The Common Good and Voter Polarization

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Abstract

Do voters see democracy entirely as a game of self-interest, or do they also view it as a search for the common good, as some democracy theorists have long conjectured? We develop an empirical model in which voters have preferences over both common-good and private payoffs, and provide a novel method to disentangle the two. Estimating the model on California ballot propositions from 1986 to 2020, we find that 46 to 87 percent of voters place significant weight on the common-good. However, we also find evidence of a significant increase in partisan polarization among the public over the last decade.

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 helps identify the common good better than decisions made by a small group or single person.¹ A more recent tradition, often called “pluralism,” sees democracy instead as an arena for

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¹The 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.”
the pursuit of self-interest by competing groups. Competition leads groups to check and balance each other, resulting in collective decisions that reflect compromise and a balancing of heterogeneous, conflicting interests. A tension has always existed between these two traditions, but it seems to have become acute recently with the metastasizing of partisan polarization. In a world where the population seems to have divided into irreconcilable camps, one may wonder if the possibility of pursuing the common good has been lost in a sea of partisanship.

We have little evidence that speaks to this issue, in part because the concepts of common good and self-interest seldom intersect in empirical work. For example, the foundational evidence on polarization, the NOMINATE scores pioneered by Poole and Rosenthal (1985, 1997), assume that votes are determined entirely by private (spatial) interests, ruling out by assumption a role for common-good considerations. Yet in practice, voters are often asked to weigh common-good considerations against their private interests. Consider the following hypothetical ballot measure:

**Proposition 1.** To fund levee improvements for flood prevention by assessing an income surtax on the wealthy.

In this example, voters must weigh the common good – preventing the levee from breaking – against the private cost that stems from the distribution of the tax burden. Existing research has little to say about how voters make this tradeoff – whether they place weight on the common-good component, or are so polarized and self-interested that they focus only on the private impact.

This paper develops an empirical approach for estimating the weight voters place on the common-good component relative to the private spatial component, and applies it to estimate voter preferences from 168 California ballot propositions in the period 1986-2020. With the hypothetical proposition above as a stepping off point, we develop a discrete choice framework in which voters choose between two policy alternatives, each of which compounds a “common-good” payoff (a payoff which moves all voters’ utilities in the same direction) and a “private-value” payoff that is represented spatially. 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 the ideal point as a voter’s “ideology.” We model the common-good component as binary – either the status quo or the proposed alternative has a higher common-good payoff – and assume voters receive independent binary signals about this state of the world. In this

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2This approach was embedded in the Constitution of the United States, as highlighted in Madison’s famous Federalist No. 10. Other well-known examples include Bentley (1908), Truman (1951), and Becker (1983).

3McCarty (2019) summarizes the literature.
framework, 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. Our model nests a pure spatial model at one extreme, and a pure common-good model at the other, thus tying together two (mostly) distinct theoretical literatures.

Combining common-good and spatial preferences creates a difficult identification problem. The challenge, intuitively, is that if many voters support a particular policy, it could be because it is closer to their ideological positions than the alternative, or because it has a higher common-good payoff. If one had separate data related to both common-good payoffs and spatial positions, the weights could be estimated directly, but such data are seldom available. Our main contribution in terms of methods is to show how the identification problem can be overcome using vote data alone. The basic idea is to identify spatial ideologies by voters’ average positions across issues, and then identify the common-good component by correlations in votes not predicted by spatial preferences. The key additional ingredient is a model of the policy proposal process. We show formally how the extra information about the distribution of proposals that this process provides is sufficient to disentangle the two preference components.

We estimate the model on 168 California ballot propositions from 1986 to 2020. Ballot proposition elections offer an attractive setting to investigate voter preferences and are central to policy making in California and other states. During our period, the propositions spanned a wide range of issues, including tax increases, tax cuts, primary elections, redistricting, same-sex marriage, capital punishment, and marijuana legalization. An indicator of the stakes involved is that proposition campaigns spent $3.4 billion during the period 2000-2020, much more than the $1.4 billion that was spent on legislative elections in the state’s assembly and senate (Matsusaka, 2020b). Ballot propositions offer some advantages over studying candidate elections. In candidate elections, voters choose between two people that make promises on a bundle of issues (often using elastic language), promises that they may or may not deliver depending on the constellation of other officeholders. Consequently, it is difficult to draw a line from votes to policy outcomes – it is not even certain that people vote based on issues, as opposed to candidate characteristics or partisan preferences. With ballot propositions, the nature of the choice is crystal clear: voters are choosing whether to adopt a specific law that will go into effect exactly as proposed.

\footnote{Previous research that used ballot propositions to estimate preferences include 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.}
We use individual-level survey data from the Field Poll and Public Policy Institute of California (PPIC) to capture vote choices on propositions. These surveys were conducted just prior to each election, and include a set of voter characteristics such as income, education, and age. We model voter preferences as a function of these voter characteristics and party identification.

Our estimates strongly reject purely spatial preferences. We find that 46 to 87 percent of voters placed a statistically significant weight on the common-good payoff, depending on the specification. In terms of magnitude, zeroing out the common-good payoff would have shifted the median voter’s probability of supporting a proposal by the same amount as shifting the voter’s ideological position one-third of the way between the median Democrat and median Republican. We estimate that Republicans placed 78 percent less weight on the common-good component than Democrats. In terms of demographics, more educated voters placed a higher weight on the common-good payoff than less educated voters, with the difference being especially pronounced for those with graduate-level education.

One advantage of allowing preferences to include common-good considerations is that the model produces arguably cleaner estimates of ideological positions than purely spatial models. While the literature on polarization of elites, particularly elected officials, is vast, evidence on polarization among ordinary citizens is scarce. One open question is whether ordinary voters are even polarized to an important degree, and if so, how their polarization has changed over time. We find that voters were indeed polarized, both in terms of divergence (the overall dispersion of preferences) and party polarization (the tendency of voters to sort ideologically by party). Hill and Tausanovitch (2015), using a spatial model and survey data related to policy, find little evidence of a general trend in divergence from 1958 to 2012, and a modest increase in party sorting. For the years in which our samples overlap, 1986-2012, we find (as their study does) some evidence of an upward trend in both measures of polarization. For the most recent period, 2013-2020, which does not appear to have been examined previously, we find a sizeable jump in polarization using both definitions. Interestingly, according to our estimates, the most recent increase was largely because of movement to the left by Democrats, not movement to the right by Republicans.

Our empirical procedure, roughly speaking, identifies the common-good component based on co-movement in votes, especially by voters that are ideologically close to indifference. We conduct robustness tests to explore the possibility that our common-good estimates are spuriously capturing other effects. Because the baseline specification assumes one-dimensional preferences, the first possibility is that the common-good component is picking up an unmeasured second (or higher) spatial dimension. To evaluate this, we reestimate the model restricting the data to tax and regulation issues, which we expect to be lower-dimensional
than the full set of issues. The estimates of the common-good weight for this restricted set of issues are similar to the model estimated using the full data.

The second possibility is that a common shock, unrelated to information about the common good, causes votes to move in the same direction. In particular, campaign activities may trigger emotional responses that are common across voters (distinct from the idea that campaigns provide information, an effect accounted for in the baseline model). To evaluate campaign effects, we introduce a separate signal precision parameter for voters who were unaware of a proposition before being surveyed, and hence could not have been exposed to campaigning. If the common-good effect is spuriously caused by campaigning, this signal precision would be noise, but we find instead that even unaware voters have informative signals.

Our empirical strategy draws from several streams in the literature. The idea that voters have spatial preferences, and that they can be inferred from variation in votes across individual issues, is in the tradition of the literature following Poole and Rosenthal (1985, 1997). Perhaps most closely related, Iaryczower and Shum (2012) develop a model of judges with spatial preferences and private information about a common payoff (the legally “correct” decision). The basic structure of our model follows theirs, but we have to overcome an empirical problem that is not present in their setup: identification of policy positions separately from the common-good payoff. This issue does not arise when considering judges because the ideological bias (pro-defendant or pro-plaintiff) is assumed to be constant across cases. From Londregan (1990a, 199b) we draw the idea of using ex ante theoretical considerations to model the policy proposal process, thereby providing additional information about the policy locations.

Substantively, our paper is related to several strands of the literature that assume voter payoffs contain a common element of some sort. Most obviously, there is the literature that attempts to estimate the quality or “valence” of candidates for office. Valence, formally, is a common-good payoff, in that it increases the utility of all voters. Kendall et al. (2015) and Cruz et al. (2019) estimate voters’ weights on the unobserved valence of candidates in the context of field experiments. Both papers utilize elicited beliefs from survey data to identify the valence component, finding substantial weights on the common-good payoffs. Other empirical research on valence utilizes direct proxies for valence. Iaryczower et al. (2020), for example, estimates the valence component of voter preferences over candidates in Brazil, assuming that valence is known to voters and proxied by observable characteristics such as education, sex, etc. They allow for unobservable (to the researcher) shocks to valence, but avoid the identification problem we address here by using donations data to identify candidates’ positions. Buttice and Stone (2012) and Beath et al. (2016) both use
(observable) education as a proxy for candidate valence. One of our contributions is to show how common-good payoffs can be inferred without having an observable empirical proxy, thus significantly widening the scope of problems that can be studied. Outside the valence literature, Londregan (1999b) estimates a legislative model with a “consensus appeal” parameter that compounds both a common-good and spatial component of a bill, although the two components cannot be isolated. Similarly, item response theory models that are used to estimate voter positions from survey data (e.g. Hill and Tausanovitch (2015,2018)) include fixed effects (sometimes called “difficulty” parameters) that compound spatial and common-good payoffs. By contrast, our methodology allows us to explicitly identify the weight voters place on the common good by disentangling it from differences in policy positions across votes.

