What Do Analyses of Elections Tell Us About Voters? Evaluating Election Models for Assessing Policy Voting

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Abstract

Recent studies of elections have largely focused on identifying policy attitudes that predict vote choice in a given election or on comparing how well a policy attitude relates to vote choice at two points in time. While appropriate for characterizing elections, it is unclear what these analyses tell us about voters' behavior. Results from cross-sectional models as well as priming models using panel data reflect a combination of policy voting during the period of interest, policy voting in the past, and persuasion in the past. I argue that, if scholars are interested in how policy attitudes influence voting behavior, they should identify policy attitudes that predict changes in vote choice with a lagged dependent variable model. This model allows scholars to identify the influence of policy preferences on vote choice during a period of interest. Conclusions about voters are strongly dependent on the model used.

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Ever since *The American Voter*, scholars have debated the extent to which policy preferences influence the way people vote. This debate has heated up in recent years with some scholars claiming that policy considerations have little or no influence on the way people vote (Achen and Bartels 2016; Lenz 2012) and others claiming that they have an important impact (Fowler 2020). This debate has huge implications for whether citizens are able to influence government policy (Lenz 2012, 2018). In conventional models of policy representation, policy voting leads to the election of policymakers who share citizens' preferences and gives re-election-seeking incumbents an incentive to follow their preferences (Downs 1957; Miller and Stokes 1963).

Despite the active debate about policy voting, a review of the literature on the 2016 US presidential election shows that, while scholars agree on the types of attitudes that are relevant, they focus overwhelmingly on claims that campaigns activate/prime certain attitudes or on identifying variables that predict vote choice rather than on policy voting per se. While valuable contributions to our understanding of campaigns, it is unclear what these analyses tell us about voting behavior. Do they tell us that policy attitudes influences or did not influence votes?

It is important to distinguish the overwhelming focus of work on the 2016 election on activation/priming and on identifying predictors of voting, on the one hand, from policy voting, on the other hand. Policy voting occurs when a policy attitude leads voters to vote for a party or candidate either in the short-run, like during an election campaign, or in the long-run over the course of their lives. Claims of activation/priming are that campaigns increase the association between certain policy preferences and candidate or party support (e.g. Hopkins 2019).[1] Predictors of vote choice tell us that respondents with a certain characteristic are more or less likely to vote for a candidate.

Two challenges to estimating policy voting explain why a focus on priming/activation

[1]Note that, while some authors distinguish the concepts of activation and priming, I use the terms interchangeably.

or on predicting vote choice does not necessarily tell us about policy voting. One is that parties or candidates influence policy preferences. This phenomenon has been called persuasion (Brody and Page 1972) and, more recently, following the leader (Lenz 2012). Most importantly, as Lenz (2012) shows, this phenomenon is not limited to parties influencing their partisans. Voters also rationalize their votes, posing a huge challenge for studying voting behavior. The other challenge is that policy preferences may have influenced voting behavior in the past.

If our interest is in policy voting, we should focus on whether people change their votes to reflect their policy preferences during a period of time. In other words, we should determine which if any policy variables predict changes in vote choice. The ideal approach to assess that possibility is to to run lagged dependent variable models of vote choice on panel data. These are models of change in vote choice (Finkel 1995) in which reported vote at the end of a period of interest is regressed on voting preference and policy preferences at the beginning of that period.

I first present the ideal lagged dependent variable model that I propose. I then present other models of voting behavior used in studies of the 2016 election and explain why they do not adequately capture policy voting in that election. Using the 2010-2014 Cooperative Congressional Election Study (CCES) panel, I show that alternative models of voting behavior are strongly vulnerable to the two challenges to estimating policy voting. I then use simulations to show that commonly-used models yield biased estimates of policy voting. I then revisit the 2016 US presidential election. Using the 2016 American National Election Study (ANES), I show that our interpretation of voting behavior hinges on the approach used to analyze policy voting.

I conclude that generalizations about whether voters can influence government are strongly dependent on the approach used to analyze election data. Models can make citizens appear like the rational voters in the folk theory of democracy dismissed by Achen and Bartels (2016). They can also make citizens appear to have voted on the basis of a scholar's proposed explanatory variable. They can alternatively make voters appear to not care about policy at all. Scholars can also use models to show that some policy preferences lead to short-run changes in vote choice during a given period of time. Such policy voting is most relevant to ensuring that citizens' policy preferences are represented by governments.

1 Policy Preferences and Vote Choice

Whether policy preferences influence voting behavior has long been a contentious subject. Early models of voting, based on economic theory, assumed that voters support the party that is closest to them on one or more policy dimensions (Downs 1957; Hotelling 1929). Scholars have since developed a variety of sophisticated models about how policy preferences influence vote choice (Adams, Merrill and Grofman 2005; Davis, Hinich and Ordeshook 1970; Kedar 2009; Krosnick 1990; Rabinowitz and Macdonald 1989). However, research by the Michigan school led to doubts about citizens' ability to vote on the basis of their policy preferences (Campbell et al. 1960; Converse 1964). They suggested that voters are too unsophisticated to vote on the basis of policy (e.g. Achen and Bartels 2016).

Beginning in the 1970s, studies found associations between policy preferences and vote choice (Boyd 1972; Carmines and Stimson 1980; Nie, Verba and Petrocik 1979; Pomper 1972). Many scholars interpreted such evidence as showing that policy or issue voting occurs (Nie, Verba and Petrocik 1979).[2] Other scholars were skeptical, because the cross-sectional analyses used do not allow scholars to distinguish the effect of policy preferences on vote choice from the possibility that parties influence those preferences (i.e. persuasion, Brody and Page 1972).

Studies of elections since then have claimed to find evidence of policy voting by running cross-sectional analyses with long lists of control variables, most importantly party iden-

[2]Note that I do not distinguish between issue and policy voting, but I use the term policy voting.

tification (e.g., Miller and Shanks 1996). However, Lenz (2012) revisited earlier concerns about the possibility of persuasion. Re-analyzing previously studied panel datasets that had been used to make claims of policy voting, he found little evidence that policy preferences mattered to vote choice but strong evidence of persuasion.

This evidence is related to the long line of research on party cue effects (e.g. Bolsen, Druckman and Cook 2014; Druckman, Peterson and Slothuus 2013). However, the argument made by Brody and Page (1972) and supported by Lenz (2012) is much broader. Citizens do not need to be partisans to be influenced by parties. They adapt their preferences to the party or candidate they support regardless of their party identification. Thus, scholars of voting behavior must be cautious when interpreting associations between policy preferences and voting behavior.

Despite his pessimism about policy voting Lenz (2012), suggests that some attitudes, notably on racial and social issues, may in fact influence vote choice (213). Similarly, Tesler (2015) argues that, while such predispositions can be primed, political elites influence policy preferences.

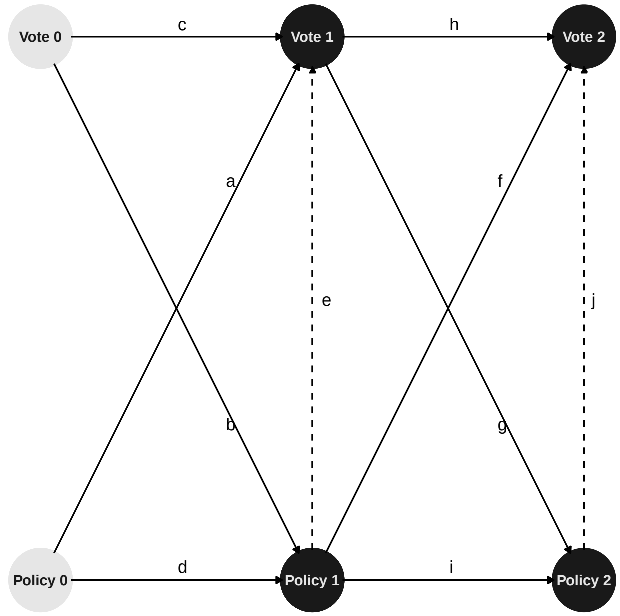
Since then, a consensus seems to have developed that attitudes towards groups influence voting behavior. However, the overwhelming focus has been on testing claims about election campaigns rather than claims that voters adjust their votes to reflect their policy preferences. Studies of voting in the 2016 US presidential election relate attitudes towards minorities and women to voting for Donald Trump (Hooghe and Dassonneville 2018; Hopkins 2019; Lajevardi and Abrajano 2019; Schaffner, MacWilliams and Nteta 2018; Mutz 2018; Sides, Tesler and Vavrek 2018; Valentino, Wayne and Oceno 2018). They either claim that such attitudes predict vote choice or that the campaign activated them. Only Hopkins (2019) clearly claims that policy attitudes (anti-Black prejudice) influenced vote choice.

