estimated ideologies by income (top panel), education (middle panel), and age (bottom panel). Each is scaled according to the fraction each type makes up in the population.

and extend it into recent years. Our evidence casts doubt on the argument that polarization among elected officials has been primarily a response to polarization among the public – to the contrary, the temporal order suggests that polarization among political elites might be fueling polarization among ordinary voters.

Although polarization by party has attracted the lion's share of research attention, party identification is not the only potential cleavage point in American society. One popular narrative is that white-collar workers in the cities have gravitated to the Democrats while blue-collar workers in the towns and people living in the countryside have become Republicans. We are interested in the amount of sorting that can be accounted for by demographic factors. We first look at income. There is an ongoing debate about whether the rich or the poor have more influence on policy decisions (Gilens and Page, 2014; Brunner et al., 2013; Lax et al., 2019). The answer matters, of course, only to the extent that the rich and the poor actually have different policy preferences. Figure 7 plots the distribution of ideology by income. Somewhat surprisingly, we find little evidence of polarization by income.

The middle panel of Figure 7 reports the ideological distributions by education. The idea that voters are polarizing along an educational axis has attracted recent public commentary, and is tied to the notion that globalization is creating an environment of high-skilled haves and low-skilled have-nots.[27] However, as with income, we find extremists at both ends of the political spectrum and moderates within each educational class.

The bottom panel of Figure 7 reports the distribution of ideology for three age groups. Again, there is little evidence for polarization by this characteristic. The conjectured tendency of young voters to group on the liberal side of the spectrum does not appear, although this might be due in part to their grouping into a single category (ages 18-39).[28]

5.2 Plausibility of Common-Good Estimates

One of the paper's contributions is the identification of a set of plausible assumptions that enable common-good and spatial payoffs to be separately estimated from voter and voting data alone. As seen, the ideology estimates conform to what we expect from previous research, lending some support to the approach. For the common good payoffs, we don't have other estimates to directly compare to, but we can asses their plausibililty by considering their source. If they stem from altruism, then the demographics we find place more weight on the common good should line up with that of other studies that correlated other-regarding preferences with demographics. If they stem from payoffs in the policies themselves, heterogeneity in the common good across types of policies should very in intuitive ways. Here, we show that our results provide suggestive evidence that both sources play a role.

5.2.1 Differences Across Individuals

Table 1 reported the correlation of common-good weights with demographic characteristics. While we do not have a strong expectation about most of those correlations, we might expect that it takes time and experience to develop ideology and thus younger voters and less educated voters will have less sharp ideological preferences and place a higher weight on the common-good component. For example, survey evidence indicates that voters aged 18-29 are the least likely to identify with a party or perceive a difference between the policies of Democratic and Republican candidates (Pew Research Center, 2021). In a slightly different vein, Enke (2023b) finds that younger, poorer, and non-whites are more universalistic, caring more about the payoff of out-group members. As these demographics tend to vote Democratic more often, this finding is also consistent with that of Fisman et al. (2017)

[27] For example, https://www.usatoday.com/story/news/politics/elections/2020/11/24/education-divide-deepens-democrats-worry-future-power/6325025002/.

[28] We report the county fixed effects as a choropleth in Appendix F, Figure F2. The expected pattern of more liberal counties along the coast and more conservative counties in the northern interior is clearly present.

who find that experimental subjects that display preferences for equality lean Democratic. Kerschbamer and Müller (2020) find that less educated voters tend to be less atruistic.[29] Our estimates are generally consistent with all of these findings: common-good weights are highest for the youngest, least-educated, poorer, and non-white voters.

5.2.2 Differences Across Issues

For each proposition, we can calculate the posterior probability of each of the three common-good states, $\tilde{\psi}_j \in \Psi \equiv \{-1, 0, 1\}$, which represent the difference in common-good payoff between the proposal and the status quo. In 85 percent of cases, the estimates place a probability greater than 0.95 on one of the states. Intuitively, if the net common-good payoff was zero, voters viewed the issue as purely spatial. We define the "common-good probability" as the estimated probability that the common-good is relevant for an issue (sum of the posteriors on the negative and positive states). The mean common-good probability is 0.47 with 47 percent of issues having a common-good probability greater than 0.5. Note that the common-good estimates are subjective in the sense that they reflect how voters perceive the issues; they do not necessarily capture the external reality of a common good payoff. It is possible that policies that economists consider to be in the interest of all are not seen that way by voters. Also, predicting how voters "should" view the payoffs is complicated by the fact that proposals often compound multiple issues, such as imposing an income tax surcharge on the wealthy and using the money to fund children's hospitals. With these caveats stated, we can nevertheless explore a few possibilities.

• *Proposals with high spending by business groups.* We conjecture that propositions with heavy business spending are less likely to have a common-good component because they are largely about rent-seeking. Focusing on 92 propositions during 2000-2020 for which we have complete campaign finance data, we find that measures in which business groups spent $5 million or more had an 11.6 percent lower common-good probability. Focusing just on issues for which business groups spent $5 million or more in support (i.e., when they were the primary sponsors), the gap was 15.7 percent.[30]

• *Bond measures.* Proposals that allocate funds to specific causes might be seen as more distributional in nature than other proposals, but as the levy example suggests, there are cases that go the other way. Bond measures are relatively clean in this respect because

[29] As their focus is on advantageous and disadvantageous inequality, it is more difficult to directly compare many of their results to ours.

[30] Campaign contribution numbers were aggregated using data on individual contributions provided by the California Secretary of State.

they authorize spending on a particular project, without increasing or creating new taxes. Bond measure are used to fund a variety of programs, including highways, school buildings, prisons, parks, and loans to veterans. By focusing on only bond measures, we can compare how voters view different types of spending, independent from the financing mechanism. Overall, bond measures had a 22.3 percent higher common-good probability than other propositions. Water bonds (to build infrastructure for clean water) and education bonds are especially likely to be viewed as having common-good elements. The sample contains only 37 bond measures, but our estimates imply that voters gave water and school bonds a 21.4 percent higher common-good probability than other bonds. The seven water bonds had a common-good probability of 78.7 percent.

- *Taxes.* Taxes are often seen as primarily distributional in nature. To the extent there is a common-good component, it might be associated with economy-wide deadweight losses that reduce overall wealth creation, but one might suspect that voters don't account for this equilibrium effect (Dal Bó et al., 2018). We find that proposals concerning taxes had an 8.2 percent lower common-good probability.

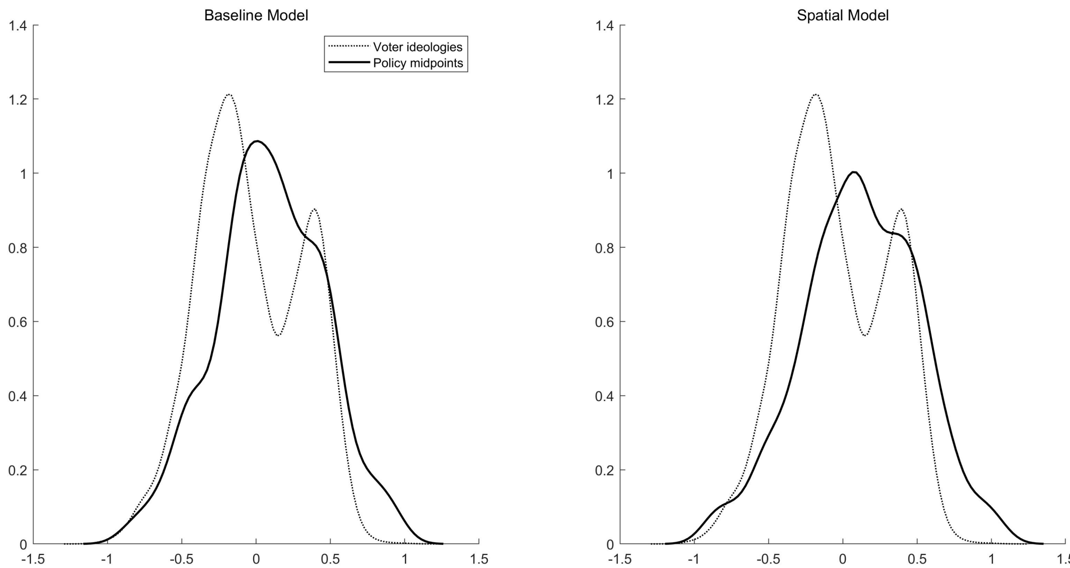
All of these estimates are based on relatively small numbers of observations (essentially the number of propositions), so we offer them only as suggestive evidence.

5.2.3 Common-good Versus Midpoints

Roughly speaking, the model estimates common-good payoffs from co-movement in voting. As mentioned above, in principle voters could swing en masse in one direction on a proposal because it has a large common-good payoff or because it has an extreme midpoint, and we pin down the estimates by assuming that moderate midpoints are more likely to occur than extreme midpoints. One may wonder then if we are mechanically identifying a high common-good component from one-sided elections, or by forcing the policy midpoints to the center. In Figure F3, we show that this is not the case by showing no obvious correlations between the common-good estimates, one-sided elections, or the policy midpoints.[31] We can also directly compare the estimated midpoints to those from a purely spatial model without policy setting. Figure 8 plots the estimated midpoints for the full model (left panel) and for a spatial model (right panel), with the density of ideologies for reference. The distributions of midpoints are very similar across models. In particular, there is no noticeable compression to centrist midpoints when we impose the policy-setting model. Overall, these results suggest

[31] Imperfect signal precisions break the mechanical relationship by allowing for idiosyncratic voter movements around the midpoint: more extreme midpoints, although penalized, may improve fit because voters only need to move the same way on average to indicate a common-good component.

Figure 8. Distribution of Policy Midpoints for Initiatives and Legislative Propositions



Note. Kernel density estimates of estimated midpoints for the baseline model, with the distribution of ideologies for reference (left panel). The right panel is for a model which does not include the common-good component or policy setting.

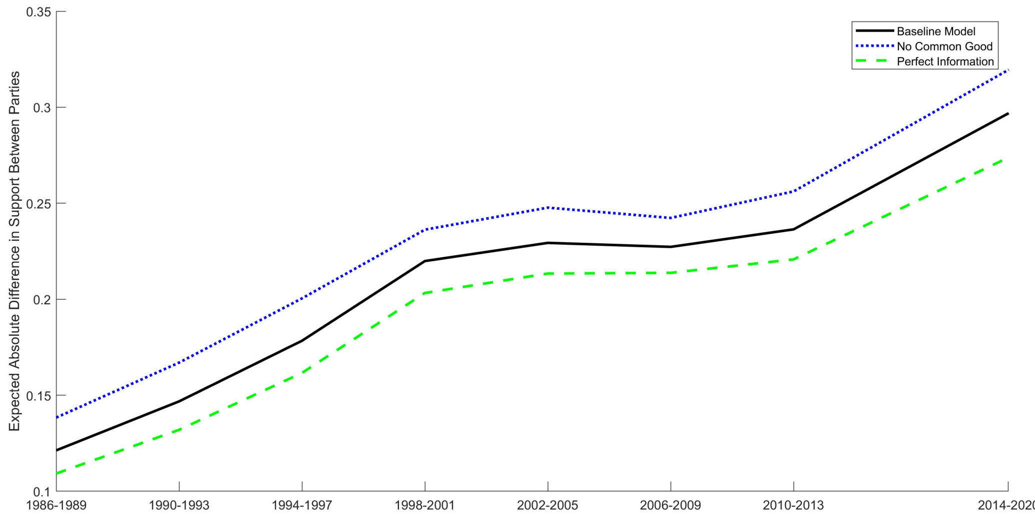
that, while the policy-setting information is necessary for identification of the common-good component, it is not mechanically producing the results.

5.3 Counterfactuals

5.3.1 Partisan Vote Difference

In this section, we report counterfactual exercises that illustrate how common-good considerations affect voting outcomes. We do so through two counterfactual specifications: (i) zero weight on the common-good payoff for all voters ($w_i = 0$), and (ii) perfect information about the common good ($\pi = 1$). The first captures a world without common-good considerations, which is a natural benchmark. The second captures a world with better information, which unlike the common-good weight, is partially a policy choice: democracies can influence the flow of information to voters by regulating advertising, media, and campaigning. Debates over campaign regulation often rely on a zero-sum or spatial model of politics, in which publicity for one campaign only hurts the other campaign. In a model with common-good features, however, campaigning potentially increases the quality of public decisions. Without taking a normative stance, we can explore how information about

Figure 9. Expected Difference in Support between Parties: Counterfactuals



Note. The figure plots of the expected absolute difference between parties in fraction of votes in support, averaged over all propositions within each time period under three scenarios: baseline model estimates, a purely spatial model with no weight on the common good, and a model with the estimated common-good weights but perfect voter information.

the common-good component feeds back into the partisan nature of voting.[32]

We first study the expected difference in votes between Republicans and Democrats; this alternative measure of polarization compounds common-good and spatial effects, thereby providing insight into how common-good considerations contribute to, or mitigate, polarization.[33] Figure 9 plots the expected partisan difference in support, averaged over all propositions within each time period (corresponding to the time dummies for ideologies) for the baseline model and two counterfactual scenarios.