Our paper also contributes to the extensive literature on political polarization. Most of that literature has focused on political elites, with the well-known finding that polarization among elites has increased since the 1970s (McCarty et al., 2016). An open question is whether this trend reflects an underlying polarization among voters or is happening independently of voters. Two prominent studies taking opposing positions are Abramowitz and Saunders (2008) and Fiorina and Abrams (2008) (arguing that voters have and have not been polarizing, respectively). Our reading of the evidence, especially Hill and Tausanovitch (2015), is that voter polarization has not significantly increased – at least through about 2010 –, but voters appear to have been sorting by party (Gentzkow, 2016; McCarty, 2019). Our contributions to this literature include providing arguably cleaner estimates of ideological positions by accounting for the common-good component of preferences, and tapping the largely unexploited pool of information latent in ballot proposition votes to infer voter preferences. We also extend the evidentiary base on voter ideology into the most recent decade, introducing the novel finding that polarization has grown significant since 2010, both in terms of divergence and party sorting. This result suggests that voters have been following, not leading, their elected representatives in polarizing. By comparing votes on the same issue over time, we are also able to identify absolute movements in ideology, unlike much of the literature which recovers only relative movements.

We introduce the model and discuss its identification in Section 2. In Sections 3 and 4, we discuss our data sources and our empirical specification. In Section 5, we describe the results and perform counterfactual exercises. We conclude in Section 6.
2 Model

We develop a two-stage model in which each citizen, \( i = 1, 2, \ldots, N \), votes on a series of issues, \( j = 1, \ldots, J \). For each issue \( j \), in the first stage one voter is randomly selected to propose a policy alternative, \( x_j \), to a randomly selected status quo policy, \( q_j \). In the second stage, voters each cast a vote for either \( q_j \) or \( x_j \). The following subsections present and analyze each stage of the model.

2.1 Policy Setting

Each voter \( i \) has an ideal point (or ideology) \( \theta_i \) in a one-dimensional policy space. Ideologies are distributed according to \( \theta_i \sim t(\theta) \). We assume the status quo policy is drawn from a normal distribution, \( q \sim Q(\theta_m) \), where \( \theta_m \) is the ideology of the median voter. For each issue \( j \), a status quo policy \( q_j \) and a voter \( i = p \) are independently drawn from their respective distributions. The randomly selected proposer, \( i = p \), chooses the policy alternative, \( x_j \).

Given that the randomly selected proposer with \( \theta_i = \theta_p \) prefers a policy located at \( \theta_p \), we assume the proposal is set at \( x_j = \theta_p \), independent of the randomly selected status quo policy. Thus, the alternative policies are distributed according to \( x_j \sim t(\theta) \).

Identification of the model requires a distribution over proposed policies; the assumption that the proposer sets \( x_j = \theta_p \) is perhaps the simplest model that induces a distribution. Choosing \( x_j = \theta_p \) can be justified on the basis that it maximizes the proposer’s utility independent of concerns or beliefs about the common-good payoff, but it does not account for the possibility that the policy may fail. One could imagine a more “rational” model of policy setting, but it would make the estimation procedure much more complex.\(^5\) In addition, the assumption that the proposer chooses his or her ideal policy reduces the information required by the proposer. To perform the rational calculus necessary to account for the possibility of policy failure, the proposer would have to know the position of the status quo policy, the distribution of voter preferences, and the distribution of information possessed by the electorate (Matsusaka and McCarty, 2001). In our simplified version, an individual instead needs only to know his or her most preferred policy. In any event, we provide evidence in Section 5.4 that the results are not particularly sensitive to our assumption about the proposal process.

\(^5\)In our specification, the distribution of policy alternatives depends only on the distribution of voter ideologies which can be approximated in a first stage without policy setting or concerns for the common good (details in Appendix C). If the proposer accounted for the possibility of a failed policy, the distribution of policy alternatives would become a function of all the parameters of the model, requiring us to recalculate the distribution within the estimation loop. See Canen et al. (2020) for an example of a model in which the proposer maximizes expected utility to determine the policy alternative.
Our assumption that a voter chooses the alternative policy is motivated by the fact that citizen initiatives make up 71 percent of the propositions in our data. This assumption is less natural for the remaining propositions which were proposed by the legislature. Although the legislature may face different incentives in setting the policy alternative, to the extent that it is representative of the electorate, its ideological preferences are likely to be similar to those of the voters. We also find that the estimated policy positions for citizen-initiated and legislature-proposed measures are similar (see Section 5.2).

2.2 Voter Decisions

After the policy alternatives \(q_j\) and \(x_j\) are determined, voters choose between the two options (we assume \(x_j \neq q_j\)). Voters derive expressive utility both from a private value (spatial) component and a common-good component. The common-good component is defined to be a payoff that moves the utility of all voters in the same direction (given the same information); voters may disagree about the importance of the common good because of heterogeneous information, or because they place different weights on the common good payoff. We let \(\psi_j \in \{1, 0\}\) denote the state of the world, where \(\psi_j = 1\) indicates that \(x_j\) provides a greater common good than \(q_j\), and conversely.\(^6\) Voter \(i\)'s utilities from voting for each policy are then given by

\[
\begin{align*}
  u(x_j) &= -\left(x_j - \tilde{\theta}_{ij}\right)^2 + w_i I(\psi_j = 1) \\
  u(q_j) &= -\left(q_j - \tilde{\theta}_{ij}\right)^2 + w_i I(\psi_j = 0)
\end{align*}
\]

where \(I()\) is an indicator function and \(\tilde{\theta}_{ij}\) is \(i\)'s ideological position on issue \(j\). The first term in each of (1) and (2) is a standard spatial utility component with quadratic utility. The second term is the common-good component, where \(w_i\) is the weight placed on the common good.\(^7\)

We assume voters are uncertain about both the spatial and common-good components of their utility functions. For the common-good component, voters share a common prior, \(\rho = Pr(\psi_j = 1)\), and each receives a binary signal, \(s_{ij}\), that correctly identifies the policy that

\(^6\)A binary common-good component greatly simplifies the likelihood function and also serves as a normalization. Were we to allow the difference in the common-good components of the policies to vary continuously, a larger average difference would be indistinguishable from an increase in the weights voters place on the common good.

\(^7\)In this interpretation, the benefit of the common good is constant across voters, but voters weight the common good heterogeneously. An alternative interpretation is that voters derive heterogeneous benefits from the common good. Our model cannot distinguish between the two interpretations.
delivers a greater common good with probability \( \pi_i \in (\frac{1}{2}, 1] \) (i.e. \( Pr(s_{ij} = \psi_j | \psi_j = \pi_i) \)).

Signals are independent across voters, conditional on \( \psi_j \), and independent of \( q_j \) and the proposer’s identity.\(^9\) The common prior is constant across issues.

For the spatial component, we assume that voters do not know the precise locations of \( q_j \) and \( x_j \), but know the midpoint between policies \( m_j \equiv \frac{x_j + q_j}{2} \), the “direction” of the proposed alternative, \( D_j \equiv I(x_t > q_t) \), and the distribution of \( x_j - q_j \) (conditional on \( m_j \) and \( D_j \)). The motivation for this assumption is that the midpoint and direction are more easily learned from party endorsements or media with known ideological positions than the individual policy locations. Empirically, the midpoint and direction are simpler to identify (ignoring common-good considerations), because voters to the left of \( m_j \) will vote for one policy while those to the right of \( m_j \) will vote for the other, with the direction pinned down by which of these two groups votes for \( x_j \).

Voter \( i \) optimally votes for \( x_j \) if it provides higher expected utility than that of \( q_j \) (the tie-breaking rule is inconsequential), conditional on his or her information:

\[
E \left[ - (x_j - \tilde{\theta}_{ij})^2 + (q_j - \tilde{\theta}_{ij})^2 \right] + w_i (Pr(\psi_j = 1 | I_{ij}) - Pr(\psi_j = 0 | I_{ij})) \geq 0
\]

\[\iff E \left[ (x_j - q_j)(\tilde{\theta}_{ij} - m_j) \right] + w_i (2Pr(\psi_j = 1 | I_{ij}) - 1) \geq 0\]

where \( I_{ij} \) indicates the information \( i \) possesses about the policies, \( q_j \) and \( x_j \), and the state, \( \psi_j \), at the time of voting on issue \( j \).

By Bayes’ rule, a voter receiving \( s_{ij} = 1 \) has belief,

\[
b_i^1 = Pr(\psi_j = 1 | s_{ij} = 1) = \frac{\rho \pi_i}{\rho \pi_i + (1 - \rho)(1 - \pi_i)}
\]

and a voter receiving \( s_{ij} = 0 \) has belief

\[
b_i^0 = Pr(\psi_j = 1 | s_{ij} = 0) = \frac{\rho(1 - \pi_i)}{\rho(1 - \pi_i) + (1 - \rho)\pi_i}
\]

so that voter \( i \) with \( s_{ij} = s \) votes for \( x_j \) if

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\(^8\)The assumption of binary signals is not necessary, but avoids convolving the signal distribution with that of voter’s idiosyncratic shocks in the estimation loop.

\(^9\)These assumptions ensure that voter beliefs are uncorrelated with their ideologies, ruling out, for example, conservative and liberal voters updating differently to the same information. Any such correlation will show up in our estimation as differences in ideology since the common-good component, by definition, is one which moves all votes in the same direction, on average.
\[ E \left[ (x_j - q_j)(\tilde{\theta}_{ij} - m_j)|\mathcal{I}_{ij} \right] + w_i (2b_i^s - 1) \geq 0. \] (3)

Given the assumptions about voter information concerning policy locations, (3) becomes

\[ E [(x_j - q_j)|m_j, \mathcal{D}_j] (\tilde{\theta}_{ij} - m_j) + w_i (2b_i^s - 1) \geq 0 \iff \alpha^d_j(\tilde{\theta}_{ij} - m_j) + w_i (2b_i^s - 1) \geq 0 \] (4)

where \( \alpha^d_j \equiv E [(x_j - q_j)|m_j, \mathcal{D}_j = d] \).

The policy setting model delivers a distribution over \( x_j \) which, together with the assumed distribution of \( q_j \), determines the distributions over policy midpoints \( m_j \), and \( x_j - q_j \). We denote these distributions, \( f^d(m|\theta, \mathcal{D}_j = d) \) and \( g^d(x - q|\theta, \mathcal{D}_j = d, m_j) \), respectively. The distribution \( g^d(x - q|\theta, \mathcal{D}_j = d, m_j) \) determines \( \alpha^d_j \) for a given \( m_j \) and \( \mathcal{D}_j \), so that we need only estimate \( m_j \) and \( \mathcal{D}_j \).