These different claims can best be understood by carefully examining the directed acyclic graph (DAG) in Figure 1 showing the relationship between a policy preference and vote choice over time. A DAG represents variables as nodes, which are connected by directed edges reflecting causal relationships (Pearl 2009). In Figure 1, unobservable variables are represented by light gray nodes, while observable variables are shown as black nodes. A slight break from convention is that simultaneous causal relationships are included as dashed edges because they are important components of many common voting models.

The DAG starts at time 0 when a policy preference and vote choice are independent. From time 0 to time 1, both policy voting (a in the DAG) and persuasion (b) occur. Moreover, there is persistence in both vote choice (c) and in the policy preference (d), meaning that both variables are partly dependent on their past values. Between times 1 and 2, both policy voting (f) and persuasion (g) again occur. There is also persistence in both variables (h and i). We may be interested in policy voting between times 0 and 2 (a + f, i.e. long-term policy voting) or during one of those periods (a or f). However, due to persistent policy voting and persuasion, we almost never have access to data on policy preferences or vote choice from a time when these variables are unrelated. Therefore, the only policy voting that can be identified is policy voting between times 1 and 2 (f). I call this short-term policy voting. Note that these time periods are very variable across applications. In most cases the period between time 0 and time 1 is much longer than that between period 1 and period 2. For example, time 0 is the emergence of a new issue, time 1 is the beginning of an election campaign, and time 2 is the end of the campaign.

In all analyzes and discussions in this paper, I scale all policy and partisan variables so that higher values indicate the more conservative option. Therefore, unless an issue changes its association with the parties over time, we can assume that all causal effects shown in Figure 1 are either positive or 0.

Figure 1: Directed Acyclic Graph of Policy Preferences and Vote Choice



Short-term policy voting can be identified by capturing changes in vote choice between times 1 and 2 that are predicted by prior policy preferences. In other words, the appropriate estimator compares changes in vote choice among voters with different policy preferences. If voters with different policy preferences make different changes in their vote choices during a given period of time, we can conclude that policy voting has occurred. The ideal experiment (Angrist and Pischke 2008) would be to manipulate people's policy preferences so that two groups have different preferences and then to compare their vote choices. However, it is difficult to imagine a way to manipulate such preferences in a way that would in turn influence voting behavior. Instead, I propose to study real-world voting using a lagged dependent variable model.

I propose to compare changes in vote choice (typically during an election campaign) among voters with different policy preferences in a baseline period (at the beginning of a campaign). In Figure 1, the change I focus on is relationship f. This is very different from more sophisticated models of policy voting which consider voters' proximities to the parties they vote for (Adams, Merrill and Grofman 2005; Davis, Hinich and Ordeshook 1970, e) or their ability to make fine distinctions among candidates (Hopkins 2019). I adopt this simpler conceptualization because data on party perceptions are less common than data on policy preferences, because such data are subject to projection effects (Brody and Page 1972), because voters may be able to use heuristics to determine which party or candidate shares their position on an issue (Sniderman, Brody and Tetlock 1991; Popkin 1994), and because voters do not usually make choices among multiple candidates with nuanced positions in general elections in the United States.

The ideal policy voting model is the lagged dependent variable model. It involves regressing vote choice at the end of a period of interest ($Vote_2$) on vote choice at the beginning of that period ($Vote_1$) and policy preferences from that earlier time as well ($Policy_1$). It is represented by Equation (1). Because it controls for the lagged dependent variable, it is a model of change (Finkel 1995). In the DAG representation, we can rule out confounders by closing back-door paths producing spurious relationships between the independent and dependent variables. By controlling for Vote 1, the lagged dependent variable model closes the path $Policy_2 \leftarrow Vote_1 \rightarrow Vote_2$. It thus rules out the possibility of persuasion between times 1 and 2. However, it does not rule out that possibility between times 0 and 1. Thus, the policy preferences that influence voting behavior between times 1 and 2 may be partly endogenous to vote choice prior to time 1. Nevertheless, the lagged dependent variable model does tell us that the preferences people have at time 1 influence the way they vote at time 2. Controlling for Vote 1 also closes the back-door path $Vote_2 \leftarrow Vote_1 \leftarrow Policy_0 \rightarrow Policy_1 \rightarrow Policy_2$. Thus, ruling out the possibility that estimated relationships are due to prior policy voting.

It is important to clarify that models of voting behavior should control for party identification because partisanship predicts vote choice and because partisans are influenced by their parties. However, controlling for partisanship does not close either back-door path. It does not close the persuasion back-door path because parties influence voters due to their tendency to rationalize their vote choice in addition to party influence on partisans. Moreover, it does not close the prior policy voting back-door path because policy voting occurs when partisanship alone does not account for vote choice.

$$Vote_2 = \alpha_0 + \alpha_1 * Vote_1 + \beta_1 * Policy_1 + ... + \epsilon_2 \tag{1}$$

The most common model of voting behavior is the cross-sectional model. It involves regressing vote choice on policy preferences and controls all from the same point in time. That model is represented by equation (2) and by dashed edge j in Figure 1. It assumes that, by controlling for a sufficient number of covariates, coefficients on policy preference variables reflect the causal effect of those preferences on vote choice (Miller and Shanks 1996). It is used by Hooghe and Dassonneville (2018), Lajevardi and Abrajano (2019), Schaffner, MacWilliams and Nteta (2018), and Valentino, Wayne and Oceno (2018) in their studies on the 2016 election.

$$Vote_2 = \alpha_0 + \beta_1 * Policy_2 + ... + \epsilon_2 \tag{2}$$

This model effectively identifies predictors of voting behavior in a given election and can thus contribute greatly to our understanding of that election. However, when using this model to learn about policy voting, scholars must consider the extent to which vote choice and policy preferences influenced each other in the past. As we can see in Figure 1, the relationship between Policy Preference 2 and Vote Choice 2 is confounded by two back-door paths, $Policy_2 \leftarrow Vote_1 \rightarrow Vote_2$ and $Vote_2 \leftarrow Vote_1 \leftarrow Policy_0 \rightarrow Policy_1 \rightarrow Policy_2$, representing persuasion and prior policy voting, respectively. Thus, while the cross-sectional model can effectively identify predictors of vote choice, the coefficient on the policy preference variable of interest represents current and past policy voting as well as persuasion.

When panel data are available, analysts can run a similar model with a lagged policy preference variable $Policy_1$ shown as equation (3). Sides, Tesler and Vavrek (2018), for example, run such models in some of their analyses by regressing vote choice in 2016 on policy attitudes in 2011. This model is an improvement with respect to estimating policy voting because it allows us to be confident that the policy preferences in the model are not influenced by vote choice between times 1 and 2. In other words, by lagging policy preferences, this estimator does not include the path $Vote_2 \leftarrow Policy_1 \rightarrow Policy_2$.

$$Vote_2 = \alpha_0 + \beta_1 * Policy_1 + ... + \epsilon_2 \tag{3}$$

However, it does include back-door paths $Vote_2 \leftarrow Vote_1 \leftarrow Policy_0 \rightarrow Policy_1$ and $Vote_2 \leftarrow Vote_1 \leftarrow Vote_0 \rightarrow Policy_1$. In other words, in addition to policy voting between times 1 and 2 (f), the coefficient on β_1 reflects policy voting between times 0 and 1 that persists to time 2 as well as persuasion between times 0 and 1. Thus, the advantage of this model is that it rules out persuasion in the short term but earlier policy voting and persuasion still influence estimates.