The baseline plot shows an increase in polarization over time, consistent with the increase in the difference between party medians observed in Figure 5. Intuitively, common-good concerns should cause people to vote the same way; in the extreme case where voters care only about the common good, they would vote identically on average. Consistent with this intuition, the dotted line when $w_i = 0$ consistently lies above the baseline case. The magnitudes are non-trivial: the partisan difference is 1.8 percentage points higher on average

[32] In the counterfactual exercises, we fix the midpoints to their estimated values, which is consistent with our baseline model in which the proposer is not concerned about the passage of the proposition. If the proposer is concerned about passage or can control the common good value, she may adjust the proposed policy in the counterfactual scenarios (as in Canen et al., ~~(~~2020~~)~~).

[33] Figure F4 in Appendix F, which plots expected against actual vote share, shows that the model fits the data reasonably well.

without the common good than in the baseline model, a 8.0 percent increase. The perfect information case allows the maximum impact for common-good considerations. Relative to the case in which citizens place no weight on the common good, partisan differences are 3.3 percentage points lower (a 15 percent decrease) when citizens have perfect information.[34]

5.3.2 Proposition Passage

We next consider how common-good considerations affect the type of proposals that voters approve. We start by classifying each proposition as "right-leaning" if a majority of Republicans voted in favor and a majority of Democrats voted against; "left-leaning" if a majority of Democrats voted in favor and a majority of Republicans voted against; and "nonpartisan" otherwise (where "votes" are expected votes under the counterfactual scenario in which citizens vote based on ideological considerations alone). Given that Democrats controlled the legislature throughout the sample period, theory suggests that citizen initiatives would have come disproportionately from conservatives, while legislative proposals would have been progressive in orientation. We find that 29 percent of initiatives were right-leaning, while only 4 percent of legislative proposals were right-leaning, supporting this theory.

Table 2 provides estimates of the expected percentage passage rates for the two counterfactual scenarios considered in the previous section (no common good and perfect information), along with those from the baseline model and the actual passage rates in the data. The model passage rate predictions are very similar to those in the actual data, indicating that the model fits the data reasonably well. Right-leaning proposals were much less likely to pass than left-leaning proposals, 36 percent versus 66 percent, consistent with the state's reputation as being left-leaning (difference significant at the 1 percent level).

With perfect information the passage rates are relatively unchanged, but with the common-good weight set to zero, the expected passage rates drop. These differences reflect *net* changes and therefore underestimate the number of outcomes that actually change under the counterfactual. Overall, when the common-good weight is set to zero, 13 percent of outcomes change: 11 percent of propositions with an estimated high common-good component switch to failing under the counterfactual, but 2 percent of propositions with an estimated low common-good component switch to passing.[35] Among left-leaning proposals, the fraction of outcomes changing is similar (14 percent and 0 percent, respectively),

[34] In the counterfactuals, we average over all the three possible common-good values using the prior weights. This mechanically reduces the differences because 50 percent of the time there's no common good component, and hence changing it's relevance makes no difference.

[35] More high common-good component proposition outcomes change because there are more of them to begin with (35 percent versus 13 percent).

Table 2. Counterfactual Proposition Passage Rates

	All Propositions	Right-leaning	Left-leaning	Nonpartisan
Number of Propositions	168	36	66	66
% Approved, actual	63	39	70	70
% Approved, baseline	64	39	71	71
% Approved, no common good	56	28	58	70
% Approved, perfect information	63	42	68	70

Note. Propositions were classified as "right-leaning" if a majority of Republicans were in favor and a majority of Democrats were against; "left-leaning" if a majority of Democrats were in favor and a majority of Republicans against; and "nonpartisan" otherwise.

but among right-leaning proposals, 22 percent switch from pass to fail (high common-good component) and 11% switch from fail to pass (low common-good component).[36] Overall, we conclude that the common-good component plays a somewhat more important role in right-leaning proposals: were it absent, about one-third of the outcomes of these proposals would have changed. This result likely reflects the fact that right-leaning proposals must be more centrist (and therefore more marginal) in order to pass in a left-leaning electorate.

5.4 Robustness

Our first robustness exercise concerns the model's assumption of independent signals. In practice signals may be correlated; for example, Democratic voters may tap similar information sources, different from those tapped by Republican voters. Our exercise allows for correlated signals within voters of the same partisan leaning (Democrat, Republican, and independent), focusing on the polar opposite case of perfectly correlated signals.[37]

Our second and third robustness exercises investigate two possible reasons our model might spuriously infer a common-good component. One possibility is that the ideological space has more than one dimension, and the common-good component is capturing a second spatial dimension. Because different propositions reflect different issues, voters may not perceive them as lying along a single dimension. Although there is no mechanical reason that a second dimension would produce a common-good weight, it seems worth considering the possibility that it is introducing bias in a nonobvious way. If the model is picking up

[36]For non-partisan propositions or under the counterfactual of perfect information, the effects are small: only a few percent of outcomes change.

[37]The likelihood function with correlated signals differs in that it first takes the product over vote probabilities conditional on signals (among voters with the same partisanship) and then sums over signals, instead of the reverse in the independent signals case (5). Proof of identification of the correlated signals model is identical to the case of independent signals as only the structure of the mixtures changes.

an unmodeled spatial dimension because propositions bundle disparate issues, the common-good weight should substantially decrease or disappear if we focus on only a single type of proposition. The second robustness exercise estimates the model on only economic issues (mainly taxes and regulation), which are the most common in the sample (103 propositions), excluding social issues, elections, voting, and government performance, which could be perceived along a different dimension.

Another possibility is that votes co-move because citizens are exposed to a common shock through campaign activities. For example, a highly-charged commercial might trigger an emotional response that affects all voters in the same way. This possibility cannot be casually dismissed because experimental evidence from field studies shows that campaigning can change voting decisions (Gerber et al., 2011; Kendall et al., 2015; Rogers and Middleton, 2015), and many California propositions involve heavy campaign spending.[38] The baseline model allows for campaign effects through the provision of information; however, campaigning that moves all voters in the same way for affective (non-informational) reasons could induce a spurious common-good effect. To explore this possibility, we rely on the observation that citizens who were unaware of a proposition before being surveyed cannot have been exposed to campaign messaging, so their votes cannot embed a spurious co-movement caused by spending. To identify responses in which voters were unaware of the issue, we use a survey question that asked respondents if they had "seen, read, or heard anything about Proposition X" (or similar language), available for 126 propositions. We then re-estimate the model allowing the signal precision to differ between voter-issue pairs for which voters were aware and unaware. If campaign persuasion is the cause of the estimated common-good effect in the baseline model, then the alternative model should produce an uninformative signal for unaware voter-issues, implying a spatial model.

Our last three robustness exercises explore the extent to which the baseline results are driven by the specifics of the policy-setting model. If interest groups or others with extreme ideal points play an outsized role in placing propositions on the ballot, then extreme proposals may be more likely than under our assumption that policies are drawn from all voters' ideal points. In the 'Uniform' robustness check, we increase the probability of extreme proposals by drawing proposals from a uniform distribution instead of from the estimated distribution of ideal points. In the second approach, we estimate the model separately for initiatives and legislative proposals. The sample of legislative proposals is largely immune to special interest groups because they can only propose policies through initiatives. In the last robustness check, we assume that the proposer chooses the policy

[38] Matsusaka (2023) contains descriptive information and analysis of spending on California propositions.

Table 3. Robustness Estimates

	Baseline	Correlated Signals	Economic Issues	Vote Awareness	Uniform Proposer	Initiative Proposals	Legislative Proposals	Passage Concerns
w_i (mean),	0.68	0.14	0.85	1.19	1.20	1.02	0.53	0.10
	(0.17)	(0.03)	(0.48)	(0.47)	(0.34)	(0.54)	(0.15)	(0.03)
Equivalent Ideological Shift (mean)	0.39	0.15	0.49	0.38	0.37	0.54	0.21	0.19
π, common	0.65	1.00	0.67	-	0.66	0.62	0.65	1.00
π, aware	-	-	-	0.46				
π, unaware	-	-	-	0.59				

Note. Asymptotic standard errors for mean w_i are in parentheses. Equivalent ideological shift is the change in ideological position that results in the same change in utility as receiving a signal, averaged across the two signals. Each reported value is the mean across voters.

closest to his or her ideal point that will receive a majority of votes in favor; recall that in the benchmark model we assume that the proposer ignores the likelihood of passage.

Table 3 reports information related to the estimated common-good component for the baseline model and the seven alternatives. A likelihood ratio test rejects, at the 1 percent level, a purely spatial model in favor of a model with the common-good in all cases.

In the model with perfectly correlated signals, the average weight placed on the common-good decreases, but remains significant at the 1 percent level, indicating that independent signals are not necessary for detection of a common-good component to voter utility functions. A Vuong test rejects the correlated signal model in favor of that with independent signals ($p < 0.001$), suggesting that signals are at least partially independent.

When the model is estimated only for economic issues, the common-good weight remains significant at the 5 percent level (it is also larger in magnitude but not statistically so). Relatedly, if a second ideological dimension is spuriously driving the common-good effect, one might also expect the common-good to be important on issues for which a purely spatial model does not predict well. Using the estimates from a purely spatial model, we find the opposite: there is actually a *positive* correlation between the fit of the spatial model (where higher fit means it predicts more votes) and the expected absolute difference in common-good payoffs across policies, calculated using the estimated posteriors. It does not appear therefore that the common-good component in the baseline model is an artifact of an unmodeled second ideological dimension.

In the third alternative model, in which the signal precision can differ with voter awareness, the average common-good weight is higher than in the baseline model. This is likely an artifact of selection on a subset of issues. The point estimate for the signal precision of unaware voter-issues is statistically significant ($p < 0.001$) and actually larger than that for aware voter-issues, contrary to what would be the case if common-good effects were entirely driven by campaigning. The fact that unaware voters have informative signals suggests that voters may have heterogeneous information that they apply when they first become aware of the issue; for the example discussed in the introduction, voters may have heterogeneous beliefs about the possibility of a flood, and therefore the value of a levy, even before they are exposed to any campaigning.

In the last four models, we continue to see a positive average common-good weight. It is significant at the 1 percent level except when we restrict to initiatives only, where it is significant at the 5 percent level. There is some variation in the magnitude of the weight across specifications, in particular with it being smaller when the proposer is concerned about proposition passage. However, Vuong tests reject this model and the uniform proposer model in favor of the baseline model ($p \leq 0.001$). We therefore prefer our baseline policy-setting model but also conclude that the presence of concerns for the common good are robust to other specifications.

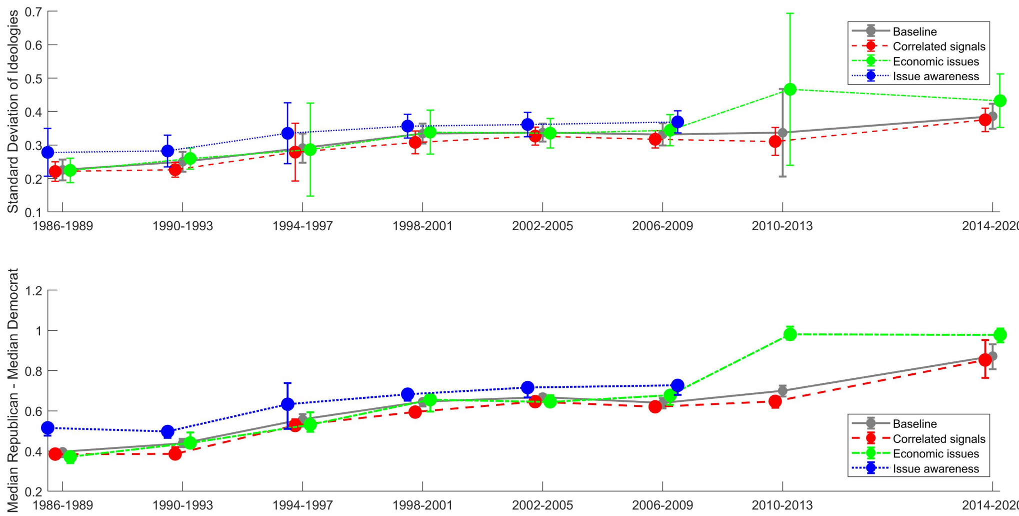
Figure 10 plots the two polarization measures – divergence in the top panel and partisan sorting in the bottom panel – for the baseline model and the first three variants.[39] For the most part, the levels and trends of both measures of polarization are similar to the baseline model for all three alternative specifications. In particular, the levels of polarization are similar when we allow for correlated signals so that ideological polarization does not appear to be driven by differences in partisan beliefs. The one noticeable difference is that when we restrict to economic issues, both divergence and sorting are higher for the most recent decade (2010-2020). For divergence, the estimates are too imprecise to draw strong conclusions, but the gap for sorting is statistically significant, suggesting that voter opinion has recently pulled apart on taxes and regulation more than other issues. Alternatively, it could be that when ideological positions are estimated across many different types of issues, voters appear more moderate, reflecting inconsistency in their positions across issues.