Lastly, we assume that voter \( i \)'s ideological position is subject to an idiosyncratic shock for each issue \( j \), \( \tilde{\theta}_{ij} = \theta_i + \varepsilon_{ij} \), where \( \varepsilon_{ij} \) is drawn from a standard normal distribution. The ideological shocks are independent across voters and independent of \( \psi_j, s_{ij}, q_j, \) and the proposer’s identity.\(^{10}\) Denote the probability that voter \( i \) votes for \( x_j \) (that is, in favor of the alternative policy) conditional on \( \psi_j = \psi \) and direction \( \mathcal{D}_j = d \) as \( \gamma_{ij}^{\psi d} \equiv Pr(Y_{ij} = 1|\psi_j = \psi, \mathcal{D}_j = d) \). For \( \psi_j = 1 \), we have

\[ \gamma_{ij}^{11} = \pi_i Pr \left( \alpha^1_j (\theta_i + \varepsilon_{ij} - m_j) + w_i (2b_i^1 - 1) \geq 0 \right) + (1 - \pi_i) Pr \left( \alpha^1_j (\theta_i + \varepsilon_{ij} - m_j) + w_i (2b_i^0 - 1) \geq 0 \right) = \pi_i \Phi \left( \theta_i - m_j + \frac{w_i}{\alpha^1_j} (2b_i^1 - 1) \right) + (1 - \pi_i) \Phi \left( \theta_i - m_j + \frac{w_i}{\alpha^1_j} (2b_i^0 - 1) \right) \] (5)

\(^{10}\)Having shocks affect ideology produces a similar specification as having shocks affect utility. However, with shocks to ideology, we can obtain approximate estimates of the ideologies in a first estimation step that is independent of the policy setting model, simplifying the estimation procedure overall. Canen et al. (2020, 2021) take a similar approach.
and

\[
\gamma_{ij}^{10} = \pi_i Pr \left( \alpha_j^0 (\theta_i + \varepsilon_{ij} - m_j) + w_i (2b_1^i - 1) \geq 0 \right) \\
+ (1 - \pi_i) Pr \left( \alpha_j^0 (\theta_i + \varepsilon_{ij} - m_j) + w_i (2b_0^i - 1) \geq 0 \right) \\
= \pi_i \Phi \left( - (\theta_i - m_j) - \frac{w_i}{\alpha_j^0} (2b_1^i - 1) \right) \\
+ (1 - \pi_i) \Phi \left( - (\theta_i - m_j) - \frac{w_i}{\alpha_j^0} (2b_0^i - 1) \right)
\]

(6)

using \( \alpha_j^1 > 0 \) and \( \alpha_j^0 < 0 \). The equations for \( \gamma_{ij}^{01} \) and \( \gamma_{ij}^{00} \) are similar to \( \gamma_{ij}^{11} \) and \( \gamma_{ij}^{10} \), respectively, with \( 1 - \pi_i \) replacing \( \pi_i \) in each.

The vote probabilities (5) and (6) nest standard spatial models as well as purely common value models through changes in the parameter, \( w_i \). With \( w_i = 0 \), the model is a standard, spatial model, but as \( w_i \) becomes very large, the model is a purely common value model akin to Condorcet’s Jury Model.

2.3 Intuition for Identification

In this section, we provide an intuitive description of the variation in the data that identifies the model parameters. Appendix B provides a formal proof.

As in most spatial models, ideologies are identified by differences in voting probabilities across voters on the same issue. The direction of each proposed alternative, \( D_j \equiv I(x_t > q_t) \), is identified by whether voters further to the right vote more or less for the alternative. The policy midpoints are identified by both the policy setting information and the differences in vote probabilities for the same voter across issues. The policy setting information is key here - without it, the locations of the midpoints cannot be separately identified from the common-good parameters.

In a purely spatial model, any vote that differs from the prediction of the spatial model is assumed to be due to an idiosyncratic shock. Thus, conditional on the spatial parameters, the votes cast by all voters should be uncorrelated. With a common good component, the votes will instead be correlated in a way not predicted by the spatial model. Furthermore, the common good weight, prior, and signal precision independently affect this correlation.

For the purposes of exposition, assume the policy alternative has the higher common good component.

The common good weight determines the range of voters around the policy midpoint that are “influenced” by the common-good component, producing correlation in their votes. If the weight is zero, all votes are cast (up to their idiosyncratic shocks) as predicted by
the spatial model. On the other hand, if the common-good weight is large, even the most extreme voters will tend to deviate from the votes predicted by their spatial positions to vote for the alternative. For intermediate values, only voters close to the policy midpoint will increase their support for the alternative.

While the weight determines the “reach” of the common-good component, the signal precision determines how correlated the voters are within the span of voters that are influenced by the common good. If the signal precision is close to 0.5, then we return to the spatial model – votes are uncorrelated. If the signal precision is one, all voters within the span will tend to increase their support for the alternative. For intermediate signal precisions, on average voters will tend to increase their support, but some will move in the opposite direction, due to incorrect signal realizations.

Finally, the prior produces variation different from the signal precisions because it affects the average propensity to support the policy alternative. If the prior is close to one-half, voters will be no more or less likely to support the policy alternative - the votes will reflect the realized state for each issue. For a prior close to one, all voters will move to support the policy alternative for every issue (independent of the state), and conversely if the prior is close to zero.

3 Data

Our data pertain to California propositions during 1986-2020. The propositions 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 qualified for the ballot by collecting signatures. Three were proposals to repeal existing laws, also qualified by petition. 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 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, with some favored by conservatives, others favored by progressives, and some difficult to locate ideologically. Some were backed by Democrats, some by Republicans, some were opposed by both parties, and some were 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 (with survey data available). 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, but the flow has been consistent 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 can expect voters to be fairly well informed about most issues, and their votes to reflect their preferences (Lupia, 1994, Lupia and McCubbins, 1998).

Propositions offer an excellent opportunity for gauging voter preferences. When voting on candidates, citizens select between two bundles of policy positions, which may or may not be implemented depending on the configuration of power in the legislature. When voting on propositions, there is a specific law at hand – usually narrowly tailored – and the election unambiguously determines its passage or failure.\footnote{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.} It is possible that when voting on candidates, citizens may load on one or two primary issue positions, in which case their
votes would reveal only a slice of their broader array of preferences.

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. The surveys asked voters how they intended to vote on select ballot propositions, their party affiliation, and demographic information. If there was more than one wave of polling before an election, we use data from 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, $f^d(m|\theta)$, and when reporting aggregate results.

The surveys cover 168 of the 395 ballot propositions that came before the voters during the period, 119 initiatives and 49 legislative proposals. These propositions were typically higher-profile issues, both in terms of media coverage and campaign spending. For the years in which we have campaign finance data (1998 to 2016), spending per proposition averaged $21.5 million for issues that were polled, compared to $11.7 million for issues that were not polled.

We focus on demographic categories for which comparable data are available across the surveys. These demographics boiled down to categorical dummies for age, education, income, race, and county of residence. After dropping observations with missing data, we have 96,213 responses given by 31,007 respondents.

For the purposes of 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 (that is, it does not mean the person has any formal connection to the party). Official registration numbers maintained by the state tend to diverge (lag) self-reported numbers because some voters do not bother to submit the paperwork to change their party preference when their identification changes.

Survey respondents indicated whether they intended to vote for, against, or were undecided about a proposition. Overall, approximately 86 percent indicated that they had an

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12 The Field Poll data is available at https://dlab.berkeley.edu/data-resources/california-polls. The PPIC data is 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 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 is unavailable. We have data on vote intentions, not actual voting decisions. 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.

13 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.
opinion for or against. We omit the 14 percent that were undecided. An alternative approach would be to treat undecided respondents as indifferent between voting for and against, as in Deacon and Shapiro (1975). We chose to drop them because more than half indicated that they had not even heard of the proposition before the survey. Later in the analysis, we make use of this additional data on voters’ prior awareness of an issue.

Information on the subject matter of propositions were taken from a database maintained 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 D.

4 Empirical Specification

Because we observe only a handful of votes for each respondent, we cannot estimate preferences at the individual level. Instead, we construct voter types from observed respondent characteristics. In particular, we assume \( \theta_i = X\beta \) where \( X \) is the set of observable characteristics described in Section 3 plus time dummies for each four-year period and their interactions with each voter’s party registration. The party-time interactions allow the effect of partisan affiliation to vary with time. We only include select interaction terms because including all possibilities would require estimating too many parameters. One potentially important limitation of this specification is that the marginal effects of demographics (age, education, etc.) are assumed to be constant over time.

We identify absolute ideological movements over time using cases in which the same issue 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 were enough repeat issues to establish links across our entire period of study, except from 2014 onward (see Appendix E for details). Given the absence of links for those years, we treat them as a single time period.

Although theoretically identified, in practice it proved difficult to simultaneously identify the common-good weights and signal precisions for very fine-grained voter types. Because our focus is on the common good weights, our main specification assumes a homogeneous signal precision and parameterizes the weights as \( w_i = \exp(W\delta) \), where \( W \) includes the same set of observables as \( X \), except that we do not allow the weights to change over time and we omit the county fixed effects.\(^{14}\) In the robustness check in which we make use of

\(^{14}\)Allowing for more fine-grained ideological types than for the common good weights and signal precisions ensures there exist multiple ideologies for each \( (w_i, \pi_i) \) pair as implicitly assumed in the proof of identification.
voters’ awareness of the issue (see section 5.4), we add a dummy for issue awareness. To ensure the signal precision is bounded between one-half and one, in this case, we specify

\[ \pi_{ij} = 0.5 + 0.5 \frac{\exp(\zeta_0 + A_{ij} \zeta_1)}{1 + \exp(\zeta_0 + A_{ij} \zeta_1)} \]

where \( A_{ij} \) is a dummy variable that is one if the voter was aware of the issue prior to the survey.

To provide the policy setting information necessary for identification to the estimation procedure, we assume the status quo is drawn from a generalized error distribution (also known as an exponential power distribution), which is a generalization of the normal distribution. We set the mean of the distribution to the ideological position of the median voter and fix the scale to half the distance between the maximum and minimum ideological positions. In our baseline specification, we set the shape parameter to two, which corresponds to a normal distribution, but in a robustness check, we set it to eight, which delivers a nearly uniform distribution over the range of voter ideological positions.