Most of the time, the bias in cross-sectional and lagged policy preference models should be positive. As Downs (1957) argued, parties have a strong incentive to keep their positions on policy issues stable over time in order to retain voters' trust and there is evidence that voters punish parties for changing their positions (Tavits 2007). Thus, prior policy voting and/or persuasion should be in the same direction as current policy voting.

The bias may occasionally be downward though. In some cases, parties change positions, voters learn a party's position they dislike, or such a position becomes salient. If voters previously voted on the basis of different party positions (or at least their perceptions of them) or, alternatively, if they were persuaded by different positions, the bias will be negative. An example of this could be abortion in the early 1980s. Prior to then, pro-life voters were more likely to support the Democrats than pro-choice voters and vice versa for the Republicans (Adams 1997). For this issue, time 1 could have been the 1980 election and time 2 the 1984 election. As the parties took clearer positions on the issue and those positions became salient, voters progressively shifted to the party that shares their position on that issue. A cross-sectional analysis run while votes were shifting might not have picked up the change even though voters were changing their party preferences to reflect their policy preferences.

Many scholars test for priming, a type of campaign effect, whereby attention to an issue by parties and the media, leads voters to increase the weight they place on that issue (Iyengar and Kinder 1987; Lenz 2009). At least three studies on the 2016 election (Hopkins 2019; Mutz 2018; Sides, Tesler and Vavrek 2018) adopt this approach. Priming tells us whether the relationship between policy preferences and voting behavior increased during a period of time (usually a campaign). Earlier studies (e.g. Berelson, Lazarsfeld and McPhee 1954) simply compared cross-sectional relationships at two different points in time (e.g. comparing j to e and concluding that priming occurred if j was significantly larger than e. However, because the difference between the two may reflect opinion change rather than priming (Lenz 2009), scholars now compare the relationship between a policy preference and vote choice at an earlier time point (e.g. time 1) and the relationship between that same policy preference and vote choice at a later point in time (e.g. time 2). In other words, in this model, which Lenz (2012) calls the two-wave priming test, priming means that f is larger than e.

This test involves stacking a dataset with post-election vote choice and pre-election policy preferences on top of a dataset with pre-election vote choice and pre-election policy preferences. Subsequently, vote choice is regressed on policy preferences, a dummy indicating the post-election period as well as an interaction between the two. Scholars then focus on the coefficient on that interaction. Equation 4 shows the two-wave priming test, which was used by Mutz (2018) in her study of the 2016 election. Sides, Tesler and Vavrek (2018) and Hopkins (2019) use slightly more sophisticated models, which I do not discuss in detail to save space. For the purposes of this discussion, we can assume they are the same as the priming model presented here (readers can rest assured that the author has assessed those models and the same conclusions that apply to this priming model apply to those as well.).

$$Vote = \alpha_1 + \beta_1 * Policy_1 + \beta_2 * post + \beta_3 * Policy_1 * post + \epsilon \tag{4}$$

While a reasonable test of priming, this model combines the lagged preference model discussed above (with policy preferences at time 1 and vote choice at time 2) with a cross-sectional model run at time 1 and thus faces the same obstacles that face those models. As we saw above, the lagged policy preference model reflects both policy voting (a) and persuasion (b) between times 0 and 1 in addition to policy voting between times 1 and 2 (f). A cross-sectional model estimated at time 1 would get us e, which reflects both policy voting (a) and persuasion (b) between times 0 and 1. Thus, priming tests whether the sum of policy voting between times 0 and 1 weighted by the persistence in vote choice between times 1 and 2 (a*h), policy voting between times 1 and 2 (f), and persuasion between times 0 and 1 (b) is greater than the sum of policy voting (a) and persuasion (b) between times 0 and 1. Because only some of the policy voting between times 0 and 1 (a) is carried forward to time 2 (h, and is thus captured by the lagged policy preference model), this model yields null results most of the time. All depends on the size of f relative to a*h. If vote choice is highly persistent between times 1 and 2 and if policy voting is strong between times 1 and 2, this model may find evidence of policy voting. When that condition is not met, it will produce null results. In some cases e may be small in magnitude and even negative increasing the likelihood that a*h + b + f is greater than e. However, given parties' incentives to keep stable positions over time (Downs 1957), such circumstances should be uncommon. Thus, unlike my expectations of the cross-sectional and lagged policy preference models, I expect priming models to underestimate policy voting.

To sum up this section, the directed acyclic graph in Figure 1 showed that there is only one period of time for which we can identity policy voting (between times 1 and 2). To identify that policy voting, we need to run a lagged dependent variable model, which closes back-door paths representing prior policy voting and persuasion. Cross-sectional and lagged policy preference models leave open back-door paths reflecting both phenomena, thus overestimating the influence of policy preferences on vote choice on most issues. Priming models on the other hand compare coefficients from a lagged policy preference model to a cross-sectional model. Because the cross-sectional model likely leads to higher estimates of policy voting than the lagged policy preference model most of the time, priming models will generally underestimate policy voting. Lagged dependent variable models, on the other hand, will correctly identify the change in vote choice caused by policy preferences during a particular period of time (i.e. period 1-2 in Figure 1).

1.1 Assessing the Performance of Each Model Using Real-World Data

To assess the performance of these models for estimating policy voting, I use the the Cooperative Congressional Election Study (CCES) panel run in the context of US congressional congressional elections held in 2010, 2012, and 2014. Respondents were interviewed before and after each of these elections. The major advantage of this study is that it includes a large number of policy questions that are asked in successive elections. Moreover, the inter-election panel allows me to determine the extent to which policy voting and persuasion are related over time.

In each pre-election study, the CCES asked a series of policy questions (see the list of issues in Table S1 in the Supporting Information). In the analyses presented below, as in all analyses presented in this paper, I coded policy variables so that 1 represents the conservative position and 0 the liberal position. Vote choice is similarly coded so that 1 represents a vote for the Republican candidate and 0 any other response option. I thus expect all coefficients to be positive, indicating a positive relationship between conservative policy preferences and Republican vote choice.

For the 2012 and 2014 elections (between the pre- and post-election waves) and inter-election period (between the pre-election surveys from different elections), I estimate the models of policy voting presented above, focusing on voting for Republican House of Representatives candidates.[3] I use linear probability models for Vote choice models because of

[3] I do not run models for the 2010 election because the panel does not include data on the prior period.

their simplicity and because they do a good job estimating marginal effects (Angrist and Pischke 2008). All models include standard controls used in studies of voting behavior in the United States (e.g. Hopkins 2019). These are: age, income, union membership, education, sex, party identification, ideology, and U.S. region.

Given that policy preferences were asked in the pre-election study, in cross-sectional models, all variables are from the pre-election wave. In lagged policy preference models, policy preferences are from prior to the election, while vote choice is from after the election. In lagged dependent variable models, policy preferences and lagged vote choice are from before the election and final vote choice is from the post-election survey.

I first run models of policy voting with separate models for each issue and then follow-up analyses including all issues with at least minimal evidence of significant influence in the first stage ($p < 0.1$). I focus my discussion here on coefficients from these second stage models. Using cross-sectional models, 15 of the 28 policy preference coefficients are significantly different from 0. Using lagged policy preference models, 13 of the 28 policy variables have significant coefficients. In the lagged dependent variable models, five of them have significant coefficients. Only one is significant in priming models. Thus, the cross-sectional model suggests the most policy voting, followed by the lagged policy preference model, then the lagged dependent variable model, and finally the priming model. See Figures S1 and S2 in the Supporting Information for all coefficients.