Lastly, we note that the determinants of the ideologies are stable across specifications (parameters reported in Table F1). With the exception of the correlated signals model and the model in which the proposer is concerned about passage of the proposition, the determinants of the common-good weights are also stable.[40]

[39] The other four variants are very similar, except that when we ~~restict~~restrict to legislative proposals the trends are noisier due to the small number of such propositions (49). See Figure F5 in Appendix F.

[40] For completeness, we also report the distributions of ideologies and common-good weights for each of the alternative specifications in Figures F6 through F13 in Appendix F. When we restrict to economic issues, we force voters that don't identify as Republicans or Democrats to have constant ideologies across

Figure 10. Robustness of Polarization Measures



Note. Divergence and party sorting polarization measures for the baseline model and three alternative specifications: correlated signals, restricted to economic issues only, and allowing the signal precision to vary with voter awareness. Error bars indicate 95% confidence intervals with asymptotic (top panel) and bootstrapped (bottom panel) standard errors.

6 Discussion

The idea that politics is in part a search for the common good – and not just a zero-sum game between partisans – has a venerable pedigree, running from Aristotle to the U. S. Constitution's stated goal of providing for "the common defense" and promoting "the general welfare." It lies at the core of a theoretical literature starting with Condorcet that envisions voting as a way to aggregate information to select policies with the highest common-good payoff. Yet empirical research on voter preferences usually assumes away common-good considerations in favor of a purely spatial model.

Our paper takes a step toward a broader analysis by estimating a model in which voters may have both common-good and spatial preferences. Our key insight is that common-good preferences cause votes to co-move, and therefore elections with one-sided voting are more likely to have had common-good features. However, one-sided voting can also be caused by extreme policy midpoints, where spatial preferences place most voters on one side of the issue. We show how these possibilities can be separated by a plausible assumption about the distribution of midpoints – that centrist midpoints are more common

time because we do not have enough similar issues to bridge ideologies across time periods. In this case, only relative movements in ideologies are identified.

than extreme midpoints. We use these ideas to develop a new estimation procedure that allows identification of the weight that voters place on the common-good payoff delivered by a policy. Using data from California ballot measures, we find evidence that common-good payoffs are an economically and statistically significant part of voter preferences.

While our estimates point to a common-good component in voter preferences, they do not reveal the source of these preferences. One view is that common-good payoffs are technological in nature, hardwired into the issues themselves. For example, the public goods literature studies government projects that provide benefits to all citizens, with national defense a common example. Another view, closely related, is that government policies seek to correct "market failures," for example, by imposing a Pigouvian tax on an externality such as gasoline consumption. If coupled with a set of compensating transfer payments, such a policy could be Pareto improving, offering benefits to all. The heterogeneity we observe in the probability of a common-good component across issue types suggests that at least part of what we are finding is due to common benefits/costs associated with the policies themselves.

Alternatively, the common-good component could stem from altruism. To the extent that voters are atomistic in a large electorate, they are unlikely to vote for instrumental reasons. If they vote for expressive reasons, they may be willing to trade off their narrow preferences against the opportunity to express broader social preferences (Fiorina, 1976; Brennan and Lomasky, 1993). If voters have even a small utility over the well-being of their fellow citizens, the perceived aggregate payoffs to the population at large may end up driving their voting decisions, resulting in a common-good component (McMurray, 2017). The fact that the demographics we identify as placing higher weight on the common good line up with those that Enke et al. (2022, 2023a) find care more about out-group members hints at a role for altruism.

Overall then, our results suggest that the common-good considerations we identify may result from both altruism and common benefits/costs built into the policies themselves. Surveying voters about their vote intentions on issues along with their perceived benefits of these issues and their other-regarding preferences may further help disentangle the two ways in which common goods can operate.

Allowing for a common-good component in voter preferences increases confidence in estimates of the spatial component of preferences by removing a potential source of bias. We find that voters were spatially polarized during our sample period, 1986-2020, and polarization grew significantly in the most recent decade. This holds for pure dispersion of preferences (divergence) and for sorting by party (partisan polarization). We find little evidence of significant or growing polarization based on income, education, or age. For the most recent period after 2012, for which there is little polarization evidence at present, we find a big jump in partisan polarization that is largely the result of Democratic voters shifting to the left, not Republicans shifting to the right.

The existence of a common-good component suggests that it might be possible to reduce polarization by giving voters more information, prompting them to place more weight on common-good considerations. Our counterfactual exercises provide suggestive evidence in favor of this hypothesis, but we are cognizant of the fact that this result rests on the assumption that voters update in a Bayesian manner. More work is needed to determine when information leads to convergence of beliefs (Kendall et al., 2015) and when it instead leads to an increase in polarization through belief divergence (Baysan, 2022).

Finally, in terms of methods, our approach may be applicable or amenable to modification to explore voting issues in other contexts. Applying the methods to estimate common-good preferences in legislative roll-call voting is almost immediate. Moreover, because the agenda structure in a legislature is more transparent and structured than for ballot measures, it may be possible to develop richer models of the proposal processes and verify the assumptions empirically. Another natural context would be shareholder voting. In all American corporations, individual shareholders have the right to bring proposals related to corporate policies to a vote of all shareholders. It's generally believed that such elections are mainly a search for the "common good" in the sense that all shareholders stand to gain or lose equally from a proposal, but there is some evidence that shareholder proposals are used to divert corporate policies in directions that provide specialized benefits to only some shareholders (Matsusaka et al., 2019). A modified version of our approach would be able to shed light on the extent to which shareholders in fact have common interests, and might be able to identify situations of special interest proposals.

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Online Appendices

Appendix A: Proof of Identification

The goal is to identify the parameter vector, $\Theta = \left\{ \{w_i, \theta_i\}_{i=1}^{N}, \{m_j, \mathcal{D}_j\}_{j=1}^{J}, \pi \right\}$.[41] We provide a constructive proof which shows how identification fails without the information derived from policy setting and then how this information resolves the issue. For ease of exposition, the proof assumes homogeneous π, but can be extended to the case in which it is a function of a voter's awareness. We make the following identifying assumptions:

IA 1. Voter $i = 1$ has $\theta_1 = 0$.

IA 2. The data are rich: there exist at least two voters, i and k, with $\theta_i \neq \theta_k$, $w_i = w_k$, and $\tilde{s}_{ij} = \tilde{s}_{kj}$ for each issue j, almost surely.

IA 3. $\pi \in \left(\frac{1}{3}, 1\right]$ and $w_i \in (0, \infty)$ for at least one i.

Assumption IA1, together with the assumption that ideological shocks have a variance of one, pin down the absolute location and scale of the ideological parameters. These normalizations are standard, necessary assumptions in spatial models.[42] Assumption IA2 facilitates identification of both the ideologies and the directions of each issue. Assumption IA3 avoids technical complications that arise with parameters at boundaries.[43]

Throughout the proof, we assume that the conditional distributions of the policy midpoints, m_j, and the difference in policies, $x_j - q_j$ are fixed. In our empirical application they are fixed within each election, but vary across elections due to the changing composition of likely voters. Identification is then obtained within each election.

Preliminaries

We begin by deriving $E\left[\tilde{\psi}_j | \tilde{s}_{ij}\right]$ for each signal realization to show that the expectations, and therefore vote probabilities associated with each signal, maintain a particular ordering for any parameterization of the model. Without this ordering, the vote probabilities in the data could be associated with more than one signal, which prevents identification (see Iaryczower and Shum, ~~(~~2012~~)~~).[44]

Bayes' rule implies

[41] In the empirical application, θ_i and w_i are constructed as a function of observables as described in Section 4.

[42] We also need to ~~also~~ normalize the scale of the common-good component in order to be able to identify the weight, as mentioned when the model is introduced in the main text.

[43] With a parameter at a boundary, some of the other parameters may not be identified. For example, if $w_i = 0$ for all i, the model reduces to a purely spatial model so that π cannot be identified.

[44] If we allow for arbitrary priors, the ordering is not guaranteed and the model is not identifiable, a fact we confirmed with Monte Carlo simulations.

$$E\left[\tilde{\psi}_j|\tilde{s}_{ij}=1\right] \;=\; \frac{\frac{1}{4}\pi-\frac{1}{4}\left(\frac{1-\pi}{2}\right)}{\frac{1}{4}\pi+\frac{3}{4}\left(\frac{1-\pi}{2}\right)};$$

$$E\left[\tilde{\psi}_j|\tilde{s}_{ij}=0\right] \;=\; \frac{\frac{1}{4}\left(\frac{1-\pi}{2}\right)-\frac{1}{4}\left(\frac{1-\pi}{2}\right)}{\frac{1}{2}\pi+\frac{1}{2}\left(\frac{1-\pi}{2}\right)}=0;$$

$$E\left[\tilde{\psi}_j|\tilde{s}_{ij}=-1\right] \;=\; \frac{\frac{1}{4}\left(\frac{1-\pi}{2}\right)-\frac{1}{4}\pi}{\frac{1}{4}\pi+\frac{3}{4}\left(\frac{1-\pi}{2}\right)}.$$

Because $\pi > \left(\frac{1-\pi}{2}\right)$, $E\left[\tilde{\psi}_j|\tilde{s}_{ij}=1\right] > 0$ and $E\left[\tilde{\psi}_j|\tilde{s}_{ij}=-1\right] < 0$, thus establishing the ordering, $E\left[\tilde{\psi}_j|\tilde{s}_{ij}=1\right] > E\left[\tilde{\psi}_j|\tilde{s}_{ij}=0\right] > E\left[\tilde{\psi}_j|\tilde{s}_{ij}=-1\right]$.

Define η_{ij}^{sd} as the probability i votes Yes on issue j conditional on $\mathcal{D}_j=d$ and $\tilde{s}_{ij}=s$. We have

$$\eta_{ij}^{s1}=\Phi\left(\theta_i-m_j+\frac{w_i}{\alpha_j^1}E\left[\tilde{\psi}_j|\tilde{s}_{ij}=s\right]\right) \tag{6}$$

and

$$\eta_{ij}^{s0}=1-\Phi\left(\theta_i-m_j+\frac{w_i}{\alpha_j^0}E\left[\tilde{\psi}_j|\tilde{s}_{ij}=s\right]\right). \tag{7}$$

Given the monotonic relationships between these conditional vote probabilities and the expectations, the vote probabilities are also ordered.

<u>Step 1</u> (identification of π):

The likelihood in (5) represents a finite mixture (over states) over finite mixtures (over signals). Given fixed priors over states, we can recover all of the parameters of the model from the inner mixtures over signals. The probability of observing a set of votes $\mathbf{Y}_j$, conditional on $\mathcal{D}_j=d$ and $\tilde{\psi}_j=\psi$ is

$$Pr\left(\left\{\mathbf{Y}_j|\mathcal{D}_j=d,\tilde{\psi}_j=\psi\right\}_{i=1}^{N}\right) \;=\; \prod_{i=1}^{N}\left(\gamma_{ij}^{\psi d}\right)^{Y_{ij}}\left(1-\gamma_{ij}^{\psi d}\right)^{(1-Y_{ij})} \tag{8}$$

with

$$\gamma_{ij}^{\psi d} = \sum_{s \in S} Pr\left(\tilde{s}_{ij} = s | \tilde{\psi}_j = \psi\right) \eta_{ij}^{sd}.$$

Equation (8) represents a standard finite mixture model with mixture probabilities given by $Pr\left(\tilde{s}_{ij} = s | \tilde{\psi}_j = \psi\right)$. By standard results, each of the conditional vote probabilities, η_{ij}^{sd}, as well as the mixing parameters, are identified (for example, see Allman et al., (2009)) up to an arbitrary classification of which vote probability in the data is associated with which signal and direction (i.e., the s and d associated with each probability must still be identified).[45] The ordering of vote probabilities established above ensures that the association between the vote probabilities and signals is known once the direction is known. From the mixture probabilities, we immediately obtain π. The expected values of the state conditional on each signal are then also known because they depend only on π.