The final parameter vector to be estimated is then \( \Theta = \{ \{ m_j, D_j \}_{j=1}^J, \beta, \delta, \zeta, \rho \} \). We construct the likelihood of observing a midpoint and a series of votes conditional on this midpoint. Because the distribution of \( \theta_i \) 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 distributions, \( f_d(m | \theta, D_j = d) \) and \( g_d(x - q | \theta, D_j = d, m_j) \), are election specific, \( f_{de}(m | \theta, D_j = d) \) and \( g_{de}(x - q | \theta, D_j = d, m_j) \), \( e = 1, \ldots, E \). In this case, we write \( j = 1, \ldots, J_e \) for the propositions in election \( e \) where \( J_1 + J_2 + \ldots + J_E = J \).

If one observed the orientation of the policies on each issue \( j \), \( D_j \), the joint log-likelihood of observing a set of midpoints and their associated votes would be given by

\[
L \left( \{ \{ Y_{ij} \}_{i=1}^N \}_{j=1}^J ; \Theta \right) = \\
\sum_{e=1}^E \sum_{j=1}^{J_e} \log \left( f_{e}^1(m_j | \theta, D_j = 1) \right)^{D_j} \left( f_{e}^0(m_j | \theta, D_j = 0) \right)^{1-D_j} + \\
\sum_{e=1}^E \sum_{j=1}^{J_e} \log \left[ \rho \prod_{i=1}^N \left( \gamma_{11}^{ij} Y_{ij}^{D_j} \left( 1 - \gamma_{11}^{ij} \right)^{1-D_j} \gamma_{10}^{ij} Y_{ij}^{(1-D_j)} \left( 1 - \gamma_{10}^{ij} \right)^{(1-Y_{ij})(1-D_j)} \right) + \\
(1 - \rho) \prod_{i=1}^N \left( \gamma_{01}^{ij} Y_{ij}^{D_j} \left( 1 - \gamma_{01}^{ij} \right)^{(1-Y_{ij})(D_j)} \gamma_{00}^{ij} Y_{ij}^{(1-D_j)} \left( 1 - \gamma_{00}^{ij} \right)^{(1-Y_{ij})(1-D_j)} \right) \right] (7)
\]

The structure of (7) follows from the fact that voters’ signals and shocks are assumed to be independent, and that we can write the joint probability of observing each \( m_j \) and a set of votes as the product of the marginal probability of observing \( m_j \) and the marginal

(specifically, in identifying the direction, \( D_j \), for each issue).
probability of observing the votes conditional on $m_j$.

We do not know $D_j$ as assumed in (7), so it must be estimated. Instead of estimating a binary parameter, we calculate the likelihood for each value of $D_j$ on each issue, $j$, and then choose the maximum of the two.\footnote{See Canen et al. (2021) for another application of this technique in a similar setting.} The likelihood becomes

$$\mathcal{L} \left( \{ \{ Y_{ij} \}_{i=1}^{N} \}_{j=1}^{J} ; \Theta \right) = \max_{d \in \{0,1\}} \left\{ \sum_{e=1}^{E} \sum_{j=1}^{J_e} \log f_e^d (m_j| \theta, D_j = d) + \sum_{e=1}^{E} \sum_{j=1}^{J_e} \log \left[ \rho \prod_{i=1}^{N} (\gamma_{ij}^{1d})^{Y_{ij}} (1 - \gamma_{ij}^{1d})^{1-Y_{ij}} + \right. \right.$$  

$$\left. \left. (1 - \rho) \prod_{i=1}^{N} (\gamma_{ij}^{0d})^{Y_{ij}} (1 - \gamma_{ij}^{0d})^{1-Y_{ij}} \right] \right\} \tag{8}$$

We estimate (8) via maximum likelihood using the custom optimization algorithm described in Appendix C. The estimates are consistent for large $N$ and $T$ (e.g. Arellano and Hahn, 2007).

5 Results

5.1 Voter Estimates

5.1.1 Common Good Parameters

Our first – and motivating – question is whether voters perceive a common good component in policy issues. We find that they do. Figure 2 plots the distribution of the estimated common good weights, $w_i$.\footnote{Because we do not allow these weights to change over time, the distributions vary little with time (due only to changes in the composition of voters) so we pool the weights and plot a single distribution.} The mean is 0.17, with standard error 0.07 ($p = 0.01$), with about 46 percent of voters having weights that can be differentiated from zero at a significance level of 5 percent. Moreover, a likelihood ratio test rejects a purely spatial model in favor of the full model with common good parameters ($p < 0.001$).

The substantive question is whether common-good considerations are economically significant. The answer depends on both the common-good weight and voters’ signal precision. We estimate the (homogeneous) signal precision to be $\pi = 0.81$ with a standard error of
0.06, indicating that voters received relatively informative signals. To assess the combined economic significance of the common-good weights and signal precisions, we focus on the voting probabilities given by (5) and (6). We calculate how much the voting probability would change if the common-good payoff vanished, and compare it to the ideological shift necessary to produce the same change in voting probability. This “equivalent ideological shift” is 0.14 at the median (after averaging across the two possible signal realizations), meaning that a common-good voter with a signal would have the same voting probability as a voter 0.14 ideological units away with no weight on the common good. This magnitude is nontrivial – it is 38 percent of the distance between the median registered Republican and median registered Democrat in 1986.

To explore the determinants of the heterogeneity in common good weights, Table 1 reports the estimates of $\delta$ and the other parameters. We find that Republicans placed 78 percent less weight on the common-good component than voters in the omitted category (mostly independents), who in turn placed less weight on the common good than Democrats (although not significant). In terms of demographics, more educated voters placed a higher weight on the common good component than less-educated voters, particularly the most educated (those with graduate education), for which the parameter estimate is statistically
Table 1. Parameter Estimates for the Baseline Model

<table>
<thead>
<tr>
<th>Variable</th>
<th>Estimate (s.e.)</th>
<th>Variable</th>
<th>Estimate (s.e.)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age: 40-64</td>
<td>-0.02 (0.22)</td>
<td>Age: 40-64</td>
<td>0.13 (0.03)</td>
</tr>
<tr>
<td>Age: 65+</td>
<td>0.04 (0.23)</td>
<td>Age: 65+</td>
<td>0.21 (0.03)</td>
</tr>
<tr>
<td>College</td>
<td>0.68 (0.38)</td>
<td>College</td>
<td>-0.06 (0.03)</td>
</tr>
<tr>
<td>College+</td>
<td>1.10 (0.38)</td>
<td>College+</td>
<td>-0.20 (0.04)</td>
</tr>
<tr>
<td>Income: 20-60k</td>
<td>0.33 (0.46)</td>
<td>Income: 20-60k</td>
<td>0.05 (0.05)</td>
</tr>
<tr>
<td>Income: &gt;60k</td>
<td>0.48 (0.47)</td>
<td>Income: &gt;60k</td>
<td>0.09 (0.04)</td>
</tr>
<tr>
<td>Asian</td>
<td>-1.22 (1.02)</td>
<td>Asian</td>
<td>0.01 (0.05)</td>
</tr>
<tr>
<td>Black</td>
<td>-0.42 (0.42)</td>
<td>Black</td>
<td>0.01 (0.08)</td>
</tr>
<tr>
<td>Hispanic</td>
<td>-0.37 (0.35)</td>
<td>Hispanic</td>
<td>-0.00 (0.03)</td>
</tr>
<tr>
<td>Democrat</td>
<td>0.37 (0.28)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Republican</td>
<td>-1.57 (0.61)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>-2.58 (0.76)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Common good (δ)</td>
<td></td>
<td>Common good (β)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.81 (0.06)</td>
<td>Income: 20-60k</td>
<td>0.05 (0.05)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Income: &gt;60k</td>
<td>0.09 (0.04)</td>
</tr>
<tr>
<td>Common good (π)</td>
<td></td>
<td>Asian</td>
<td>0.01 (0.05)</td>
</tr>
<tr>
<td>Common good (ρ)</td>
<td>0.33 (0.15)</td>
<td>Black</td>
<td>0.01 (0.08)</td>
</tr>
</tbody>
</table>

Notes: 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 registered as Republicans or Democrats. Asymptotic standard errors are reported in parentheses. Bold coefficients for δ, β, and π indicate significance at the 5% level or less. For π, we test the one-sided hypothesis that the coefficient is greater than one-half.

These patterns can be also be interpreted as saying that Republicans and less-educated people voted more consistently with their ideology. Perhaps equally interesting is what does not matter: income and age. The age parameters are small in magnitude and statistically indistinguishable from zero. The income variables are positive and somewhat larger, but also statistically insignificant. Similarly, none of the race variables can be distinguished from zero statistically, perhaps due to the small number of minority voters in the sample.

5.1.2 Ideological Parameters and Polarization

Estimates of polarization among the general public – as opposed to among politicians – are rare (see Hill and Tausanovich (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 component, we are able to extract spatial preferences that are arguably cleaner than estimates from models that assume voting is entirely spatial.\(^{17}\)

The literature has advanced two concepts of polarization. The first, which we call “diver-
gence” following Hill and Tausanovitch (2015), is simply the dispersion of ideologies, $\theta_i$. An increase in divergence reflects the replacement of moderate voters by more extreme voters, independent of their party affiliation. Figure 3 plots the standard deviation of ideologies over time. The point estimates suggest that the variance of preferences grew from the start of our study period in 1986 until about 2005, declined slightly for a decade, then diverged sharply in 2020. However, 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 does seem apparent.

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 1958-2020 period can be described as: yearly fluctuations with no evidence of a trend from 1958 until around 1990; a gradual increase in divergence from then on – albeit with annual fluctuations – with a clear increase by 2020.\footnote{We should note that the post-2012 jump appears prior to the 2016 election, so appears to be more than a Trump phenomenon.}

The second measure of polarization, called “sorting,” is the extent to which ideological preferences are correlated with partisan identity. Figure 4 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 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.\footnote{Figure 4 also illustrates an increase in voters that are neither registered Democrats nor registered Republicans. This increase mainly comes at the expense of registered Republicans - the fraction of registered Democrats is fairly stable.} Furthermore, in contrast to existing evidence on elite polarization in which polarization is mainly attributed to Republicans moving right over time, our results suggest that the most recent jump in sorting is due to Democrats moving to the left.\footnote{See Canen et al. (2021), for results that also dispute this standard view.}

Another measure of party sorting is the distance between the ideology of the median
Figure 3. Standard Deviation of Ideologies, $\theta_i$, Over Time

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

Figure 4. Distribution of Ideologies by Party

Notes: Kernel density estimates of estimated ideologies broken down by party affiliation and scaled according to the fraction each type makes up in the population (as obtained from the survey sample weights).
Democrat and the median Republican, shown in Figure 5. As with divergence, we observe an increase from the start of our period until about 2003, a slight regression over the next decade, and then a large jump in recent years. From 1986 to 2020, polarization by this measure grew by 124 percent, more than doubling. Hill and Tausanovitch (2015) report a gradual increase in party sorting beginning in the mid-1980s and running through 2012, when their sample ends. Similarly, using data from primary elections, Hill and Tausanovitch (2018) report a gradual increase in polarization over the same time frame. Our evidence roughly squares their evidence for the years in which our samples overlap. Appending our post-2012 evidence to the overall time series produces a more pronounced picture of rising polarization in recent times.