As argued above, there are two reasons cross-sectional and lagged policy preference find so much evidence that policy preferences matter and why priming models find so little such evidence: persuasion and earlier policy voting. How common is persuasion? To determine how frequent it is, I run a reverse version of the lagged dependent variable model in each inter-election period (2010 to 2012 and 2012 to 2014). In other words, I regress policy preferences from the 2012 and 2014 pre-election surveys on vote intentions and policy preferences from the pre-election 2010 and 2012 waves, respectively. Equation (5) is the persuasion model.

$$Policy_2 = \alpha_1 + \alpha_1 * Policy_1 + \beta_1 * Vote_1 + ... + \epsilon_2 \tag{5}$$

By regressing a policy preference at time 2 on that same preference at time 1 as well as vote choice at that earlier time, this model allows us to estimate the extent to which prior vote choice influences changes in policy preferences. Note that the controls represented by ... include party identification, thus ruling out the possibility that voters are simply influenced by the parties with which they identify.

I consider changes between pre-election waves because most policy preferences were asked in those waves. I find evidence of persuasion effects on eight of the 13 issues between 2010 and 2012 and on 12 of the 15 issues between 2012 and 2014 (See Figures S3 and S4 in the SI). Persuasion thus occurred 71 per cent of the time (note that I can only include in each analysis issues that were asked in both years). I also tested for evidence of persuasion in another panel study, the Views of the Electorate Research Survey (VOTER) that ran from 2011 to 2016. In that dataset, I found evidence of persuasion on 16 of 17 issues (see Figure S9 in the SI). Given how common it is, persuasion should certainly not be ignored when considering the influence of policy preferences on voting behavior.

To determine whether persuasion and prior policy voting influence estimates of policy voting, I leverage the fact that the CCES repeats most issues in subsequent elections. I rerun the above policy voting analyses using the CCES limited to issues that were asked about in subsequent elections. I create a policy-election dataset with the coefficients on the policy preference variables in the lagged dependent variable model from the 2012 and 2014 elections (to ensure the policy voting I pick up occurs during the appropriate period of time). I also add policy voting coefficients from the previous election, 2010 and 2012, respectively, as well as from the previous inter-election period (2010-2012 and 2012-2014, respectively). I focus on lagged dependent variable measures of policy voting because it limits the assessment of policy voting to a particular period. I also add persuasion coefficients from the preceding inter-election period. I find that policy voting is strongly persistent between the inter-election period preceding an election and that election ($\rho = 0.62$). Policy voting in an election is moderately correlated with policy voting during the previous election ($\rho = 0.33$) and with persuasion between the previous two elections ($\rho = 0.39$). Policy voting during an election campaign is thus far from independent of voting behavior and persuasion prior to that campaign.

To assess how prior persuasion and policy voting influence estimates of policy voting, I run each of the models of policy voting in the 2012 and 2014 elections for all issues that were repeated in subsequent elections. I then assess how deviations from lagged dependent variable estimates are influenced by policy voting and persuasion in the past. I regress the cross-sectional, lagged policy, and priming estimates on the lagged dependent variable estimate from the election in question, as well as the estimates of persuasion and policy voting from the previous inter-election period (note that all policy voting measures on the right hand side are lagged dependent variable measures in order to capture policy voting during the relevant period of time). I also include fixed effects for election.

Table 1 shows the results. As we can see, persuasion and policy voting during the preceding inter-election period lead to greater cross-sectional and lagged policy preference estimates of policy voting compared to the lagged dependent variable model. However, they have a smaller effect on lagged policy preference estimates. On the other hand, they have a negative influence on estimates from the priming model. Thus, when policy voting and persuasion occurred in the past, cross-sectional and lagged policy preference models yield overestimates of policy voting, while priming models yield underestimates. It is important to keep this dependence of estimates of policy voting on past behavior in mind when interpreting policy voting models. Nevertheless, these analyses use estimates from the lagged dependent variable model as a benchmark and we still do not know how accurate those estimates are. In the next section, I assess these models using simulated data in which we know the true amount of policy voting.

Table 1: Models of Policy Voting Estimates (2012 and 2014)

	Cross-Sectional	Lagged Policy	Priming
Intercept	-0.04^{*}	-0.03^{*}	0.01^{*}
	(0.01)	(0.01)	(0.01)
Prior Persuasion	0.37^{*}	0.24^{*}	-0.13^{*}
	(0.11)	(0.08)	(0.06)
Prior Policy Voting	0.50^{*}	0.29^{*}	-0.22^{*}
	(0.09)	(0.07)	(0.05)
Lagged Dependent Variable Estimate	0.09	1.02^{*}	0.92^{*}
	(0.16)	(0.12)	(0.09)
N	28	28	28
Adjusted R^2	0.76	0.91	0.81

Standard errors in parentheses

Models Include Election Fixed Effects

* indicates significance at $p < 0.05$

For the rest of this paper, I focus on the lagged policy preference model instead of the cross-sectional model because it is more likely to reflect the type of data found in conventional election surveys (policy preferences asked in the pre-election wave). Moreover, the results in Table 1 show that it is subject to the same biases as the cross-sectional model but to a lesser extent. Thus, any biases I find in the lagged policy preference model in simulations are likely an understatement of the true biases facing cross-sectional analyses.

2 Monte Carlo Evidence that Prior Persuasion and Policy Voting Can Bias Estimates of Policy Voting

Because we do not know the true effects of policies in the real world, the analyses above do not necessarily tell us which estimators are biased. To show that prior persuasion and policy voting are a problem for estimating policy voting, I create simulated data in which I set the amount of policy voting and persuasion in the past and in the present corresponding to the DAG shown in Figure 1. I first create data on policy preferences and voting propensity at time 0 when they are unrelated to each other. I assume that distributions of both policy preferences and voting propensity are bell-shaped, with most voters in the center. I focus on voting propensity rather than vote choice per se because working with vote choice would require making assumptions about how a latent variable relates to binary vote choice at each period. I create vote choice ($Vote_0$) and policy preference data ($Policy_0$) for 1000 simulated survey respondents in this initial period.

$$Vote_0 \sim \mathcal{N}(0,1)$$
$$Policy_0 \sim \mathcal{N}(0,1)$$

Policy preferences and voting propensity then influence each other by a certain amount between times 0 and 1. I vary the magnitude of this mutual influence across scenarios (a and b) from -1 to +1 (in 0.1 increments). Each variable in the next period is also influenced by a variety of other variables that I consider random error (note that I omit intercepts to avoid trending in a particular direction). I set the coefficients on the lagged dependent variables at the mean value of analogous coefficients in the CCES models presented above (0.54 for vote choice and 0.15 for policy preferences).

$$e_1 \sim \mathcal{N}(0,1)$$
$$u_1 \sim \mathcal{N}(0,1)$$
$$Vote_1 = 0.54 * Vote_0 + a * Policy_0 + e_1$$

$$Policy_1 = 0.15 * Policy_0 + b * Vote_0 + u_1$$

Finally, policy preferences influence vote choice by a fixed amount (either 0.1 when policy voting occurs or 0 when it does not) between times 1 and 2.

$$e_1 \sim \mathcal{N}(0, 1)$$
$$Vote_2 = 0.54 * Vote_1 + \beta_1 * Policy_1 + e_2$$

I set the policy voting coefficient to 0.1 in the positive case because estimates of the influence of important issues in my analysis of CCES data, like the Affordable Care Act and the environment, were around that amount. I generate data according to this data-generating process and run each of the models presented above 1000 times for each combination of a and b.

Figure 1 is a three-dimensional scatterplot showing the mean lagged dependent variable estimate when the amount of policy voting is 0.1 at all combinations of the simulated values of a and b. The shade of gray shows the proportion of simulations that produce significant results (at the 0.05 level). As we can see, biases are very small at all values of a and b. The largest bias across the scenarios I consider is smaller than 0.003. The major limitation of this estimator is that it leads to false negatives more often than 5 per cent of the time when prior policy voting and persuasion are both zero or weak (the highest rate of false negatives is 13.6 per cent at 0 persuasion and 0 policy voting). However, given the evidence from the CCES analyses above that current policy voting is correlated with prior persuasion and policy voting, such scenarios should be rare.