Step 2 (identification of θ_i and $\mathcal{D}_j$):

We first define a normalized vote probability by combining (6) and (7) and then taking the inverse of the monotonic normal cdf:

$$\Phi^{-1}\left(\eta_{ij}^{sd}\right) = (-1)^{1-d}\left(\theta_i - m_j + \frac{w_i}{\alpha_j^d} E\left[\tilde{\psi}_j | \tilde{s}_{ij} = s\right]\right). \tag{9}$$

The core identification problem can be seen from (9). To see it most easily, assume that all voters learn the state perfectly. Because only one state is realized for each issue, one can simultaneously adjust the weights, w_i, and the midpoints, m_j, without changing the probabilities. For example, if one increases all of the weights, then for all issues for which the expectation of the state is positive, one can increase the midpoint, while decreasing it for issues for which the expectation of the state is negative.

Even in the presence of this identification problem, we can still identify the ideologies. We use Assumption IA2 to calculate the difference between the normalized vote probabilities of two voters, i and k, who have the same weight, $w_i = w_k$, and signal, s:

$$\Phi^{-1}\left(\eta_{ij}^{sd}\right) - \Phi^{-1}\left(\eta_{kj}^{sd}\right) = (-1)^{1-d}\left(\theta_i - \theta_k\right). \tag{10}$$

The left-hand side of (10) comes from the data.[46] Suppose it is positive (a similar argument holds when it is negative). Using Assumption IA1, we can set $\theta_i = \theta_1 = 0$ so that there

[45] It is because of the results on identifiability of finite mixtures that we assume discrete sets of states and signals.

[46] Because (10) holds for all three signal realizations, it does not matter which signal corresponds to the vote probabilities in the data, which we only know once the direction is identified.

are two possibilities: $d = 0$ and $\theta_k < 0$ or $d = 1$ and $\theta_k > 1$. This multiplicity is standard in discrete choice voting models: one can always flip all of the ideologies through $\theta_i = 0$ (with associated changes in the midpoints and directions) without changing the observable probabilities. We deal with this global identification issue by locating Republicans to the right of Democrats. Under this normalization, each θ_k as well as each $\mathcal{D}_j$ is identified through (10).

Step 3 (identification of m_j and w_i):

To identify the weights, take some issue with $\mathcal{D}_j = 1$ so that the normalized vote probability is

$$\Phi^{-1}\left(\eta_{ij}^{s1}\right) = \theta_i - m_j + \frac{w_i}{\alpha_j^1} E\left[\tilde{\psi}_j | \tilde{s}_{ij} = s\right]. \tag{11}$$

Intuitively, the weight is identified by how different signal realizations affect the vote probability, but we cannot take the difference in (11) across different signal realizations because we observe only one signal realization on a given issue. We proceed by instead looking at the average vote probability across issues with $\mathcal{D}_j = 1$. Taking the expectation of (11) across proposers and status quo policies, we have

$$E_{x,q}\left[\Phi^{-1}\left(\eta_{ij}^{s1}\right)|\mathcal{D}_j = 1\right] = \theta_i - E_{x,q}\left[m_j|\mathcal{D}_j = 1\right] + w_i E_{x,q}\left[\frac{1}{\alpha_j^1}|\mathcal{D}_j = 1\right] E\left[\tilde{\psi}_j|\tilde{s}_{ij} = s\right]. \tag{12}$$

The policy-setting model pins down both $E_{x,q}\left[m_j|\mathcal{D}_j = 1\right]$ and $E_{x,q}\left[\frac{1}{\alpha_j^d}|\mathcal{D}_j = 1\right]$ because the identified ideologies determine the distribution over x_j and the distribution over q_j is exogenous. Given the known direction, we also know how which η_{ij}^{s1} is associated with each signal realization so that (12) pins down w_i (e.g., with $\mathcal{D}_j = 1$, the highest vote probability, η_{ij}^{11}, is associated with $\tilde{s}_{ij} = 1$ and $E\left[\tilde{\psi}_j|\tilde{s}_{ij} = 1\right]$ is known).

Finally, we can recover m_j from (9) because all of the other parameters are known, so that Θ is identified.

Appendix B: Additional Models

Unidimensional Model

In the unidimensional model, the common-good component exists in the same space as the spatial component. We set $\tilde{V}(k_j) = -\left(k_j - \tilde{\psi}_j\right)^2$ so that the farther the policy is from some *common* ideal location, $\tilde{\psi}_j$, the greater the loss. Here the common-good component is innately tied to the spatial location of the policies. For example, an extreme liberal proposition that proposes substantial redistribution may have a deadweight loss associated with the required taxes (and therefore a lower common-good component). We let $\tilde{\psi}_j$ take on three possible values: $\tilde{\psi}_j \in \Psi \equiv \{l, c, h\}$, where $l = \theta_{min}$ corresponds to the spatial position of the voter with the lowest ideology (leftmost), $c = \theta_{med}$ is that of the voter with a centrist (median) ideology, and $h = \theta_{max}$ is that of the voter with the highest ideology (rightmost).

Voters have a uniform prior over the three states and receive a signal, $\tilde{s}_{ij} \in S \equiv \{l, c, h\}$ that correctly identifies the true state with probability $\pi_i \in [\frac{1}{3}, 1]$, $Pr(\tilde{s}_{ij} = a|\tilde{\psi}_j = a) = \pi_i$ for $a = \{l, c, h\}$. With probability $\frac{1-\pi_i}{2}$, the signal indicates each of the other two states.

As in the baseline model, a voter votes for the alternative, x_j, if

$$\alpha_j^d(\tilde{\theta}_{ij} - m_j) + w_i E\left[V(x_j) - V(q_j)|\mathcal{I}_{ij}\right] \quad \geq \quad 0,$$

where

$$E\left[\tilde{V}(x_j) - \tilde{V}(q_j)|\mathcal{I}_{ij}\right] = \alpha_j^d \left(E\left[\tilde{\psi}_j|\tilde{s}_{ij}\right] - m_j\right),$$

so that the expected distance between policies, α_j^d, drops out of a voter's decision. The conditional vote probabilities become

$$\gamma_{ij}^{\psi 1} = \sum_{s \in S} Pr\left(\tilde{s}_{ij} = s|\psi\right) \Phi\left(\theta_i - m_j + w_i\left(E\left[\tilde{\psi}_j|\tilde{s}_{ij} = s\right] - m_j\right)\right); \tag{13}$$

$$\gamma_{ij}^{\psi 0} = \sum_{s \in S} Pr\left(\tilde{s}_{ij} = s|\psi\right)\left(1 - \Phi\left(\theta_i - m_j + w_i\left(E\left[\tilde{\psi}_j|\tilde{s}_{ij} = s\right] - m_j\right)\right)\right). \tag{14}$$

For policy setting, the proposer chooses x_j to maximize his or her utility, leading to $x_j = \frac{\theta_p + w_p E\left[\tilde{\psi}_j|s_{pj}=s\right]}{1+w_p}$, where we allow the proposer to be informed through his or her private signal.[47] The likelihood is almost identical to the baseline model except that the distributions of the midpoints now depend on the state of the world (through the proposer's information):

[47] Given that the proposer is informed at the time she sets the alternative, x_j, voters receive a noisy signal of $\tilde{\psi}_j$ through their observation of the midpoint between policies, m_j. As updating based on this signal is quite complex,~~;~~ for tractability, we assume voters ignore the signal, basing their votes on their private signals only.

$$\mathcal{L}\left(\left\{\{Y_{ij}\}_{i=1}^{N}\right\}_{j=1}^{J};\Theta\right) =$$

$$\max_{\{D_j\in\{0,1\}\}_{j=1}^{J}} \left\{\sum_{e=1}^{E}\sum_{j=1}^{J_e}\log\left[\sum_{\psi\in\Psi} Pr(\psi)\left[\left(f_e^{\psi 1}\right)^{\mathcal{D}_j}\left(f_e^{\psi 0}\right)^{1-\mathcal{D}_j}\right.\right.\right.$$

$$\left.\left.\left.\prod_{i=1}^{N}\left(\gamma_{ij}^{\psi 1}\right)^{Y_{ij}\mathcal{D}_j}\left(1-\gamma_{ij}^{\psi 1}\right)^{(1-Y_{ij})\mathcal{D}_j}\left(\gamma_{ij}^{\psi 0}\right)^{Y_{ij}(1-\mathcal{D}_j)}\left(1-\gamma_{ij}^{\psi 0}\right)^{(1-Y_{ij})(1-\mathcal{D}_j)}\right]\right]\right\}.$$

where we have suppressed the arguments of $f_e^{\psi d} \equiv f_e^{\psi d}(m_j|\boldsymbol{\theta}, \mathcal{D}_j = d, \tilde{\psi}_j = \psi)$.

Identification

We begin with the conditional expectations of the state:

$$E\left[\tilde{\psi}_j|\tilde{s}_{ij} = h\right] = \frac{\frac{1}{3}\pi\theta_{max} + \frac{1}{3}\left(\frac{1-\pi}{2}\right)(\theta_{med} + \theta_{min})}{\frac{1}{3}\pi + \frac{2}{3}\left(\frac{1-\pi}{2}\right)};$$

$$E\left[\tilde{\psi}_j|\tilde{s}_{ij} = c\right] = \frac{\frac{1}{3}\pi\theta_{med} + \frac{1}{3}\left(\frac{1-\pi}{2}\right)(\theta_{max} + \theta_{min})}{\frac{1}{3}\pi + \frac{2}{3}\left(\frac{1-\pi}{2}\right)};$$

$$E\left[\tilde{\psi}_j|\tilde{s}_{ij} = l\right] = \frac{\frac{1}{3}\pi\theta_{min} + \frac{1}{3}\left(\frac{1-\pi}{2}\right)(\theta_{max} + \theta_{med})}{\frac{1}{3}\pi + \frac{2}{3}\left(\frac{1-\pi}{2}\right)}.$$

These expectations lead to the ordering, $E\left[\tilde{\psi}_j|\tilde{s}_{ij} = h\right] > E\left[\tilde{\psi}_j|\tilde{s}_{ij} = c\right] > E\left[\tilde{\psi}_j|\tilde{s}_{ij} = l\right]$ regardless of the parameters of the model, which is a necessary condition for identification. The vote probabilities, conditional on $\mathcal{D}_j = d$ and $\tilde{s}_{ij} = s$, are:

$$\eta_{ij}^{s1} = \Phi\left(\theta_i - m_j + w_i\left(E\left[\tilde{\psi}_j|\tilde{s}_{ij} = s\right] - m_j\right)\right) \tag{15}$$

and

$$\eta_{ij}^{s0} = 1 - \Phi\left(\theta_i - m_j + \left(w_i E\left[\tilde{\psi}_j|\tilde{s}_{ij} = s\right] - m_j\right)\right). \tag{16}$$

<u>Steps 1 and 2</u> (identification of π, θ_i, and $\mathcal{D}_j$):

These steps are identical to that of the baseline model with one minor technical exception. Given that the mixing probabilities depend upon $\boldsymbol{\theta}$, we must first identify the ideologies and then recover π from the (identified) mixing probabilities.

Step 3 (identification of m_j and w_i):

Combining (15) and (16), and inverting the monotonic function, $\Phi()$, we can define the transformed vote probability,

$$\Phi^{-1}\left(\eta_{ij}^{sd}\right) = (-1)^{1-d}\left(\theta_i - m_j + w_i\left(E\left[\tilde{\psi}_j|\tilde{s}_{ij} = s\right] - m_j\right)\right). \tag{17}$$

Intuitively, we want to compare (17) across signal realizations to separate the ideology from the weight. However, because we don't observe different signal realizations for the same voter on the same issue, we must first construct average probabilities by taking the expectation of (17) over issues (proposers, proposer signals, and status quos). Unlike in the baseline model though, the expectation of m_j is not immediately pinned down because the proposed policy depends on the proposer's w_i. We proceed by taking the expectation over the subset of issues with direction $\mathcal{D}_j = 1$ (for example) conditional on i receiving signal s and some other voter k receiving signal s':

$$\begin{aligned} E_{x,q}\left[\Phi^{-1}\left(\eta_{ij}^{s1}|\mathcal{D}_j = 1, \tilde{s}_{kj} = s'\right)\right] &= \theta_i - E\left[m_j|\mathcal{D}_j = 1, \tilde{s}_{ij} = s, \tilde{s}_{kj} = s'\right] \\ &+ w_i E\left[\tilde{\psi}_j|\tilde{s}_{ij} = s\right] \\ &- w_i E\left[m_j|\mathcal{D}_j = 1, \tilde{s}_{ij} = s, \tilde{s}_{kj} = s'\right]. \end{aligned} \tag{18}$$

Note that $E\left[\tilde{\psi}_j|\tilde{s}_{ij} = s\right]$ is a constant - $i's$ expectation of the state given signal s - so taking its expectation conditional on $\tilde{s}_{kj} = s'$ leaves it unchanged.