Taken together, 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. This finding adds an important data point to the debate because it uses a standard utility framework and (intended) votes on issues, which is the same methodology used in establishing the polarization of members of Congress. This evidence does not lay a strong foundation for the argument that polarization among elected officials is primarily a response to polarization among the public – indeed, 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 affiliation 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. Table 1 shows that demographic factors account for some of the variation in ideology: for example, older and richer voters are more conservative, while highly educated voters are more liberal.

To assess the extent of sorting on other characteristics, we begin with income. A large literature debates 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. The top panel of Figure 6 plots the distribution of ideology by income. Somewhat surprisingly, at least in terms of popular narratives, we find little evidence of polarization by income.

The middle panel of Figure 6 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. 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 6 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 including ages 18-39.

We also explored geographical sorting; the county fixed effects are reported as a choropleth in Appendix A, Figure A1. The expected pattern of more liberal counties along the coast and more conservative counties in the northern interior is clearly present. If we plot the average ideology instead of the fixed effect, the pattern is similar suggesting that a substantial amount of geographic sorting occurs along unobservable characteristics. The fixed effects or mean ideologies mask heterogeneity within each county, however.

A final quantity of interest is the correlation between ideological extremism and the common-good weights. One might conjecture that voters with extreme ideologies place less weight on the common good. However, we find little correlation between ideological extremism and common good weight apart from that due to Republicans being more to the right and weighting the common good less (see Figure A2 of Appendix A).

5.2 Initiatives versus Legislative Proposals

The model also yields estimates of the midpoints between the two policy alternatives. We can use this information to compare the common-good payoff and ideological orientation of proposals that come from citizens with those that come from the legislature. Citizen initiatives require collection of signatures equal to 5 percent of the votes cast at the previous gubernatorial election for statutes, and 8 percent for constitutional amendments. Collecting signatures is intended to ensure that proposals have broad support before they appear on the ballot. However, the vast majority of signatures are collected by signature petition firms, who employ petitioners to stand with clipboards outside grocery stores, in malls, and in other public places, soliciting signatures from passerbys; expert observers believe that if a sponsor is willing to pay a petition firm a few million dollars, the requisite signatures can be collected for just about any proposal. As a practical matter, almost all propositions that reach the ballot have deep-pocketed sponsors, often wealthy individuals, but also business groups, unions, and activist organizations. This fact has led some observers to conclude that the process is a tool of special interests that use it to advance their narrow agendas.

Legislative proposals go through very different processes to reach the ballot. Constitutional amendments, which make up the preponderance of the legislative propositions in our data, require a two-thirds vote in each house. Bond proposals require a simple majority in each house but also the governor’s signature. In either case, fragmented authority and
sometimes supermajority requirements are likely to screen out extreme proposals – any law that can pass the multiple gatekeepers is likely to have broad support, both among legislators and their constituents.

We first compare the common-good component of initiatives versus legislative proposals. For almost all proposals (93 percent), the posterior probability of having a high common-good value is either less than 0.02 or greater than 0.98, implying a high degree of certainty. For 57 percent of these near-certain propositions, the common-good value was higher for the proposed law than the status quo. Initiatives were notably different than legislative proposals: 46 percent of initiatives proposed a common-good increase, while 64 percent of legislative measures proposed a common-good increase. As might be expected from a process that requires broader consensus, legislative proposals delivered a higher common-good return.

Proposals can also be tailored in terms of their ideological appeal. The different approval processes suggest that legislative proposals are likely to have broader appeal across the ideological spectrum than initiatives. They certainly differ in terms of their orientation: 61 percent of initiatives and 86 percent of legislative propositions proposed to move policy to the left. The leftward orientation of legislative proposals is to be expected since the Democrats controlled both chambers throughout our sample period.

The left panel of Figure 7 plots kernel densities of the policy midpoints for citizen initiatives and legislative proposals. The distribution of initiative midpoints is similar to the distribution of ideologies in the population. We find no evidence that initiatives catered only to extremists, or that particular ideological viewpoints monopolized the proposal process. Legislative proposals also tended to mirror the ideology of the electorate, except that the midpoint of most legislative proposals was squarely among the conservative voters. Recalling that these proposals are overwhelmingly progressive in orientation, the support from many conservatives testifies to their broad appeal. Legislative proposals receive a much higher fraction of votes in favor than initiatives receive. According to our estimates, this occurs both because they embed a high common-good payoff, and appeal to a broader segment of the voters ideologically.

One assumption of our model is that initiatives and legislative proposals are drawn from the same distribution. Figure 7 provides some qualitative assurance of this assumption – both distributions are single-peaked, take values between -1 and 1, and are centered around zero. However, as noted, a difference in ideological appeal exists, so the assumption is only an approximation.

In the right panel of Figure 7, we report corresponding estimates of the distribution of policy midpoints for a model without the common good (a purely spatial model) and one which does not impose policy setting. Compared to our full model, we find very similar
Figure 7. Distribution of Policy Midpoints for Initiatives and Legislative Propositions

Notes: Kernel density estimates of estimated midpoints for the baseline model, broken down by their source (legislature or citizen initiative), with the distribution of ideologies for reference (left panel). The right panel is for a model which does include the common good component or policy setting.

estimates indicating that policy setting, while providing enough information to identify the model, is not imposing severe constraints on the allowable policy midpoints.

A higher common-good value does not guarantee a positive outcome, or conversely. Eighteen of 79 propositions with a high common-good value failed to garner support from a majority of voters and 35 of 77 propositions with a low common-good value failed to attract majority support.\textsuperscript{22} Of course, we should not expect all high common-good value propositions to pass. Because both common-good and spatial considerations enter each voter’s calculus, the distribution of ideologies, as well as the location of the policy midpoint also determine which propositions pass and fail.

\textsuperscript{22}These comparisons utilize support as indicated in the survey. If we instead look at the actual vote outcomes, 31 of 79 propositions with a high common-good value failed and 25 of 77 propositions with a low common-good value passed. The drop off in the number of propositions that actually passed relative to those expected to pass based on surveys is consistent with the fact that propositions tend to lose support over time, roughly 6 percent on average from the last pre-election to poll to the election itself (Matsusaka, 2016).
Figure 8. Expected Difference in Support between Parties: Counterfactuals

Notes: Plots of the expected absolute difference between parties in fraction of votes in support, averaged over all propositions within each pair of years 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.

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 study expected votes because voting decisions are stochastic in the model. Figure A3 in Appendix A, which plots the expected vote shares using the baseline model against the actual vote shares, shows that the model fits the data reasonably well.

We first study the expected difference between votes cast in favor by Republicans and Democrats, which can be seen as another measure of polarization. In contrast to measures based entirely on spatial preference parameters (such as Figure 4), this outcome-based measure compounds common-good and spatial effects, allowing quantification of how common good considerations contribute to, or mitigate, polarization in the voting booth. Figure 8 plots the expected partisan difference in support, averaged over all propositions within each time period (corresponding to the time dummies for ideologies). We show the full baseline model, for reference, and two counterfactual scenarios: (i) zero weight on the common good payoff for all voters \( w_i = 0 \), and (ii) perfect information about the common good \( \pi = 1 \). Common-good effects arise through the interaction of these two parameters.
The baseline plot shows an increase in polarization over time, consistent with the increase in the difference between party medians observed in Figure 4. 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 \( w_i = 0 \) is almost always above the line for the baseline case. The magnitudes are sometimes nontrivial: the partisan difference is 2.3 percentage points higher on average without the common good than in the baseline model, an 11 percent increase. By 2020, the gap between the no-common-good model and the baseline model reaches 3.4 percentage points. Even though polarization appears extreme in recent years, the model suggests it is being somewhat attenuated by common good considerations.

Unlike the common-good weight, which is a preference parameter, the probability of being informed is partially a policy choice. Democracies can influence the flow of information to voters by regulating advertising, media, and campaigning. They can reduce information by restricting campaign spending or restricting media coverage; they can increase information by providing information directly (e.g., in the form of voter guides), subsidizing campaign spending (e.g., through public funding of campaigns), or requiring media outlets to provide free advertising to campaigns. 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. In our model, information is hard-wired to influence only the common-good component, so we cannot compare alternative information effects, but we can explore how information about the common good component feeds back into the partisan nature of voting and the ideological tenor of the measures that pass.

The perfect information case provides the maximum impact for common good considerations, since there is no uncertainty obscuring its value. Surprisingly, the vote difference with perfect information lies above that of the baseline model in many years. On average, the difference is 0.8 percentage points, or 1.3 percent higher than the baseline case, suggesting that providing better information about the common good value actually increases polarization.

This finding masks heterogeneity across time periods, however. In the first time period, perfect information indeed increases polarization over the baseline model. One might think that better information about which policy yields the highest common-good payoff should increase the alignment of Democratic and Republican votes, as they gravitate toward the outcome with the highest common-good payoff. This intuition is correct, but when there is considerable ideological overlap between parties, another possibility arises if members of one party place more weight on the common good than the other party. In such a case, more accurate information can increase the difference in votes across parties because members of
the party that value the common good more will move together toward the high-common-good outcome, away from the members of the other party that vote based primarily according to their spatial preferences. According to our estimates, Democrats placed a higher weight on the common-good component, and the different weights between the parties is enough to increase polarization in the hypothetical case of perfect information in the first time period when substantial overlap between the ideological preferences of the two parties exists. In recent time periods where no such overlap exists, perfect information does in fact reduce polarization. In terms of policy, these findings demonstrate that allowing a greater flow of information during campaigns may contribute to, or mitigate, polarization. However, even when it increases polarization, it does so not by accentuating ideological differences, but by causing one group of partisans to load more on the common good. This sort of polarization is not obviously undesirable.