Figure 2: Policy Voting Estimates from Lagged Dependent Variable Model ($\beta_1 = 0.1$)

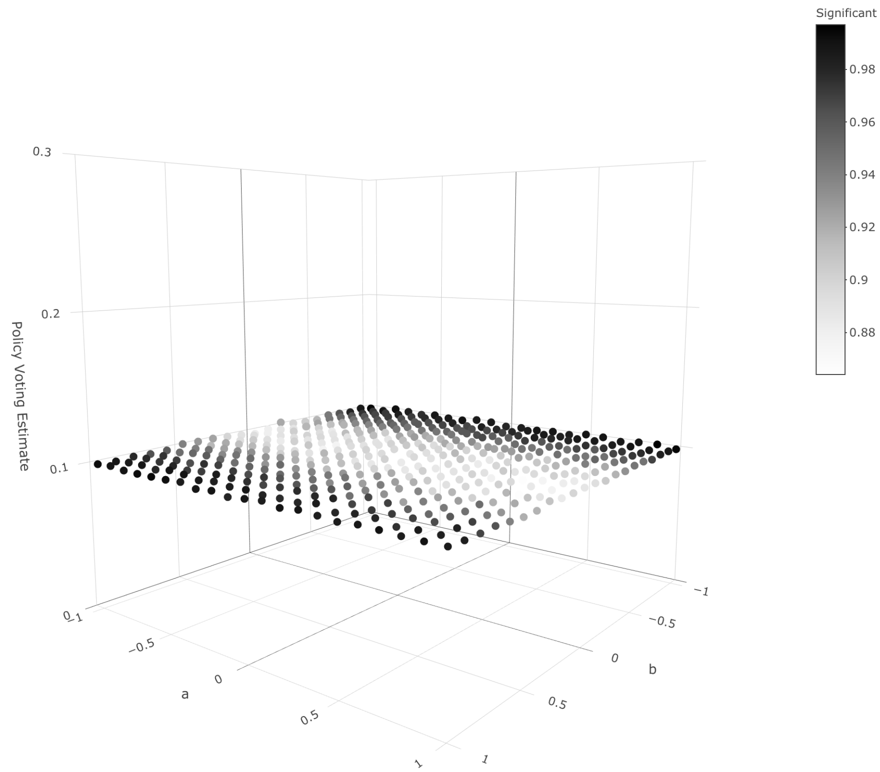


Figure 3 shows mean policy voting estimates from the lagged policy preference model on the vertical axis by the amount of prior persuasion for three possible values of prior policy voting. For simplicity, I placed the three-dimensional scatterplot showing mean estimates at all possible values of prior persuasion and prior policy voting in the Supporting Information (Figure S5). As we can see, the model is unbiased when there is no prior persuasion or policy voting. However, prior policy voting and especially persuasion lead to biases. In the usual situation of prior policy voting and persuasion in the same direction as in the period of interest, the model leads to an upward bias (top-right of the figure). However, if policy voting and/or persuasion change directions, the bias can be downward and may lead to null results. In extreme cases with strong prior policy voting and persuasion in the opposite direction, this estimator can lead to results that are significant but of the wrong sign (See Figure S5 in the SI). This would be the case with unusual issues on which parties change positions, voters learn positions on an issue on which they disagree with their party or if such an issue becomes salient. Given that this situation is rare, the lagged policy preference model should rarely produce false negatives or significant results of the wrong sign.

Figure 3: Policy Voting Estimates from Lagged Policy Preference Model ($\beta_1 = 0.1$)

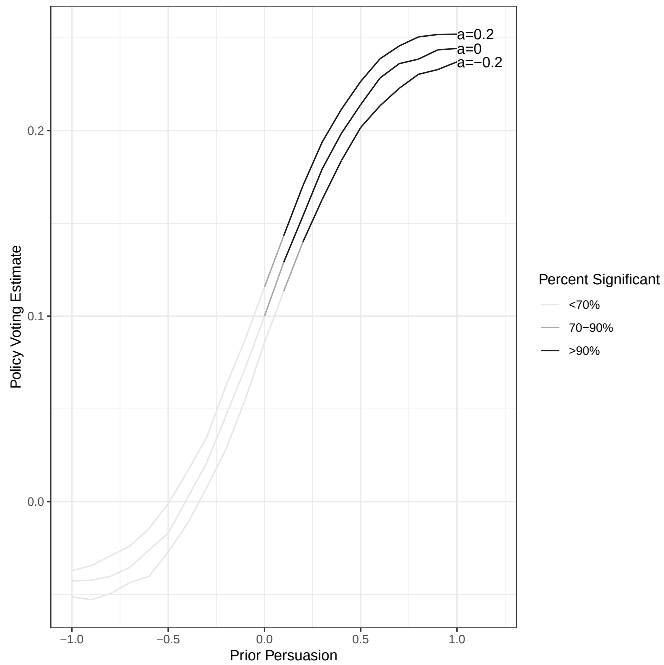


Figure 4 shows mean estimates from the priming model across the values of prior persuasion I consider and at three representative values of prior policy voting (See Figure S6 in the SI for estimates at all values). It shows that results are strongly dependent on prior persuasion and policy voting. More positive prior persuasion and policy voting lead to lower estimates of policy voting in the period of interest and frequent null results. The model only reliably finds evidence of policy voting in unusual cases of negative prior persuasion. Thus, with this model, we need to be concerned about false negatives.

Figure 4: Policy Voting Estimates from Priming Model ($\beta_1 = 0.1$)

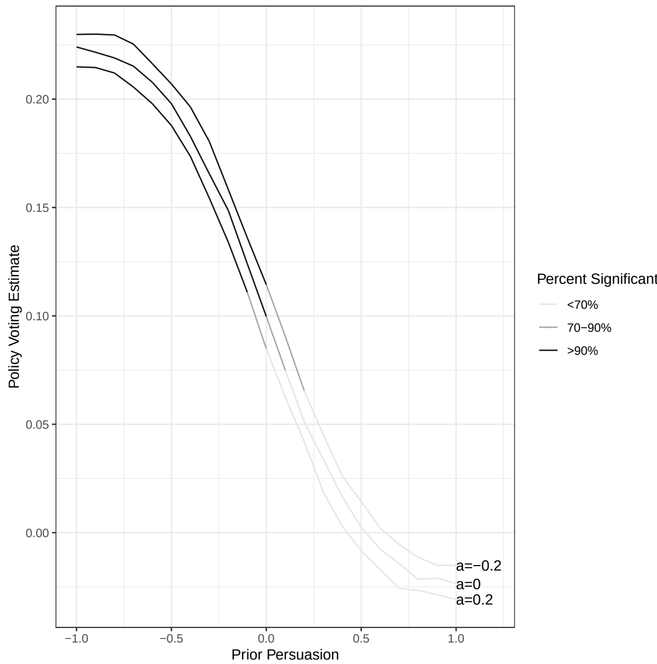


Figure 5 shows mean estimates of policy voting from the lagged dependent variable model across the range of possible values of prior policy voting and persuasion when there is no policy voting during the period of interest. It shows that the estimator is unbiased in all possible scenarios. Moreover, it produces false positives about as often as would be expected by chance (between 3.3 per cent and 7.2 per cent of the time). The lagged dependent variable model thus once again performs strongly.