Knowing the direction, we know which vote probabilities in the data correspond to which signal realization. We take the difference in i's vote probabilities for high and low signals, conditioning on voter k receiving the opposite signals (i.e., when using the highest probability in the data for i, average over the cases in which k's received the low signal, and vice versa). Differencing (18), we have

$$
\begin{aligned}
& E\left[\Phi^{-1}\left(\eta_{ij}^{h1}|\mathcal{D}_j=1,\tilde{s}_{kj}=l\right)\right]-E\left[\Phi^{-1}\left(\eta_{ij}^{ld}|\tilde{s}_{kj}=h\right)\right] \\
= \;& (1+w_i)\left(E\left[m_j|\mathcal{D}_j=1,\tilde{s}_{ij}=l,\tilde{s}_{kj}=h\right]-E\left[m_j|\mathcal{D}_j=1,\tilde{s}_{ij}=h,\tilde{s}_{kj}=l\right]\right) \\
+ \;& w_i\left(E\left[\tilde{\psi}_j|\tilde{s}_{ij}=h\right]-E\left[\tilde{\psi}_j|\tilde{s}_{ij}=l\right]\right) \\
= \;& w_i\left(E\left[\tilde{\psi}_j|\tilde{s}_{ij}=H\right]-E\left[\tilde{\psi}_j|\tilde{s}_{ij}=L\right]\right) \qquad (19)
\end{aligned}
$$

where the last equality comes from the fact that the two expectations over the midpoint are the same, because it does not matter which voter receives which signal.[48] (19) uniquely identifies the weight, w_i, because the left-hand side comes from the data and the expectations on the right-hand side are known.

Finally, we can recover m_j from (17) because all of the other parameters are known, so that Θ is identified.

Results

The average common-good weight is 1.34, higher than in the baseline model and statistically significant at the 5 percent level. The distribution over weights is provided in Figure B1. 94 percent of voters have a common-good weight that is significantly different from zero at the 5 percent level. These results indicate that particular assumptions are not driving our finding of a common-good component to voter's utility functions.[49]

We report the parameter estimates in Table C1 below. We omit the graphs of ideologies and polarization but note that the results are extremely similar to the baseline case.

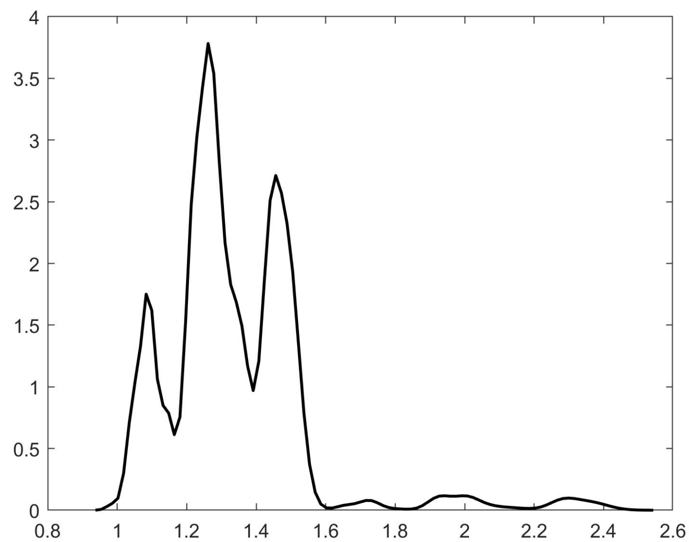
Linear Model

In the baseline model, we assumed quadratic utility around the voter's bliss point. Here we show that the likelihood function for a linear utility function, under most parameterizations, is the same up to a difference in a scale factor. For a linear utility function, a voter votes Yes if

[48] We can't only condition on i receiving two different signals because $i's$ signals are correlated with the proposer's signals so that $E\left[m_j|\mathcal{D}_j=1,\tilde{s}_{ij}=l\right]\neq E\left[m_j|\mathcal{D}_j=1,\tilde{s}_{ij}=h\right]$. Also note that the policy-setting model is necessary even though the expectations cancel out as it ensures the expectations are fixed in the data.

[49] We observe a significantly positive correlation of 0.14 ($p=0.04$) in the common-good components of issues across models. The correlation is somewhat reduced by the fact that the baseline model allows an issue to have a zero common-good component whereas the unidimensional model can do so only in non-generic cases in which the midpoint and state are identical. In 75 percent of cases in which the baseline model predicts a non-zero common-good component, the unidimensional model predicts the same sign for it.

Figure B1. Estimated Distributions of Common-Good Weights (Unidimensional)



Note. Kernel density estimates of estimated common-good weights.

Table B1. Parameter Estimates for the Unidimensional Model

	Variable	Estimate		Variable	Estimate
Common good (δ)	Age: 40-64	0.04 (0.13)	Ideology (β)	Age: 40-64	**0.12 (0.03)**
	Age: 65+	0.01 (0.15)		Age: 65+	**0.20 (0.03)**
	College	0.10 (0.16)		College	-0.05 (0.04)
	College+	-0.05 (0.18)		College+	**-0.20 (0.04)**
	Income: 20-60k	-0.02 (0.23)		Income: 20-60k	0.04 (0.05)
	Income: >60k	-0.19 (0.27)		Income: >60k	0.06 (0.05)
	Asian	0.46 (0.29)		Asian	0.06 (0.05)
	Black	0.02 (0.36)		Black	0.02 (0.07)
	Hispanic	-0.06 (0.16)		Hispanic	-0.00 (0.04)
	Constant	0.28 (0.48)			
Common good (π)		0.41 (0.12)			

Note. We do not report the time fixed effects, party coefficients, or their interactions. The omitted categories are voters with a high school education or less, voters with annual incomes below $20,000, voters under the age of 40, whites, and voters not identifying as Republicans or Democrats (β only). Asymptotic standard errors are in parentheses. Bold coefficients for δ, β, and π indicate significance at the 5 percent level or less. For π, we test the one-sided hypothesis that the coefficient is greater than one-third.

$$E\left[-|x_j - \tilde{\theta}_{ij}| + |q_j - \tilde{\theta}_{ij}| + w_i\tilde{\psi}_j|\mathcal{I}_{ij}\right] \geq 0$$

There are three cases that depend upon the location of the voter's ideal point relative to those of the policies (we consider the case of $q_j < x_j$; the other case is similar). For $q_j < \tilde{\theta}_{ij} < x_j$,we have

$$2\left(\tilde{\theta}_{ij} - m_j\right) + w_i E\left[\tilde{\psi}_j|\mathcal{I}_{ij}\right] \geq 0$$

which is the same as (2) up to the scale factor on the $\tilde{\theta}_{ij} - m_j$ term. When $\tilde{\theta}_{ij} < q_j < x_j$, we instead have

$$E\left[q_j - x_j + w_i\tilde{\psi}_j|\mathcal{I}_{ij}\right] \geq 0$$

and when $q_j < x_j < \tilde{\theta}_{ij}$,

$$E\left[x_j - q_j + w_i\tilde{\psi}_j|\mathcal{I}_{ij}\right] \geq 0$$

Given unbounded ideology shocks, $\tilde{\theta}_{ij} = \theta_i + \varepsilon_{ij}$, for ε_{ij} sufficiently small or large, we will be in one of the latter two cases. In these cases, the voter always votes Yes if the inequality is satisfied, and No otherwise. In most cases, therefore, the likelihood function will be the same as in the baseline model (up to the scale factor mentioned previously). For example, as long the inequality is satisfied in the third case, the voter will vote Yes for shocks larger than the cutoff value determined by the first inequality, as in the baseline model. However, for some parameter values, the vote probability becomes exactly zero or one. For example, if the voter receives a signal that the common-good component is negative, and x_j and q_j are sufficiently close together, the third inequality can become negative so that the voter votes No with probability one. Dealing with these corner cases complicates construction of the likelihood function so we prefer the quadratic model.

Appendix C: Issue Classification

The subject matter of each ballot proposition was classified by three researchers: a coauthor of this paper, a finance PhD student with a law degree, and a public policy PhD student. Each classifier was given a list of ballot propositions together with a short description of each proposal drawn from a database maintained by the Initiative and Referendum Institute, and a classification rubric (below). The rubric contains five broad categories and a residual "other" category. Each researcher assigned one or more categories to each proposition. The classifiers were in complete agreement on 74 percent of the measures, and there was a majority view on 97 percent. For 3 percent, there was no consensus.

Rubric

Each proposition is to be assigned to one or more of the following categories:

- (E) Elections, voting, campaigns, redistricting, term limits, recall, initiative and referendum
- (G) Government processes: procedures for budget approval, civil service reform, organization of legislature, operation of administrative agencies, legislator pay, operation of courts
- (O) Other: Issues not elsewhere classified
- (R) Regulation of business and labor markets
- (S) Social issues: abortion, civil rights, crime and punishment, gay rights, marriage, race, animal rights, drug legalization
- (T) Taxes, government spending, government borrowing (including education)

Examples from most recent election (November 2020), with proposed classifications:

Table C1. Example Issue Classifications for the November 2020 General Election

Prop	Description	Classification
14	$5.5 billion bond issue for stem cell research	T
15	Removes limits on property tax assessment increases for property owned by businesses	T
16	Removes prohibition on government using racial preferences in college admissions and hiring	S
17	Restores voting rights to felons	E
18	Allows 17-year-olds to vote	E
19	Allows disabled elderly homeowners to transfer their property tax exemption to a new home	T
20	Restricts parole for certain offenses	S
21	Allows local governments to control rents, overriding state controls	R
22	Allows rideshare workers to be employed as independent contractors	R
23	Requires physician during kidney dialysis treatment at corporate facilities	R
24	Allows consumers to restrict sale of their digital information	R
25	Eliminates bail payments	S

Our classification scheme resulted in 83 propositions classified as tax issues, 29 classified as regulation issues, 11 classified as government issues, 20 classified as social issues, 25 classified as election issues, and 3 classified as other issues; 6 propositions were not classified and 10 were classified into two categories.

Table D1. Repeated Ballot Propositions

Year	Proposition	Description
2005	73	Abortion: parental notification and 4-8 hour waiting period for minor to have abortion
2006	85	
2008	4	
1998	226	Union dues: prohibits use of union dues for political purposes without member consent
2005	75	
2012	32	
2010	19	Legalizes marijuana
2016	64	
2000	22	Defines marriages as solely between one man and one woman
2008	8	
1988	106	Limits attorney contingency fees to 15% (prop 202) and 15% to 25% (prop 106)
1996	202	
1996	198	Allows for open primaries
2004	62	
2010	14	
1990	119	Citizen redistricting commission: 12 members selected by retired judeges (prop 119) or 14 membes selected randomly (prop 20)
2008	11	
1988	99	Tobacco tax: increase (prop 99) and subsequent repeal (prop 28)
2000	28	

Appendix D: Repeated Issues

In order to compare the ideology of a voter across time, we must observe his or her vote on the same issue in different years. Fortunately, similar ballot propositions appear in more than one year, allowing us to link together time periods. Table D1 provides a list of the pairs or triplets of issues that together link ideologies across time.