5.3.2 Proposition Passage

Here, we are interested in 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 voters vote based on ideological considerations alone). Given that Democrats controlled the legislature throughout the sample period, theory suggests citizen initiatives would have come disproportionately from conservatives, while legislative proposals would have been progressive in orientation. We find that 25 percent of initiatives were right-leaning, while only 6 percent of legislative proposals were right-leaning, supporting this theory.

Table 2 provides estimates of the expected 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 rate in the data (63 percent). The baseline model predicts an overall passage rate of 62 percent, again indicating that the model fits the data reasonably well. Right-leaning proposals were much less likely to pass than left-leaning proposals, 27 percent versus 59 percent, consistent with the state’s reputation as being left-leaning (difference significant at the 1 percent level).

With the common-good weight set to zero, the expected passage rate is 12 percent higher than the baseline case. The passage rate rises because voter priors are that the status quo has a higher common good payoff than the proposal. Shutting down the common-good payoff has dramatically different effects on the prospects of right-leaning versus left-leaning proposals: the passage rate for right-leaning proposals more than doubles, increasing 31 percent, to 55
Table 2. Counterfactual Proposition Passage Rates

<table>
<thead>
<tr>
<th>Number of Propositions</th>
<th>All Propositions</th>
<th>Right-leaning</th>
<th>Left-leaning</th>
<th>Nonpartisan</th>
</tr>
</thead>
<tbody>
<tr>
<td>% Approved, actual</td>
<td>168</td>
<td>33</td>
<td>63</td>
<td>72</td>
</tr>
<tr>
<td>% Approved, baseline</td>
<td>63</td>
<td>27</td>
<td>59</td>
<td>83</td>
</tr>
<tr>
<td>% Approved, no common good</td>
<td>62</td>
<td>24</td>
<td>56</td>
<td>85</td>
</tr>
<tr>
<td>% Approved, perfect information</td>
<td>74</td>
<td>55</td>
<td>71</td>
<td>85</td>
</tr>
</tbody>
</table>

Notes: 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.

percent; the passage rate for progressive proposals also increases, but by a comparatively modest 15 percent. Setting the common-good weight to zero has no effect on the passage rate of nonpartisan proposals.

Under perfect information, the overall approval rate increases by 4 percent compared to the baseline model. Perfect information increases the approval rate of both right-leaning and left-leaning proposals, but the effect is not as disproportionate as in the previous counterfactual: the passage rate increases 9 percent for right-leaning proposals and 6 percent for left-leaning proposals. In terms of campaign policies, this evidence suggests that enhancing provision of information would result in more proposals passing but would not tilt the ideological direction of laws strongly in one direction or the other.

5.4 Robustness

Our empirical procedure estimates the common-good component through co-movement in votes; roughly speaking, if voters move in the same direction – especially those with ideologies near the cutpoint – our estimation procedure picks it up as weight on the common good. In this section, we investigate three possibilities that might cause our model to spuriously infer a common-good component.

The first possibility is that the ideological space has more than one dimension, and the common good component is capturing a “second dimension.” A second dimension is plausible because the propositions combine issues that voters may not perceive as lying along a single dimension, such as tax issues versus social issues. 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.

Our strategy to address this possibility relies on the observation that if the model is picking up an unmodeled spatial dimension because propositions bundle disparate issues,
the problem should disappear if we focus on only a single type of proposition. To implement this test, we focus on tax and regulation issues, which are the most common in the sample (103 propositions); the excluded propositions then pertain mainly to social issues, elections, voting, and government performance. If bundling of issues produces a spurious common-good component in the baseline model, then the common-good weight should shrink when the model is estimated on the narrower set of tax and regulation issues.

A second 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., 20110; Kendall et al., 2015; Rogers and Middleton, 2015), and many California propositions involve heavy campaign spending. The record was $225 million on Proposition 22 in 2020 (allowing rideshare companies to employ drivers as independent contractors), and campaign spending in excess of $100 million no longer raises eyebrows. To put these numbers in perspective, consider that Donald Trump spent $775 million across the entire nation in his presidential re-election campaign.\footnote{Matsusaka (2020b) contains descriptive information and analysis of spending on California propositions.} The baseline model allows for campaign effects through 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 address this possibility, we rely on the observation that citizens who were unaware of a proposition before being surveyed cannot have been exposed to campaigning about that proposition when they responded to the survey. The votes of “unaware” citizens therefore cannot embed a spurious co-movement caused by campaigning. 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 a completely uninformative signal for unaware voter-issues, indicating no correlation within this subset of responses.\footnote{An alternative strategy would be to allow the common-good weights to vary with awareness. In this case, we would expect unaware responses to have a weight of zero, indicating no correlation. In either case, a positive weight with a signal precision different from 0.5 indicates correlation among the unaware responses, contrary to the campaign hypothesis. We chose our approach because it seems more natural to think that awareness affects voter information rather than voter preferences (common-good weights).}

A third possibility is that our assumed distribution of status quo policies drives the
Table 3. Robustness Estimates

<table>
<thead>
<tr>
<th></th>
<th>Baseline</th>
<th>Robustness: Tax and regulation</th>
<th>Robustness: Vote awareness</th>
<th>Robustness: Near-uniform $q$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean $w_i$</td>
<td>0.17</td>
<td>0.50</td>
<td>0.22</td>
<td>0.13</td>
</tr>
<tr>
<td>% $w_i &gt; 0$</td>
<td>46</td>
<td>69</td>
<td>70</td>
<td>87</td>
</tr>
<tr>
<td>Equivalent ideological shift</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Overall</td>
<td>0.14</td>
<td>0.30</td>
<td>0.19</td>
<td>0.16</td>
</tr>
<tr>
<td>Republican</td>
<td>0.05</td>
<td>0.18</td>
<td>0.07</td>
<td>0.07</td>
</tr>
<tr>
<td>Democrat</td>
<td>0.31</td>
<td>0.41</td>
<td>0.34</td>
<td>0.30</td>
</tr>
<tr>
<td>Other</td>
<td>0.23</td>
<td>0.36</td>
<td>0.27</td>
<td>0.21</td>
</tr>
<tr>
<td>$\pi$</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Homogeneous</td>
<td>0.81</td>
<td>0.70</td>
<td>-</td>
<td>0.82</td>
</tr>
<tr>
<td>Aware</td>
<td>-</td>
<td>-</td>
<td>0.90</td>
<td>-</td>
</tr>
<tr>
<td>Unaware</td>
<td>-</td>
<td>-</td>
<td>0.80</td>
<td>-</td>
</tr>
</tbody>
</table>

Notes: 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 value is the median change across voters.

estimates of the common-good weight. Although there is no theoretical reason to expect the distribution to spuriously produce correlation in votes, to be conservative we examine sensitivity of the findings to this assumption. We re-estimate the model with a near-uniform distribution of the status quo policies (modeled as a generalized error distribution with a shape parameter set to eight) instead of the normal distribution assumed in our baseline specification. The near-uniform specification more heavily penalizes status quos outside of the support of the range of voters’ preferences and more equally weights those within the support as illustrated in Figure A4.

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

When the model is estimated only for tax and regulation issues, the common-good weights are systematically larger than the baseline model, and the percent of observations with a positive weight rises from 46 to 69 percent. The magnitude, in terms of the equivalent ideological shift, points in the same direction. These results thus undercut the idea that the common-good component in the baseline model is an artifact of an unmodeled second ideological dimension. On a substantive level, this finding suggests that voters may place more weight on the common good for economics-related issue than for social, election, or governance issues, which could account for the limited popularity of soak-the-rich taxes and the prevalence of sin taxes and (arguably Pigouvian) taxes on gasoline and oil extraction. The signal precision is 0.70 in this model, down from the baseline value of 0.81, suggesting that voters have worse information about economic issues than other issues. When it comes to the impact on votes, poorer quality information partially offsets the higher common-good
Turning to the second alternative model, in which the signal precision differs with voter awareness, the distribution of the common-good weight is similar to the baseline model. The key estimates are those for the signal precision. As should be the case, the signal precision is higher for aware than unaware voter-issues, 0.90 versus 0.80; the difference is not statistically different from zero. The key finding is that the precision for unaware voter-issue pairs is far from 0.50, both quantitively and statistically, contrary to what would be the case if common-good effects were entirely driven by campaigning. The estimates suggest that voters may have heterogeneous information even before becoming 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.

For the third alternative, with a near-uniform distribution for the status quo, the mean common-good weight is similar to the baseline model, but the percent positive is almost twice the size. The equivalent ideological shift values are roughly similar. If anything, the alternative specification suggests a greater prevalence of common-good components than the baseline model. The signal precision and the effects of demographic variables on the common-value weights remain similar to the baseline model. Thus, the main results do not appear to be driven by the assumed status quo distribution.

Figure 9 plots the two polarization measures – divergence in the top panel and partisan sorting in the bottom panel – for the baseline model and the three alternatives. For the most part, the levels and trends of both measures of polarization are similar to the baseline model for all three alternative specifications. The one noticeable difference is that when we restrict to tax and regulation issues, both divergence and sorting are quite a bit higher for the most recent decade (2010-2020). For sorting, the estimates are too imprecise to draw strong conclusions, but the gap for divergence is statistically significant. Taken at face value, voter opinion has substantially pulled apart in recent years 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 both the common-good weights and the ideologies are quite robust across specifications (parameters reported in Table A1). For completeness, we also report the distributions of ideologies and common good weights for each of the alternative specifications in Figures A5 through A8.  

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25 The only notable exception is that the determinants of the common-good weights are different when we restrict to tax and regulation issues. In this specification, Democrats and more educated voters no longer place significantly more weight on the common good, perhaps due to the smaller sample size.