Figure 5: Policy Voting Estimates from Lagged Dependent Variable Model ($\beta_1 = 0$)

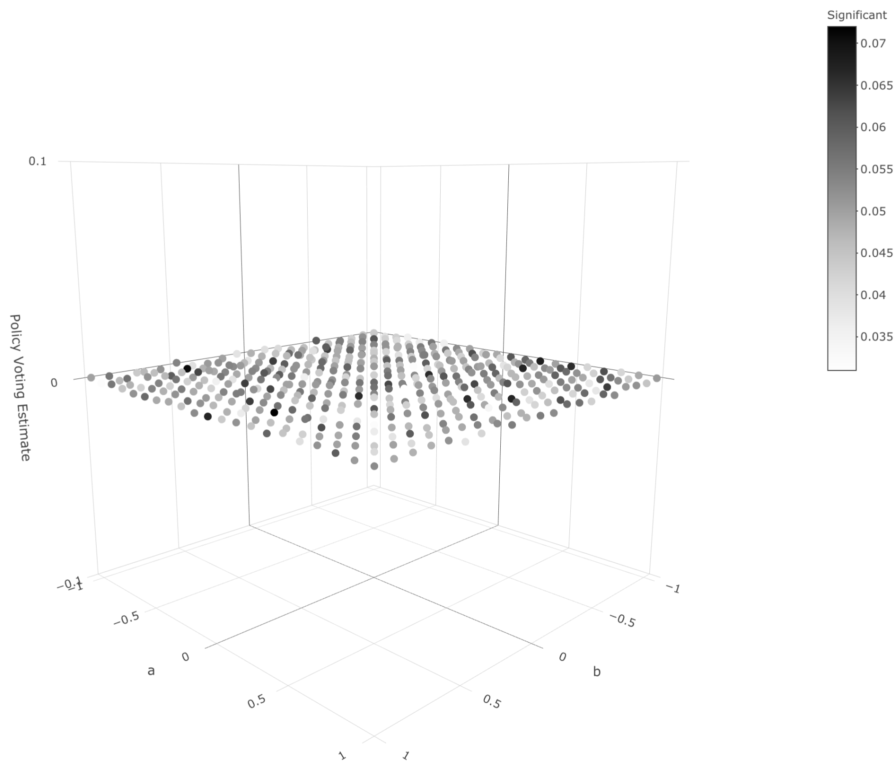


Figure 6 shows mean coefficient estimates across the range of values of prior persuasion at three representative values of prior policy voting from the lagged policy preference model. As we can see, the lagged policy preference model leads to false positives in the presence of even relatively weak prior policy voting and persuasion. For example, the mean estimate at 0.2 prior persuasion and policy voting is 0.07 and estimates are significantly positive 51 per cent of the time. The lagged policy preference model is thus strongly vulnerable to false positives. Given that biases faced by the lagged policy preference model are magnified by the cross-sectional model, we should be even more concerned about these biases affecting that model.

Figure 6: Policy Voting Estimates from Lagged Policy Preference Model ($\beta_1 = 0$)

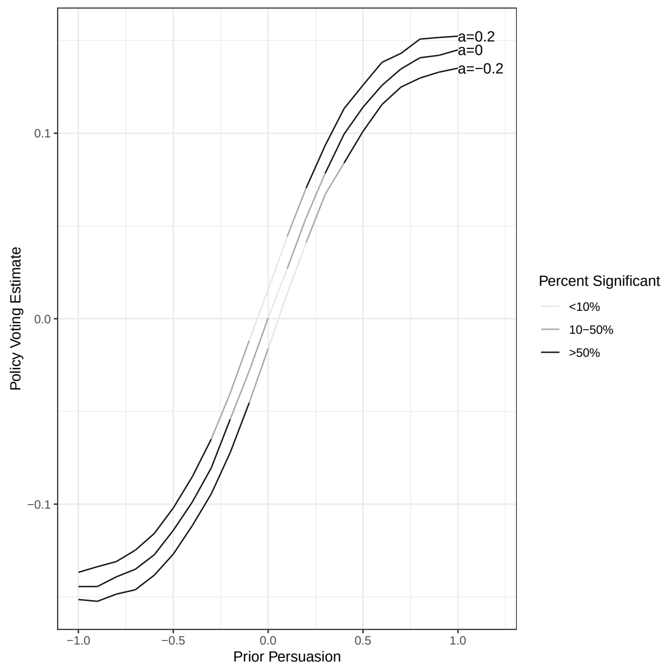
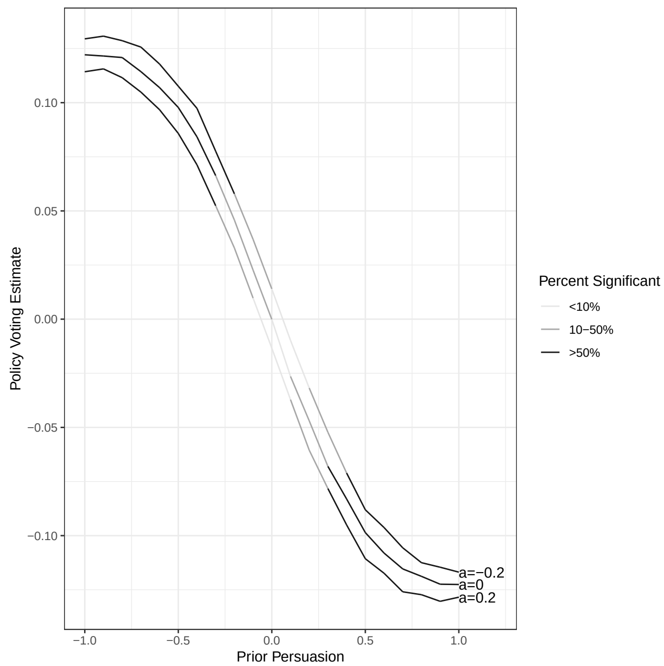


Figure 7 shows mean estimates from the priming model across the range of values of a and b for the scenario of no policy voting. Its performance again is strongly dependent on prior behavior. Moderate amounts of positive prior persuasion notably lead to downward bias, while moderate amounts of negative prior persuasion lead to upward bias. The good news is that it rarely leads to false positives when there is no prior persuasion or policy voting and that remains true when prior policy voting and/or persuasion are moderately positive. Thus, the priming model can be seen as a conservative test of policy voting.

Figure 7: Policy Voting Estimates from the Priming Model ($\beta_1 = 0$)



To sum up, I have found that the lagged policy preference model is an upwardly biased estimator of the impact of policy issues when persuasion and policy voting occur in the same direction over time. Nevertheless, when there is a positive policy voting effect, it can usually pick it up. The priming model, on the other hand, leads to false negatives in common scenarios in which policy voting and persuasion occur in the same direction over time. It can even produce false positives in unusual cases in which policy voting and/or persuasion change sign. The lagged dependent variable model, on the other hand, rarely leads to either false positives or false negatives. Thus, the only way to be sure of estimates of policy voting is to use lagged dependent variable models.

Nevertheless, lagged policy preference models, and likely also cross-sectional models, can be useful at ruling out policy voting on certain issues. Unless policy voting and/or persuasion change signs, both types of models should pick up whatever policy voting does occur. For example, Hooghe and Dassonneville (2018) find that voting for Trump is not associated with low trust in politics or with low levels of satisfaction with democracy. If we can assume that voters with low trust and democratic satisfaction did not vote disproportionately for one of the parties prior to 2016, we can safely assume that these attitudes did not lead to changes in vote choice in 2016. Such analyses can be extremely important and do not require panel data.

Priming models, on the other hand, can be used as conservative tests of policy voting. If they find effects of an issue, we can be confident that that issue mattered as long as there was no change in the direction of policy voting or persuasion. Sides, Tesler and Vavrek (2018) find evidence that negative immigration attitudes were more strongly associated with Republican vote choice in 2016 than in 2012. Since they show that they were not negatively associated with voting Republican in 2012, we can be confident that their results imply policy voting. The following section applies what we now know about these models to analyze voting in the last presidential election.