Appendix E: Estimation Details

The likelihood given in (5) is highly non-convex and therefore poses difficulty for standard estimation procedures, including the expectation-maximization (EM) algorithm that is commonly used for estimating finite mixture models. In particular, we found that the likelihood function is highly non-monotonic in the policy midpoint (holding the other parameters fixed). After extensive experimentation, we discovered that a version of steepest descent that incorporates momentum in the gradient (Adam et al. (2015)) proved much more efficient and robust. Its one drawback is that it is only defined for unconstrained optimization problems, but this drawback is more than compensated for in terms of speed and robustness.[50] Given non-monotonicity in the policy midpoints, we developed the following

[50] In particular, running Matlab's standard unconstrained or constrained optimizers, fminunc and fmincon, proved futile. The algorithms rarely converged to the same maximum, and the parameters varied significantly across runs. Moreover, the maxima we found with the estimation procedure outlined here were significantly larger.

multi-stage estimation procedure:

1. Begin with a spatial model without the common good. Estimate the ideological parameters, β and midpoints, m_j, as follows:
   (a) Estimate the model without policy setting. We begin with a global search over 108 randomized starting points for which we calculate the likelihood and take the best 72. For each of the best 72, we perform a grid search over the policy midpoints for each issue. Then, for the resulting 12 best parameters sets, we iterate between using Adam and a policy midpoint grid search until convergence. Convergence is achieved when (i) the midpoint grid search did not change any of the T policy midpoints, and (ii) the Adam algorithm converged (change in the likelihood is less than 0.01 and the infinity norm of the gradient is less than one).
   (b) For the best parameter set resulting from step a), we re-estimate the model imposing policy setting. Within each estimation loop, we calculate the distributions for the policy midpoints, $f^d(m|\boldsymbol{\theta}, \mathcal{D}_j = d)$, and expected policy distance parameters, α_j^d, for each election for the current ideological parameters. In this estimation step, we run Adam until either convergence is achieved or 500 iterations have completed.
2. Beginning from the ideological parameters estimated with the spatial model, estimate the full model. As for the spatial model, we do this in two steps:
   (a) Holding the ideological parameters and the policy-setting information (i.e., the distributions and expected distances they imply) fixed, re-estimate the policy midpoints, as well as the common-good parameters. The procedure is as in step 1a) above.
   (b) As in step 1~~2~~b) above, re-estimate the model allowing all of the parameters to change.[51]

This estimation procedure allows robust estimation of the likelihood function, and produces very similar parameter estimates over several runs with different (random) parameter initializations.

[51] Because we must recalculate the policy-setting information within this estimation loop, each iteration is quite time-consuming so we stop after 500 iterations even if convergence is not achieved. The parameter values change very little in this final step so that even if convergence is not achieved, they are close to optimal.

Appendix F: Additional Tables and Figures

Table F1. Robustness: Parameter Estimates

		Correlated Signals	Economic Issues	Vote Awareness	Uniform Proposer
	Variable	Estimate (s.e.)	Estimate (s.e.)	Estimate (s.e.)	Estimate (s.e.)
δ	Age: (40-64)	0.34 (0.22)	-1.47 (0.91)	-0.55 (0.29)	-0.35 (0.27)
	Age: (65+)	**0.53 (0.21)**	**-2.12 (0.96)**	-1.32 (0.73)	-0.43 (0.30)
	College	0.53 (0.28)	-0.31 (0.63)	-0.60 (0.46)	**-0.61 (0.26)**
	College+	**0.60 (0.24)**	-0.49 (0.79)	-1.41 (0.076)	-1.02 (0.73)
	Income: 20k-60k	0.63 (0.58)	-0.86 (0.99)	0.08 (0.45)	-0.50 (0.27)
	Income: >60k	0.88 (0.53)	1.66 (1.19)	-0.10 (0.45)	**-1.00 (0.41)**
	Asian	-1.20 (1.03)	2.74 (1.49)	1.43 (0.95)	**1.44 (0.52)**
	Black	-1.51 (1.22)	1.62 (1.29)	1.27 (0.78)	**1.07 (0.42)**
	Hispanic	-1.33 (0.76)	1.66 (0.94)	0.81 (0.77)	**1.07 (0.37)**
	Constant	**-3.26 (0.84)**	0.70 (0.65)	**1.15 (0.45)**	**0.97 (0.44)**
π	Homogeneous	**1.00 (0.03)**	**0.67 (0.04)**	-	**0.66 (0.03)**
	Aware	-	-	0.40 (0.04)	
	Unaware	-	-	**0.56 (0.04)**	
β	Age: 40-64	**0.12 (0.03)**	**0.15 (0.06)**	**0.14 (0.05)**	**0.12 (0.03)**
	Age: 65+	**0.20 (0.03)**	**0.21 (0.04)**	**0.23 (0.05)**	**0.20 (0.04)**
	College	**-0.06 (0.04)**	-0.05 (0.04)	-0.06 (0.05)	**-0.09 (0.04)**
	College+	**-0.20 (0.04)**	**-0.23 (0.07)**	**-0.20 (0.04)**	**-0.24 (0.05)**
	Income: 20k-60k	0.04 (0.06)	0.08 (0.09)	0.03 (0.06)	0.02 (0.05)
	Income: >60k	0.08 (0.04)	0.12 (0.07)	0.08 (0.06)	0.05 (0.05)
	Asian	0.01 (0.04)	-0.07 (0.15)	-0.10 (0.12)	0.02 (0.08)
	Black	0.02 (0.07)	-0.03 (0.20)	-0.07 (0.11)	0.05 (0.10)
	Hispanic	0.00 (0.04)	-0.03 (0.08)	-0.02 (0.06)	0.06 (0.05)

		Initiative Proposals	Legislative Proposals	Passage Concerns
	Variable	Estimate (s.e.)	Estimate (s.e.)	Estimate (s.e.)
δ	Age: (40-64)	-0.49 (0.46)	**-0.95 (0.27)**	0.32 (0.23)
	Age: (65+)	-0.77 (0.50)	**-1.18 (0.16)**	**0.54 (0.26)**
	College	**-0.73 (0.37)**	-0.45 (0.26)	0.21 (0.19)
	College+	-1.01 (1.00)	**-0.67 (0.14)**	-0.02 (0.21)
	Income: 20k-60k	-0.89 (0.54)	-0.23 (0.13)	0.42 (0.35)
	Income: >60k	-1.53 (0.87)	**-0.77 (0.17)**	0.48 (0.39)
	Asian	**1.96 (0.85)**	**1.15(0.09)**	-0.76 (0.98)
	Black	1.75(0.93)	**2.17 (0.22)**	-0.49 (0.59)
	Hispanic	**1.67 (0.60)**	**1.80 (0.08)**	-0.55 (0.38)
	Constant	0.93 (0.76)	**-0.34 (0.15)**	**-2.99 (0.58)**
π	Homogeneous	**0.62 (0.03)**	**0.65 (0.02)**	**1.00 (0.00)**
	Aware	-	-	
	Unaware	-	-	
β	Age: 40-64	**0.12 (0.04)**	**0.18 (0.06)**	**0.12 (0.04)**
	Age: 65+	**0.21 (0.04)**	**0.22 (0.07)**	**0.20 (0.04)**
	College	-0.08 (0.04)	**-0.08 (0.04)**	-0.04 (0.04)
	College+	**-0.21 (0.05)**	**-0.28 (0.09)**	-0.17 (0.04)
	Income: 20k-60k	0.04 (0.07)	0.02 (0.08)	0.04 (0.04)
	Income: >60k	0.07 (0.08)	0.07 (0.08)	**0.09 (0.04)**
	Asian	0.06 (0.12)	**-0.21 (0.09)**	0.01 (0.08)
	Black	0.07 (0.12)	-0.15 (0.11)	-0.00 (0.09)
	Hispanic	0.09 (0.08)	-0.14 (0.11)	-0.01 (0.05)

Note. Estimated coefficients for robustness specifications: (1) correlated signals, (2) restricting to economic issues only, and (3) allowing the signal precision to differ across votes in which the voter was aware and not aware of the issue, (4) restricting to initiatives only, (5) restricting to legislative proposals only, (6) proposer drawn from a uniform distribution, and (7) proposer cares about proposition passage. For β, we do not report the time fixed effects, party coefficients, or their interactions. The omitted categories for β and δ are voters with a high school education or less, voters with incomes below \$20,000/year, voters under the age of 40, Whites, and voters not identifying as Republicans or Democrats (β only). Asymptotic standard errors are reported in parentheses. Bold coefficients for δ, β, and π indicate significance at the 5 percent level or less. For π, we test the one-sided hypothesis that the coefficient is greater than one-third.

Figure F1. Correlation Between Ideology and Common-Good Weight

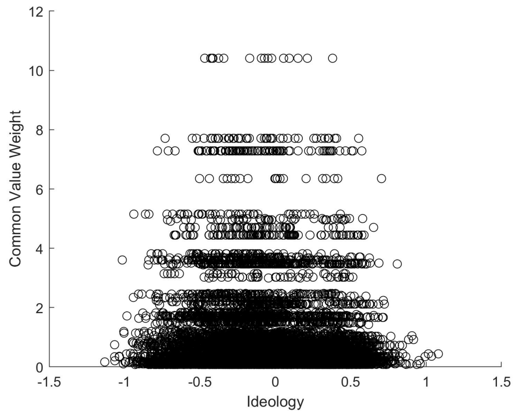
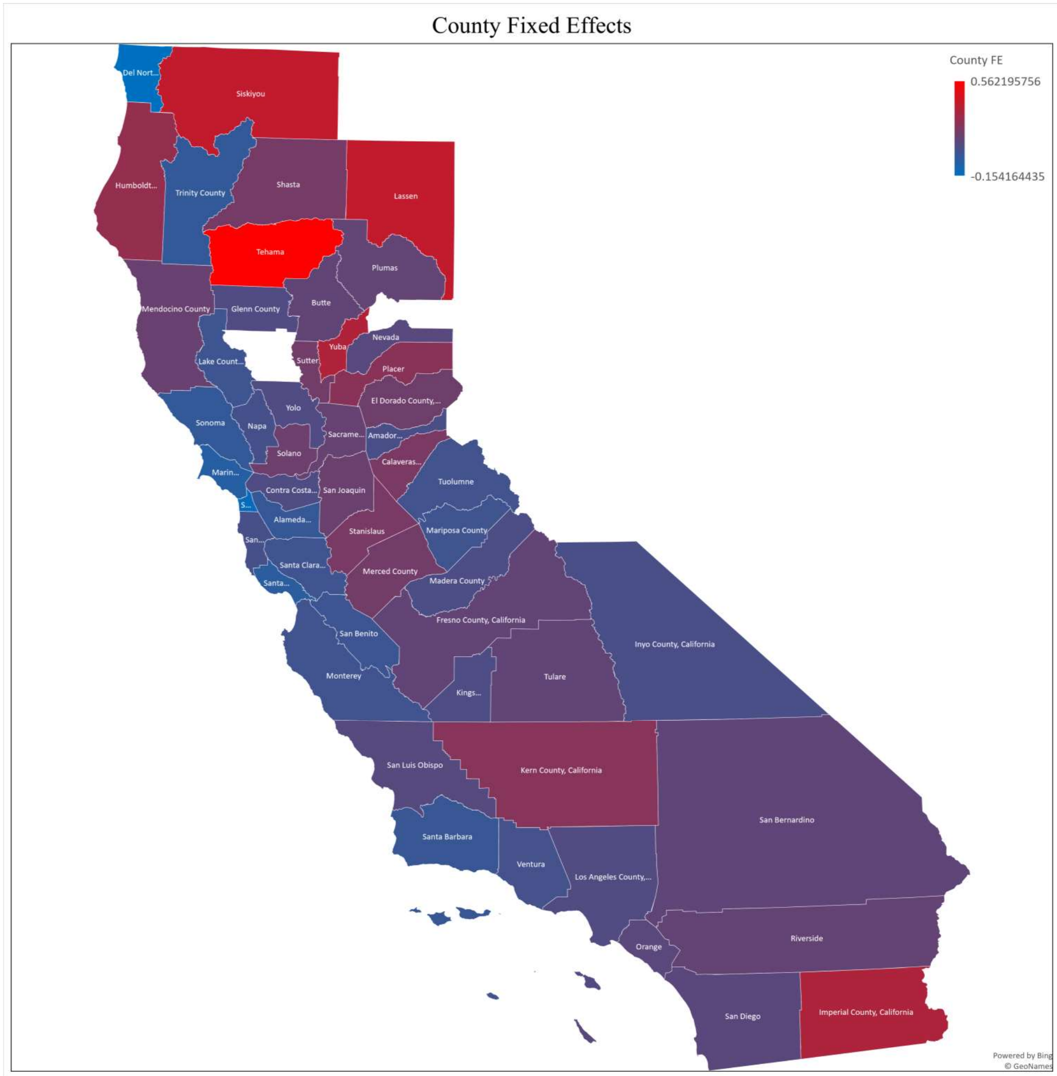
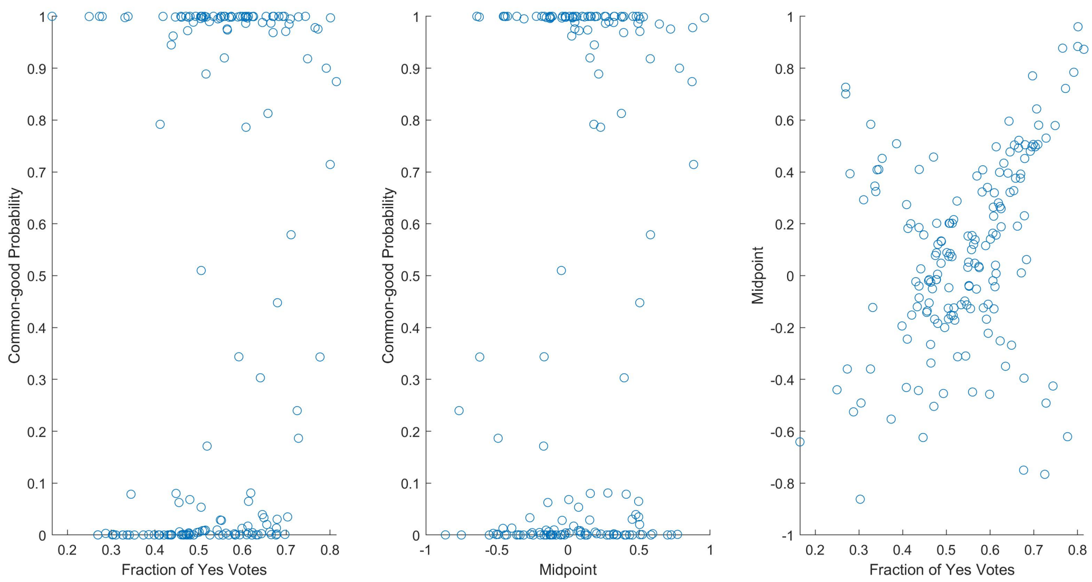