26 When we restrict to tax and regulation issues, we force voters that don’t identify as Republicans or
Figure 9. Robustness Polarization Measures

Notes: Divergence and party sorting polarization measures for the baseline model and three alternative specifications: restricted to tax and regulation issues only, allowing the signal precision to vary with voter awareness, and assuming a near-uniform distribution for the status quo policies. 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 fleshing out the picture by estimating a model in which voters may have both common-good and spatial preferences. Our key insight is that common-good preferences can be inferred from co-movements in voting behavior, especially for voters with spatial preferences near the cutpoint. Based on this idea, we develop a new estimation procedure that allows identification of the weight that voters place on the uncertain common good delivered by a policy. Using data from California ballot measures, we find that common-good payoffs are an economically and statistically significant part of voter preferences.

Democrats to have constant ideologies across 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.
While our estimates point to a common-good component in voter preferences, they do not elucidate the source of these preferences. Several possibilities seem worth future investigation. One view is that common-good payoffs are technological in nature, hardwired into the essence of public decisions themselves. For example, the extensive literature on public goods 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.

Alternatively, the common-good component could stem from altruism. To the extent that voters are atomistic in a large electorate, they are unlikely to be voting for instrumental reasons. If they vote for expressive reasons, as many voting scholars believe, they may set aside their narrow preferences and take 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).

Allowing for a common-good component in voter preferences allows greater 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. In contrast to some of the literature, we find that partisan polarization in the most recent years 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. However, we find that this intuition is only partially correct. If, as we find, one group (Democrats) places more weight on the common-good payoff than the other, and the groups are not very polarized, increasing the available information can theoretically increase polarization by causing Democrats to converge on the outcome with the highest common-good payoff, separating from Republicans whose voting is driven by spatial consideration. Indeed, in our counterfactual exercises, we find that giving voters more information reduces polarization only when the groups are very separated ideologically.

In addition to the substantive empirical contribution, we believe our study offers a useful contribution in terms of methods. Because our estimation strategy requires only voting
data to identify the common good component, it can be readily applied in other contexts. Applications to voting in legislatures and candidate elections seem natural. Such applications could explore the importance of common-good considerations in other contexts, provide arguably more robust estimates of polarization, and be used to investigate the determinants and quality of information that voters receive.

References


[45]

### Table A1: Robustness: Parameter Estimates

<table>
<thead>
<tr>
<th>Variable</th>
<th>Tax and Regulation</th>
<th>Issue Awareness</th>
<th>Near-uniform $q$ Distribution</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age: (40-64)</td>
<td>-0.45 (0.25)</td>
<td>-0.02 (0.23)</td>
<td>0.01 (0.16)</td>
</tr>
<tr>
<td>Age: (65+)</td>
<td><strong>-0.71 (0.30)</strong></td>
<td>0.02 (0.19)</td>
<td>-0.02 (0.21)</td>
</tr>
<tr>
<td>College</td>
<td>-0.15 (0.22)</td>
<td>0.44 (0.26)</td>
<td>0.67 (0.41)</td>
</tr>
<tr>
<td>College+</td>
<td>0.13 (0.46)</td>
<td><strong>0.78 (0.24)</strong></td>
<td><strong>1.01 (0.39)</strong></td>
</tr>
<tr>
<td>Income: 20k-60k</td>
<td>-0.33 (0.32)</td>
<td>0.16 (0.38)</td>
<td>0.36 (0.36)</td>
</tr>
<tr>
<td>Income: &gt;60k</td>
<td>-0.67 (0.56)</td>
<td>0.32 (0.32)</td>
<td>0.50 (0.40)</td>
</tr>
<tr>
<td>Asian</td>
<td><strong>1.15 (0.41)</strong></td>
<td>-0.46 (0.59)</td>
<td>-0.61 (0.44)</td>
</tr>
<tr>
<td>Black</td>
<td>0.59 (0.38)</td>
<td>-0.23 (0.39)</td>
<td>-0.45 (0.42)</td>
</tr>
<tr>
<td>Hispanic</td>
<td><strong>0.65 (0.27)</strong></td>
<td>-0.29 (0.29)</td>
<td>-0.38 (0.31)</td>
</tr>
<tr>
<td>Democrat</td>
<td>0.12 (0.57)</td>
<td>0.25 (0.37)</td>
<td>0.41 (0.27)</td>
</tr>
<tr>
<td>Republican</td>
<td>-0.53 (0.65)</td>
<td><strong>-1.42 (0.46)</strong></td>
<td><strong>-1.18 (0.49)</strong></td>
</tr>
<tr>
<td>Constant</td>
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<td><strong>-1.91 (0.61)</strong></td>
<td><strong>-2.97 (0.67)</strong></td>
</tr>
<tr>
<td>Homogeneous</td>
<td><strong>0.70 (0.02)</strong></td>
<td>-</td>
<td>0.82 (0.05)</td>
</tr>
<tr>
<td>Awareness</td>
<td></td>
<td>0.90 (0.06)</td>
<td>-</td>
</tr>
<tr>
<td>Unaware</td>
<td></td>
<td>0.80 (0.16)</td>
<td>-</td>
</tr>
<tr>
<td>ρ</td>
<td>0.53 (0.02)</td>
<td>0.33 (0.16)</td>
<td>0.36 (0.12)</td>
</tr>
<tr>
<td>Income: 20k-60k</td>
<td><strong>0.18 (0.05)</strong></td>
<td><strong>0.11 (0.04)</strong></td>
<td><strong>0.14 (0.03)</strong></td>
</tr>
<tr>
<td>Income: &gt;60k</td>
<td><strong>0.26 (0.06)</strong></td>
<td><strong>0.20 (0.03)</strong></td>
<td><strong>0.21 (0.03)</strong></td>
</tr>
<tr>
<td>College</td>
<td>-0.03 (0.07)</td>
<td>-0.04 (0.05)</td>
<td>-0.05 (0.03)</td>
</tr>
<tr>
<td>College+</td>
<td><strong>-0.21 (0.09)</strong></td>
<td><strong>-0.18 (0.06)</strong></td>
<td><strong>-0.21 (0.04)</strong></td>
</tr>
<tr>
<td>Asian</td>
<td>-0.16 (0.13)</td>
<td>-0.05 (0.08)</td>
<td>0.01 (0.06)</td>
</tr>
<tr>
<td>Black</td>
<td>-0.07 (0.16)</td>
<td>0.01 (0.06)</td>
<td>-0.00 (0.07)</td>
</tr>
<tr>
<td>Hispanic</td>
<td>-0.08 (0.10)</td>
<td>0.02 (0.04)</td>
<td>0.00 (0.05)</td>
</tr>
</tbody>
</table>

Notes: Estimated coefficients for three robustness specifications: (1) restricting to tax and regulation issues only, (2) allowing the signal precision to differ across votes in which the voter was aware and not aware of the issue, and (3) a different specification for the distribution of the status quo (a near uniform distribution). For $\beta$, we do not report the time fixed effects, party coefficients, or their interactions. The omitted categories for $\beta$ and $\delta$ 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 registered as Republicans or Democrats. Asymptotic standard errors are reported in parentheses. Bold coefficients for $\delta$, $\beta$, and $\pi$ indicate significance at the 5% level or less. For $\pi$, we test the one-sided hypothesis that the coefficient is greater than one-half.
Notes: Estimates of county-level fixed effect parameters for voter ideologies. The omitted category is the county of Alameda.
Figure A3: Model Fit

Notes: Plot of the expected vote share for each proposition in the data given the baseline model estimates and (estimated) state of the world. The dotted line indicates the actual vote shares in the polling data and the data is sorted in order of these shares.

Figure A2: Correlation Between Ideology and Common Good Weight (Baseline)
Figure A4: Assumed Status Quo Distributions

Notes: Plots of the generalized error distribution used for the status quo distribution. The baseline case (shape = 2) corresponds to a normal distribution. The near-uniform case (shape = 8) is used in a robustness check. The illustrated distributions are for the 2018 general election, where the scale of the distribution is determined by the support of the ideologies in this time period.

Figure A5: Estimated Distribution of Ideologies for Tax and Regulation Issues

Notes: Kernel density estimates of estimated ideologies broken down by party affiliation and scaled according to the fraction each type makes up in the population.
Figure A7: Estimated Distribution of Ideologies with Near-uniform Status Quo Distribution

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

Figure A6: Estimated Distribution of Ideologies with Issue Awareness

Notes: Kernel density estimates of estimated ideologies broken down by party affiliation and scaled according to the fraction each type makes up in the population.
Notes: Distributions of the estimated common good weights under three alternative specifications: restricted to tax and regulation issues only, allowing the signal precision to vary with voter awareness, and assuming a near-uniform distribution for the status quo policies. The baseline model estimates are included for reference.

**Appendix B: Proof of Identification**

We seek to identify the parameter vector, $\Theta = \left\{ \{w_i, \theta_i, \pi_i\}_{i=1}^N, \{m_j, D_j\}_{j=1}^J, \rho \right\}$. In constructing the proof, we show formally how identification fails absent the information derived from policy setting and then how this information resolves the issue. The proof assumes homogeneous $w$ and $\pi$, but extends immediately to the case in which each are a function of observables, as in the empirical specification. We make the following assumptions.

**Assumption ID:**

1. Voter $i = 1$ has $\theta_1 = 0$.
2. $w \in (0, \infty), \pi \in \left(\frac{1}{2}, 1\right]$, and $\rho \in (0, 1)$

Assumption ID1, together the assumption that ideological shocks have a variance of one, serve to pin down the absolute location and scale of the ideological parameters. These normalizations are standard, necessary assumptions in spatial models.

Assumption ID2 avoids technical complications that arise with parameters at boundaries. With a parameter at a boundary, some of the other parameters may not be identified. For example, if $w = 0$, the model reduces to a purely spatial so that only the $\theta_i, m_j, D_j$ parameters relevant to the spatial model are identified. As all of our parameter estimates are interior, these identification problems do not arise.
We denote the conditional distributions of the policy midpoints, $m_j$, and $x_j - q_j$ that arise from the policy setting model, $f^d(m|\theta, D_j = d)$ and $g^d(x - q|\theta, D_j = d, m_j)$. Throughout the proof, we assume these distributions 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.