3 Revisiting the 2016 Presidential Election

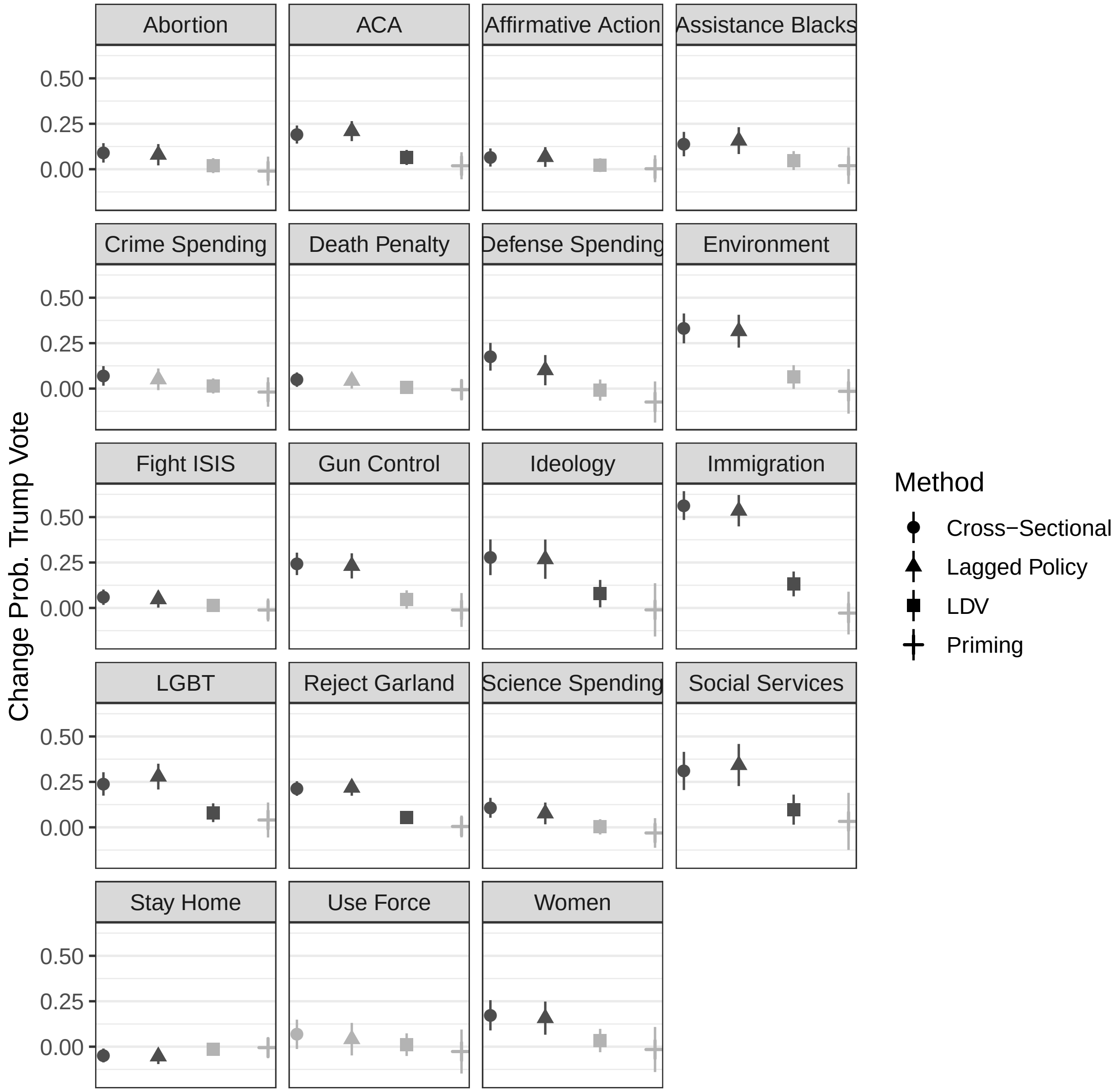
We saw above that most studies on the 2016 presidential election use cross-sectional models, three of them use the priming model, while only one uses the lagged dependent variable model. Do the different models also affect our assessment of the impact of policies on voting behavior in 2016?

I use the 2016 American National Election Study (ANES), which interviewed respondents before and after the 2016 election, to assess policy voting in 2016. My expectation is that cross-sectional approaches overestimate the impact of policy issues that have long been salient in US politics due to prior policy voting and/or persuasion. Moreover, I expect the priming model to find nearly no impact of policy preferences on voting behavior, with the possible exception of new issues or issues on which parties or candidates announce positions that go against what they had expressed in the past.

I use all questions that either directly assess policy preferences or that ask about attitudes with clear policy implications. For example, I consider the question about whether global warming is happening a policy issue. I also include a scale based on four items assessing attitudes towards women because previous research (Schaffner, MacWilliams and Nteta 2018; Valentino, Wayne and Oceno 2018) finds that sexism helps account for the Trump vote. I create scales wherever possible to reduce measurement error (Ansolabehere, Rodden and Snyder 2008). I create a social services scale, an LGBT scale, an immigration and refugees scale, an attitudes towards women scale, and an environment scale.

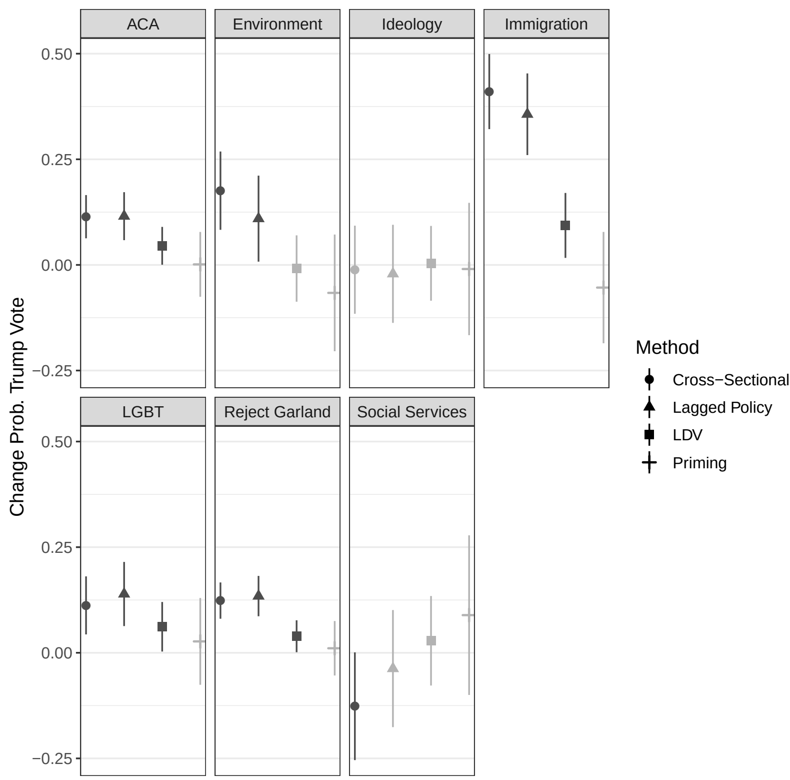
I follow the same approach as in the analyses of the CCES panel. I first assess the influence of policy issues in separate models. Figure 8 shows coefficients from separate models applied to each policy preference. We can see that the cross-sectional model suggests that all policy attitudes except a question about whether force should be used to solve international problems influenced voting for Trump. The lagged policy preferences model suggests that all of the same issues except preferences for increased crime spending and support for the death penalty influenced support for Trump. Once we move to the lagged dependent variable model though, most issues cease to have significant effects. The only attitudes that mattered according to that model were support for the Affordable Care Act, liberal-conservative ideology, immigration preferences, attitudes towards LGBT, attitudes towards Obama's Supreme Court nominee, and social services preferences. The priming model suggests that none of the policy attitudes mattered. In short, as expected, cross-sectional and lagged policy preference models make most issues that have been on the political agenda in recent elections appear to matter in 2016, while the priming model suggests that policy preferences did not matter at all.

Figure 8: Policy Voting in 2016 ANES (Separate Model for Each Issue)



I then run a model with all policy issues with some evidence that they matter in these initial models (coefficient that is significant at $p < 0.1$ in the lagged dependent variable model). Figure 9 shows coefficients for each of these policies. Analyses using the lagged dependent variable model show that the policy preferences that mattered during the 2016 campaign are opposition to the Affordable Care Act, to immigration, to LGBT rights, and to Obama's Supreme Court nominee (Merrick Garland). Cross-sectional and lagged policy models suggest that environmental attitudes mattered as well. The cross-sectional model also suggests that liberal attitudes on social services predicted support for Trump before the election. However, there is no evidence that these influenced support for Trump in any of the other models. The priming model still suggests that policy preferences had no influence on vote choice.