Figure F2. Estimated Ideologies By County



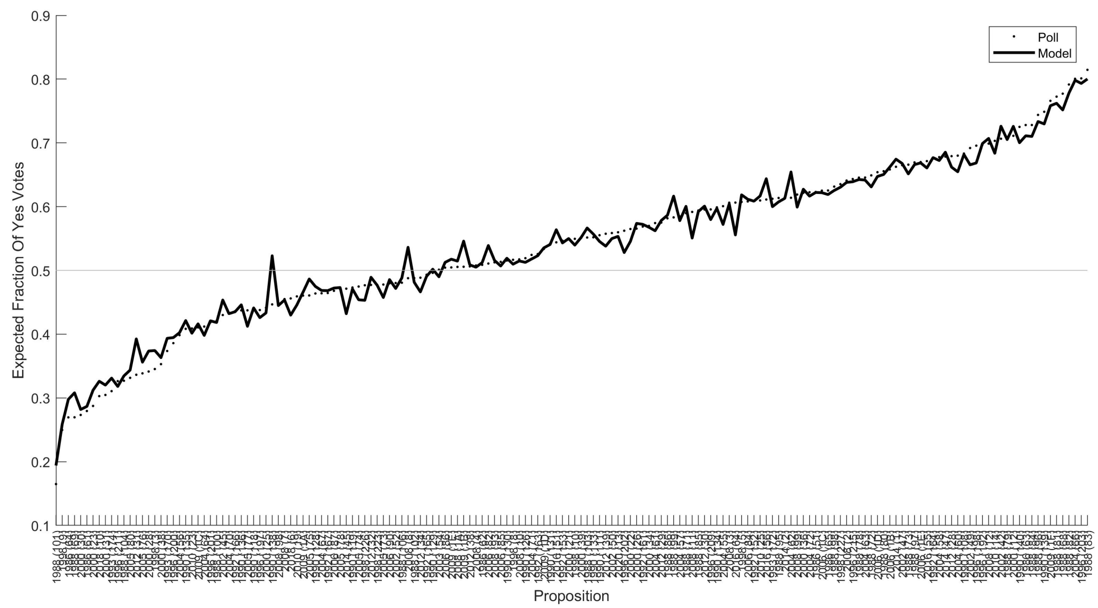
Note: The figure reports estimates of county-level fixed effect parameters for voter ideologies. The omitted category is the county of Alameda.

Figure F3. Common-good Probabilities, Yes Votes, and Midpoints



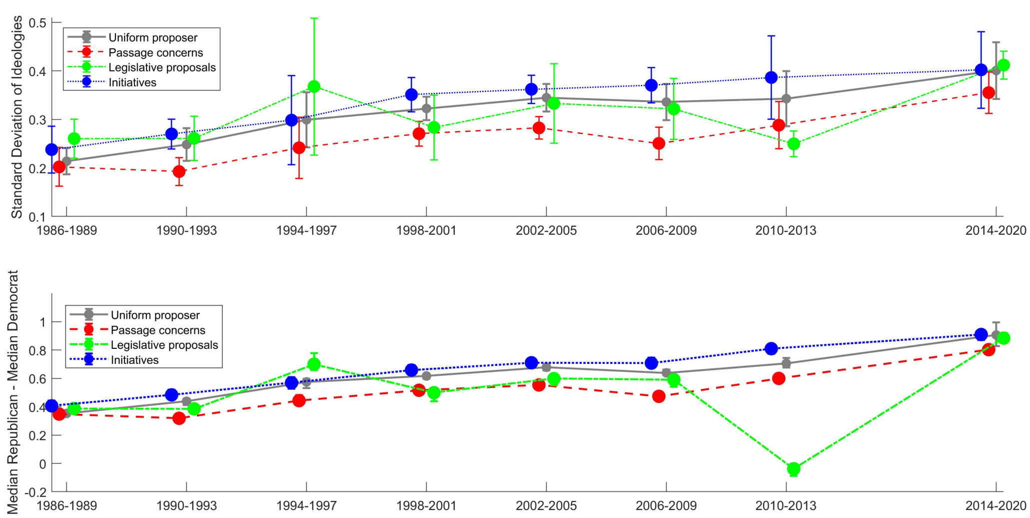
Note: The left panel shows a scatter plot of the common-good probability against the percentage of Yes votes for each proposition. If the estimates were mechanically imputing a high common-good from one-sided elections, we would observe high common-good estimates only when Yes votes were near 0 percent or near 100 percent, which is not the case. The middle panel plots the common-good probability against the estimated midpoint. If the estimation was imputing a high-common good by mechanically forcing the policy midpoint to the center, we would observe high common-good estimates mainly when the midpoint is near zero; however, we see high common-good probabilities for a wide range of policy midpoints. The right panel plots the midpoints against the percentage of votes in favor to see if the estimation mechanically forces the midpoint to the middle for one-sided elections; there is no sign of a mechanical relation.

Figure F4. Model Fit



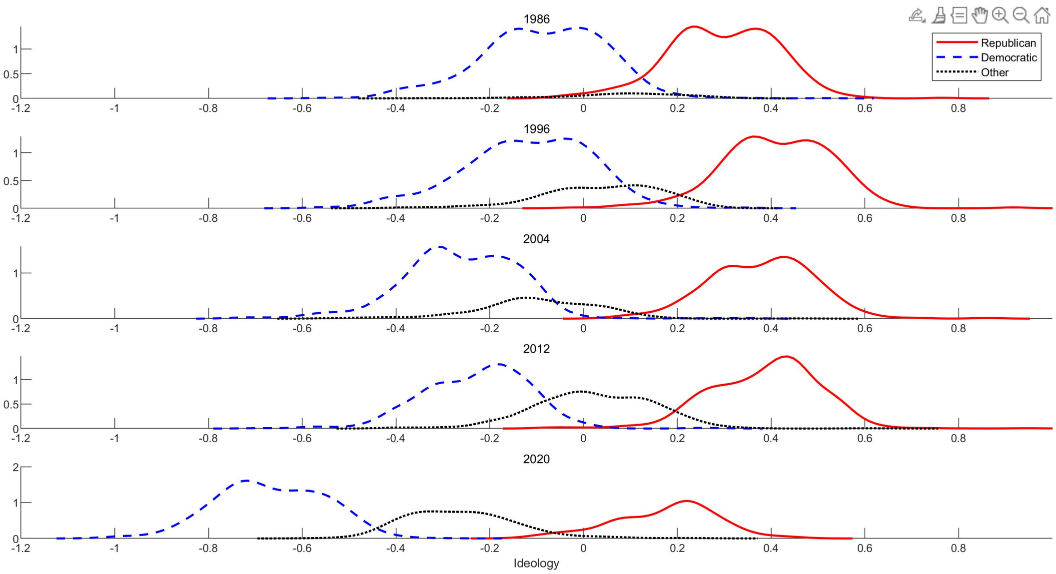
Note: The figure plots the expected vote share for each proposition given the model estimates and estimated state of the world. The dotted line indicates the actual vote shares in the polling data and the data are sorted in order of these shares.

Figure F5. Robustness of Polarization Measures



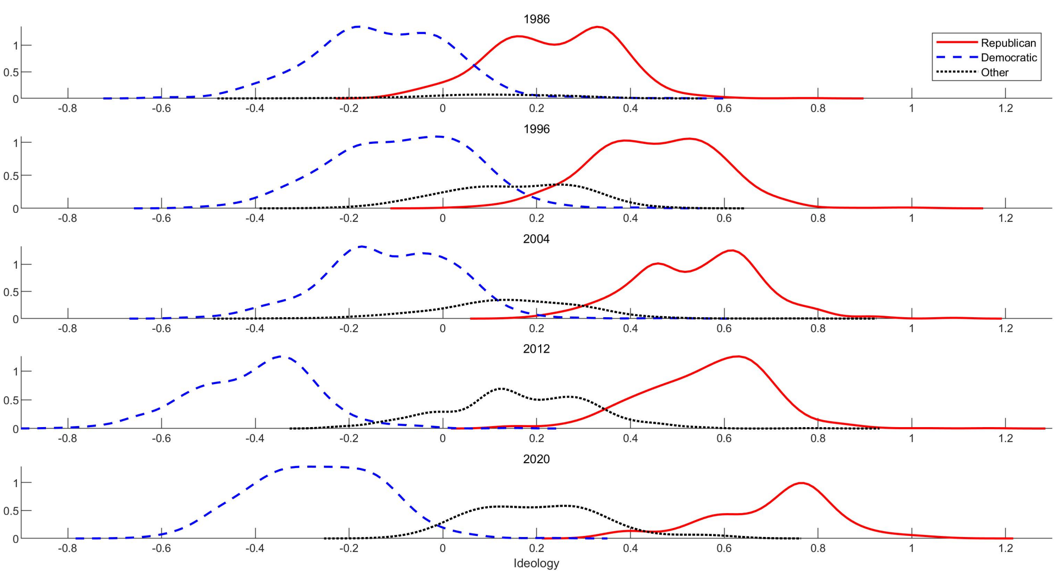
Note. Divergence and party sorting polarization measures for (1) the model in which the proposer is drawn from a uniform distribution, (2) the model where the proposer is concerned about proposition passage, (3) restricting to legislative proposals only, and (4) restricting to initiatives only. Error bars indicate 95% confidence intervals with asymptotic (top panel) and bootstrapped (bottom panel) standard errors.

Figure F6: Estimated Distribution of Ideologies (Correlated Signals)



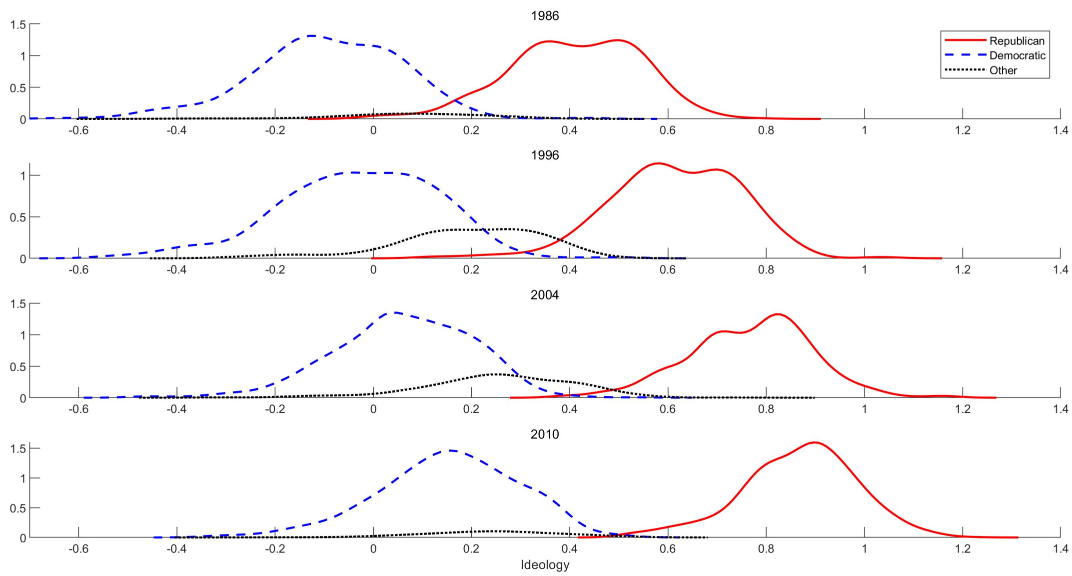
Note: Kernel density estimates of estimated ideologies broken down by party identification and scaled according to the fraction each type makes up in the population.