**Step 1 (identification of $D_j$, $\pi$, and $\theta_i$):**

If $D_j = 1$, the probability that we observe the set of votes across all voters on issue $j$, conditional on $\psi_j$ is given by

$$Pr\left(\{Y_{ij} = 1|D_j = 1, \psi_j\}_{i=1}^N\right) = \prod_{i=1}^N \gamma_{ij}^{11}$$

$$= \prod_{i=1}^N \left[\tau \Phi\left(\theta_i - m_j + \frac{w}{\alpha_j} (2b^1 - 1)\right)
+ (1 - \tau) \Phi\left(\theta_i - m_j + \frac{w}{\alpha_j} (2b^0 - 1)\right)\right]$$

$$= \tau \prod_{i=1}^N \Phi\left(\theta_i - m_j + \frac{w}{\alpha_j} (2b^1 - 1)\right)
+ (1 - \tau) \prod_{i=1}^N \Phi\left(\theta_i - m_j + \frac{w}{\alpha_j} (2b^0 - 1)\right) \quad (9)$$

where $\tau = \pi$ if $\psi_j = 1$ and $\tau = 1 - \pi$ if $\psi_j = 0$. (9) represents a standard finite mixture model with mixing probability, $\tau$. With $N \geq 3$, by standard results, each of the vote probabilities, $\eta_{ij}^{11} \equiv \Phi\left(\theta_i - m_j + \frac{w}{\alpha_j} (2b^1 - 1)\right)$ and $\eta_{ij}^{01} \equiv \Phi\left(\theta_i - m_j + \frac{w}{\alpha_j} (2b^0 - 1)\right)$, as well as the mixing parameter, $\tau$, are identified (for example, see Allman et al. (2009)). $\eta_{ij}^{11}$ represents the probability with which a voter $i$ votes Yes on issue $j$ with direction $D_j = 1$ and signal, $s_{ij} = 1$. $\eta_{ij}^{01}$ is the same probability but with signal, $s_{ij} = 0$.

If $D_j = 0$, $\eta_{ij}^{10} \equiv \Phi\left(m_j - \theta_i - \frac{w}{\alpha_j} (2b^1 - 1)\right)$, $\eta_{ij}^{00} \equiv \Phi\left(m_j - \theta_i - \frac{w}{\alpha_j} (2b^0 - 1)\right)$, and $\tau$ are similarly identified. Therefore, independent of the direction, $D_j$, we know $\tau$, which indirectly provides sufficient information to identify $\pi$. $b^1$, a voter’s belief with $s_{ij} = 1$ is strictly greater than $b^0$, his or her belief with $s_{ij} = 0$. Therefore, $\eta_{ij}^{1d} > \eta_{ij}^{0d}$, so that if we calculate $\eta_{ij}^{1d}$ and $\eta_{ij}^{0d}$ with $\tau$ in place of $\pi$, $\eta_{ij}^{1d} > \eta_{ij}^{0d}$ implies $\tau = \pi$ and $\eta_{ij}^{1d} < \eta_{ij}^{0d}$ implies $\tau = 1 - \pi$.

For either direction, $D_j$, we can identify each $\theta_i$. If $D_j = 1$, we have identified $\eta_{ij}^{11} = \Phi\left(\theta_i - m_j + \frac{w}{\alpha_j} (2b^1 - 1)\right)$. Inverting the monotonic function, $\Phi()$, we recover the $\theta_i$ parameters by taking the difference across two voters, $i$ and $i'$.  

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\[
\Phi^{-1} (\eta_{ij}^{11}) - \Phi^{-1} (\eta_{ij}^{11}) = \theta_i - \theta_i^\prime
\] (10)

If, instead, \( D_j = 0 \), we can similarly construct the differences across two voters. In either case, each \( \theta_i \) is identified up to a constant, which is pinned down by Assumption ID1, \( \theta_1 = 0 \).

Given each \( \theta_i \), we can recover \( D_j \) because if \( D_j = 1 \), from \( \eta_{ij}^{11} \equiv \Phi (\theta_i - m_j + \frac{w}{\alpha_j} (2b^1 - 1)) \), a voter further to the right (larger \( \theta_i \)) will vote Yes more often. On the other hand, if \( D_j = 0 \) from \( \eta_{ij}^{0} \equiv \Phi (m_j - \theta_i - \frac{w}{\alpha_j} (2b^1 - 1)) \), a voter further to the right will vote Yes less often. Thus, each direction, \( D_j \), is identified. Given this fact, we proceed to identify the remaining parameters assuming \( D_j = 1 \). For \( D_j = 0 \), the arguments are identical.

Step 2 (identification of \( m_j \), \( \rho \), and \( w \)):

Dropping the superscript for the direction on the vote probability, the two identified probabilities for the normalized voter (\( \theta_1 = 0 \)) are given by

\[
\eta_{ij}^0 = \Phi (-m_j + \frac{w}{\alpha_j} (2b^0 - 1))
\]

Absent policy setting information, two degrees of freedom exist for each issue, \( m_j \) and \( \alpha_j \), which creates a clear identification problem. For example, one could simultaneously increase \( w \) and decrease each \( \alpha_j \) without changing the observed probabilities.\(^{28}\)

Policy setting information provides the necessary information to identify the remaining parameters. Specifically, consider the known quantity, \( \Phi^{-1} (\eta_{ij}^1) = -m_j + \frac{w}{\alpha_j} (2b^1 - 1) \).

Taking the expectation across issues, we have

\[
E [\Phi^{-1} (\eta_{ij}^1)] = -E [m_j] + E \left[ \frac{w}{\alpha_j} (2b^1 - 1) \right] = -E [m_j] + w (2b^1 - 1) E \left[ \frac{1}{\alpha_j} \right]
\] (12)

\(^{27}\)Technically, we obtain only local identification of the spatial parameters because one can always flip all of the ideologies, directions, and policy midpoint through \( \theta_i = 0 \) without changing the observable probabilities. We deal with this global identification issue in estimation by (if necessary) flipping the estimated results such that registered Republicans lie right of registered Democrats.

\(^{28}\)This identification problem is not a consequence of the assumptions on voter information. If voters instead knew \( q_j \) and \( x_j \), these two parameters would again provide two degrees of freedom creating a similar identification problem.
The left-hand side of (12) comes from the data, and \( E[m_j] \) and \( E\left[\frac{1}{\alpha_j}\right] \) are known from the policy setting model. Rearranging (12) gives

\[ w(2b^1 - 1) = \frac{E\left[\Phi^{-1}(\eta_{ij})\right] + E[m_j]}{E\left[\frac{1}{\alpha_j}\right]} \]  

(13)

Similarly,

\[ w(2b^0 - 1) = \frac{E\left[\Phi^{-1}(\eta_{ij}^0)\right] + E[m_j]}{E\left[\frac{1}{\alpha_j}\right]} \]  

(14)

Denote the known right-hand sides of (13) and (14) \( r^1 \) and \( r^0 \), respectively. We have

\[ r^1 (2b^0 - 1) = r^0 (2b^1 - 1) \]

\[ r^1 \left(\frac{2\rho\pi}{\rho\pi + (1 - \rho)(1 - \pi)} - 1\right) = r^0 \left(\frac{2\rho(1 - \pi)}{\rho(1 - \pi) + (1 - \rho)\pi} - 1\right) \]

\[ r^1 (\rho\pi - (1 - \rho)(1 - \pi)) = r^0 (\rho(1 - \pi) - (1 - \rho)\pi) \]

\[ r^1 (\rho + \pi - 1) = r^0 (\rho - \pi) \]

\[ \rho = \frac{r^1 - \pi r^0 - \pi r^1}{r^1 - r^0} \]  

(15)

\( \rho \) is therefore identified because all of the quantities on the right-hand side of (15) are known or have been previously identified. Given \( \rho \), we recover \( w \) from (13). Finally, knowing \( \rho \) and \( w \), each \( m_j \) (with associated \( \alpha_j \)) is recovered from either equation in (11), completing the proof of identification of \( \Theta \).

In the preceding proof, we assumed \( \theta_i \) is constant for all time, whereas in our empirical specification, we allow it to vary. The proof then applies within each time period up to a constant location shift, which is normalized to zero in the first time period, \( t = 0 \). In subsequent periods, we generically have \( \theta_{it} = \theta_{i0} + c_t \), where \( \theta_{i0} \) is the identified ideology in the first time period, and \( c_t \) is a constant. In order to identify \( c_t \), we require identical issues which link time periods together. Otherwise, one could simultaneously change both the midpoint parameters in time period \( t \) and \( c_t \) without changing the vote probabilities. Assume then that we have two midpoints, \( j \) and \( k \) where \( m_j = m_k = m^* \), and issue \( j \) and \( k \) are in the first and some subsequent time period, respectively. Differencing across the transformed vote probabilities for voter \( i \), \( \Phi^{-1}(\eta_{ij}) \) and \( \Phi^{-1}(\eta_{ik}) \), we have \( \theta_{i0} - m^* - (\theta_{i0} + c_t - m^*) = c_t \) if the directions are the same, \( \mathcal{D}_j = \mathcal{D}_k \). If the directions are different, we instead have \( \theta_{i0} - m^* - (\theta_{i0} - c_t + m^*) = 2\theta_{i0} - 2m^* + c_t \). In either case, because \( m^* \) and \( \theta_{i0} \) are identified
from the first time period, $c_t$ is identified.

**Appendix C: Estimation Details**

The likelihood given in (8) 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. It’s 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.\(^\text{29}\) Given non-monotonicity in the policy midpoints, we developed the following multi-stage estimation procedure:

1. Begin with a spatial model without the common good. Estimate the ideological parameters, $\beta$ 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, $f^d(m|\theta, \mathcal{D}_j = d)$, and expected policy distance parameters, $\alpha^d_j$, 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\(^\text{29}\)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.

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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 2b) above, re-estimate the model allowing all of the parameters to
change.\footnote{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.}

With this estimation procedure, we are able to robustly estimate the likelihood function, ob-
taining very similar parameter estimates over several runs with different (random) parameter
initializations.

**Appendix D: 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 classified each proposition as relating to one or more issues. 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 assigned to one or more of the following categories:

- (E) Elections, voting, campaigns, redistricting, term limits, recall, initiative and refer-
  endum
- (G) Government processes: procedures for budget approval, civil service reform, orga-
  nization 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 E1: Example Issue Classifications for the November 2020 General Election

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

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.

**Appendix E: 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 do occur repeatedly, allowing us to link together time periods. Table F1 provides a complete list of the pairs or triplets of issues that together link ideologies across time.
Table F1: Repeated Ballot Propositions

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