Figure F7: Estimated Distribution of Ideologies (Economic Issues)



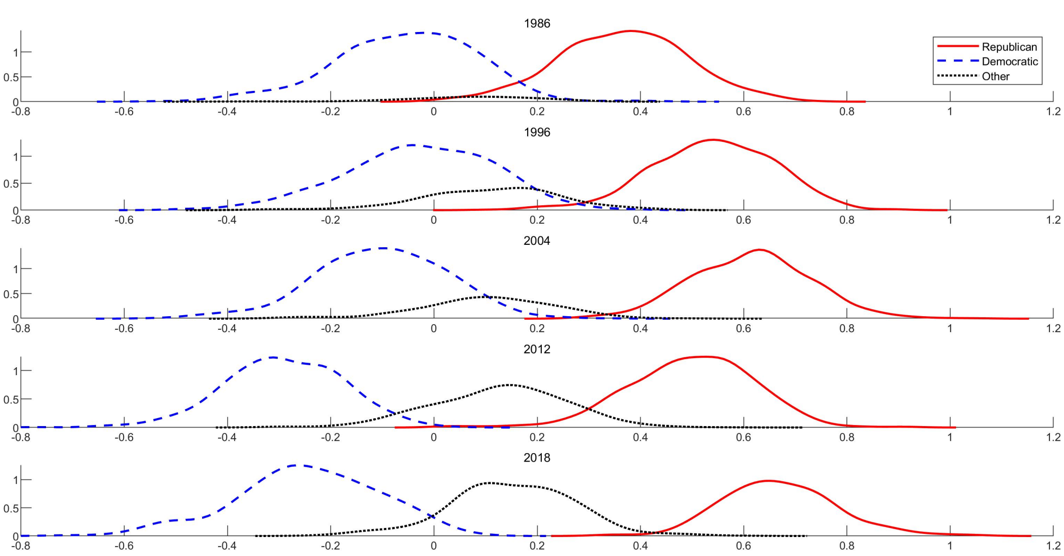
Note: Kernel density estimates of estimated ideologies broken down by party identification and scaled according to the fraction each type makes up in the population. In this specification, only relative movements in ideologies across party identification are identified because we do not have enough similar issues with which to link ideologies across time.

Figure F8: Estimated Distribution of Ideologies (Vote Awareness)



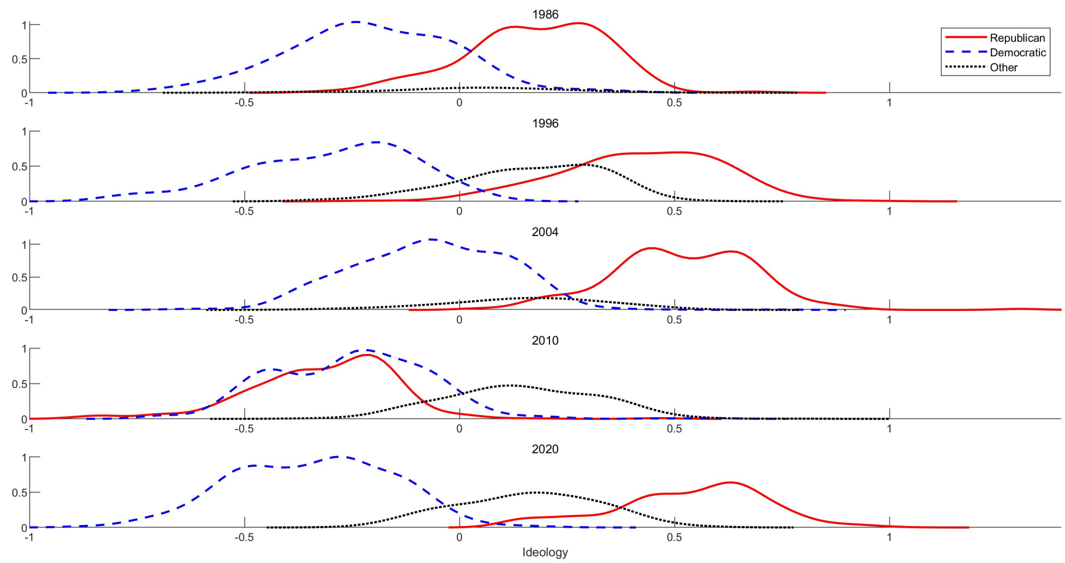
Note: Kernel density estimates of estimated ideologies broken down by party identification and scaled according to the fraction each type makes up in the population.

Figure F9: Estimated Distribution of Ideologies (Initiatives)



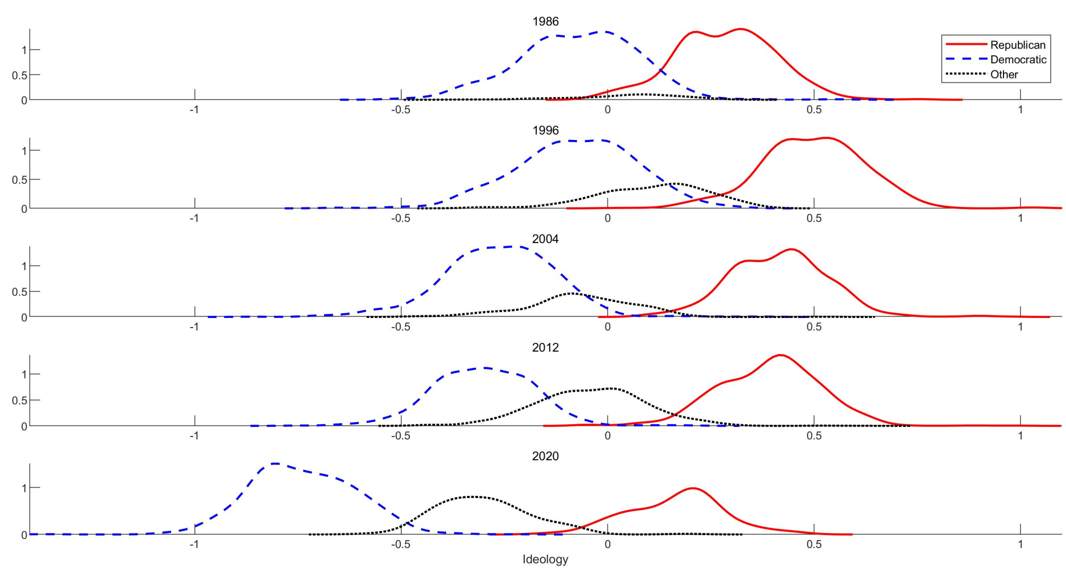
Note: Kernel density estimates of estimated ideologies broken down by party identification and scaled according to the fraction each type makes up in the population.

Figure F10: Estimated Distribution of Ideologies (Legislative Proposals)



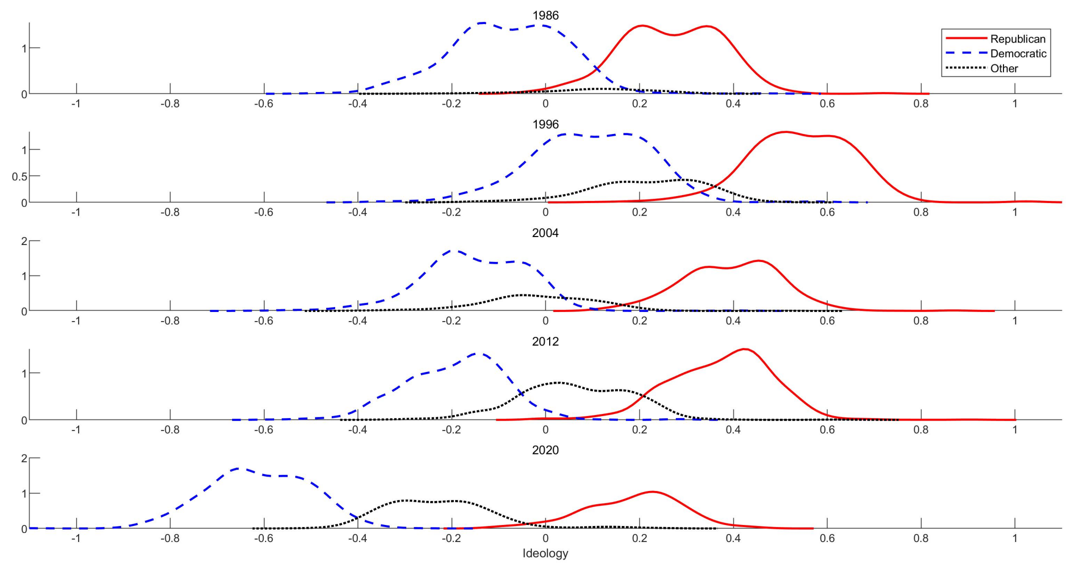
Note: Kernel density estimates of estimated ideologies broken down by party identification and scaled according to the fraction each type makes up in the population.

Figure F11: Estimated Distribution of Ideologies (Uniform Proposer)



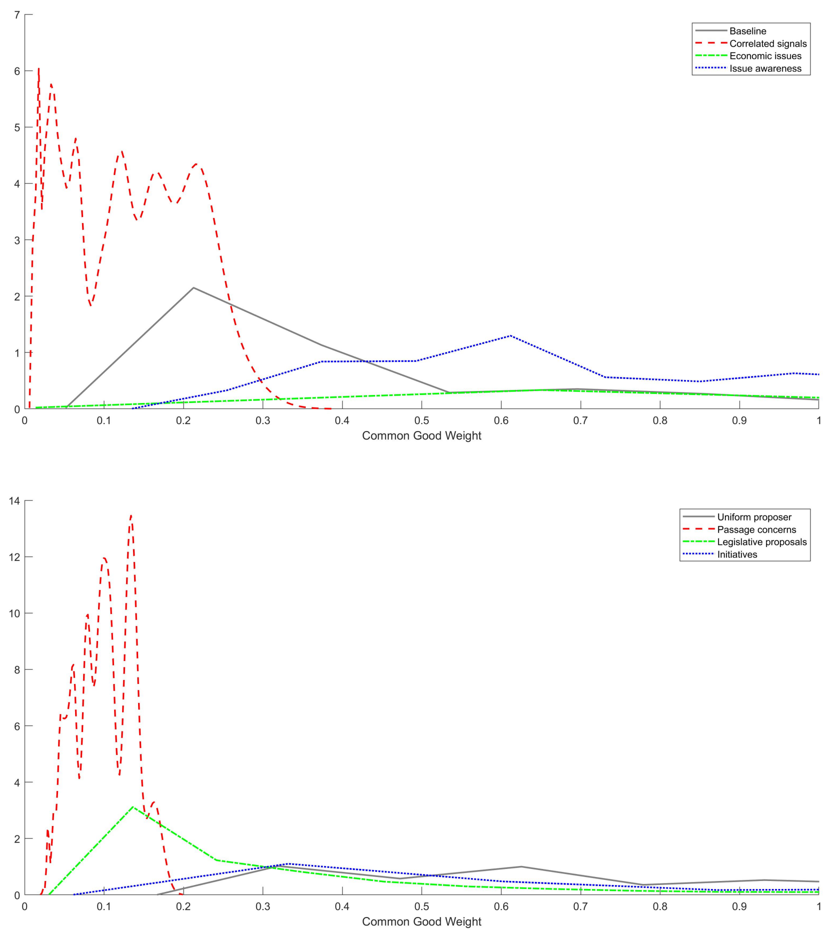
Note: Kernel density estimates of estimated ideologies broken down by party identification and scaled according to the fraction each type makes up in the population.

Figure F12: Estimated Distribution of Ideologies (Passage Concerns)



Note: Kernel density estimates of estimated ideologies broken down by party identification and scaled according to the fraction each type makes up in the population.

Figure F13: Robustness: Common-Good Weights



Note: Distributions of the estimated common-good weights under robustness specifications: (1) correlated signals, (2) restricting to economic issues only, and (3) allowing the signal precision to differ across votes in which the voter was aware and not aware of the issue, (4) restricting to initiatives only, (5) restricting to legislative proposals only, (6) proposer drawn from a uniform distribution, and (7) proposer cares about proposition passage. The baseline model estimates are included for reference.