Figure 9: Policy Voting in 2016 ANES (All Issues in Same Model)



The take-away of these analyses is that conclusions about policy voting are strongly dependent on the type of analysis we conduct. Cross-sectional analyses find significant effects of most issues. Thus, significant effects of policy attitudes in cross-sectional analyses do not convincingly show that those attitudes mattered to vote choice. However, null results from cross-sectional models do rule out policy voting on an issue as long as prior persuasion and/or policy voting did not change direction. Priming models will usually show that policy preferences have no influence on voting behavior. Thus, any evidence that policy preferences mattered from such models nearly always implies strong evidence of policy voting. The lagged dependent variable model usually provides the assessment of policy voting we are interested in.

4 An Alternative Explanation

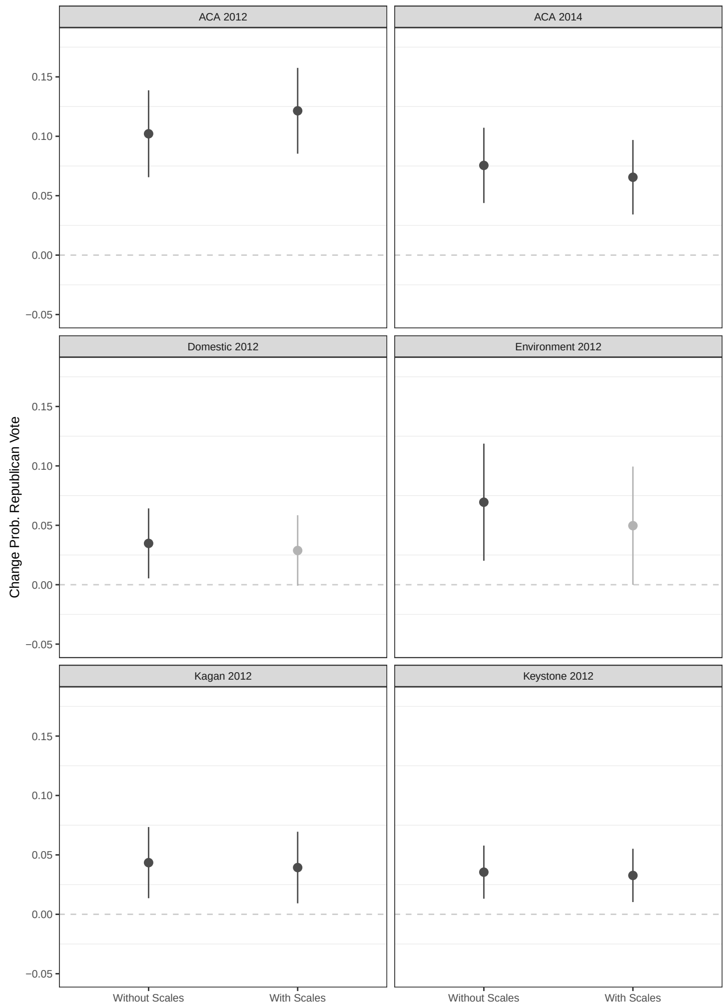
One objection to the policy voting results from the lagged dependent variable models presented above is that the policy preference variables are picking up the effect of a latent propensity for voters to support one party or the other. If that is the case, those models overestimate policy voting. To rule out this possibility, I reanalyzed the CCES data including as many controls for prior partisanship and prior vote choice as possible. The CCES asked about party identification before and after each of the elections included in the panel as well as vote intentions for House, Senate, and gubernatorial elections in each pre-election study and vote choice for those elections in each post-election study. They also asked for 2008 presidential election vote choice in each of the pre-election surveys and for 2012 presidential election vote choice in the pre-election survey that year. By creating scales combining all these measures of party identification and voting behavior, I should at least partly tap into the kind of hypothetical tendency to support one party over the other. Scales reduce the measurement error of individual items (Ansolabehere, Rodden and Snyder 2008) and should thus better account for a propensity to support one party than single measures of partisanship or prior voting behavior.

For the 2012 and 2014 elections, I take the lagged dependent variable models with all issue variables with significant effects ($p < 0.1$) when included on their own and add a party identification scale and a Republican voting scale. For each of those models, I create a party identification scale by taking the mean of all measures of party identification asked prior to the election in question and a Republican voting scale by adding up the number of times a respondent expressed a Republican vote intention or actual vote before the election.

The party identification scale in the 2012 model includes party identification measured in the 2010 pre- and post-election surveys as well as in the 2012 pre-election survey. The Republican voting propensity scale is the sum of dummy variables indicating a Republican response to eight vote intention/vote choice questions (see Section 5 of the SI) . The 2014 party identification scale includes partisanship measured in the 2010 and 2012 pre- and post-election surveys as well as in the 2014 pre-election survey. The Republican voting propensity variable in 2014 includes 14 measures of Republican support (see Section 4 of the SI). Note that both models also continue to include House vote intentions from the year in question (i.e. the lagged dependent variable).

As in all previous analyses, all variables are coded so that higher values indicate Republican or conservative preferences. If the policy effects I find are due to a latent propensity to support the Republican Party, we should find that coefficients on the policy variables weaken when adding these variables. Figure 10 shows the coefficients on policy preferences with significant effects in the models presented above. It shows coefficients from models with and without the extensive controls. As we can see, in spite of the large number of expressions of Republican support included in these models, coefficients on policy preferences barely shift. Even when introducing strong controls for a possible tendency to support the Republican Party, I find evidence that four of the six issues continue to matter. My analyses thus pick up real policy voting effects.

Figure 10: Estimated Coefficients with and Without Controls for Republican Support



5 Conclusion

I have addressed the long-standing debate about whether voters are capable of expressing their policy preferences when they vote and, in turn, are able to influence government. I reviewed recent studies of policy attitudes in the 2016 US Presidential election and pointed out that, while they seem to agree on the type of attitudes that matter, attitudes towards women and minorities, they focus more on testing whether variables predict vote choice or arguments about activation/priming rather than on policy voting per se. Most of these studies use cross-sectional analyses to show that their attitude of interest mattered in 2016, three use priming models, and one uses a lagged dependent variable model.

I argue the analyses in these studies do not usually lead to clear conclusions about policy voting. Most models used in these studies lead to results that partly reflect past policy voting and persuasion.

I show that prior persuasion and policy voting influence estimates of policy voting using the Cooperative Congressional Election Study (CCES) Panel from 2010 to 2014. I find evidence of persuasion on most issues. I also find that the issues that matter in one election also tend to have mattered in the past and that there is a strong tendency for persuasion to have occurred on these issues as well. I show that prior persuasion and policy voting lead to greater cross-sectional estimates and lagged policy preference estimates of policy voting and to weaker priming model estimates of policy voting.

I then create simulated data in which I set the amount of persuasion and policy voting in a recent period and an earlier baseline period and show that both lead to over-estimates of the influence of policy attitudes using the lagged policy preference model, while prior persuasion and policy voting also lead to underestimates of the influence of policy attitudes using the priming model.

Returning to real data, I analyze the 2016 American National Election Study (ANES) and show that the model used makes a huge difference to conclusions about policy voting in the 2016 Presidential Election. Cross-sectional and lagged policy preference models make voters appear to have cared about nearly all policy issues the ANES asked about. The priming model, on the other hand, makes voters appear entirely unmotivated by policy considerations. The lagged dependent variable model shows that voters who were opposed to the ACA, to immigration, to LGBT rights and to Barack Obama's Supreme Court nominee changed their vote choice to support Trump. In short, conclusions about voting for Trump are strongly dependent on the model used.

Finally, I address a possible alternative explanation for the policy voting results I find. I consider the possibility that policy preference coefficients pick up the effect of a latent tendency to support one party over the other. Reanalyzing the CCES data, I control for this possibility by creating a party identification scale based on multi-wave measures of party identification as well as a vote propensity scale based on multiple measures of past voting behavior. With these controls, I clearly show that lagged dependent variable estimates reflect real policy voting.

Scholars should think carefully assumptions underlying each model when deciding which one to use. Most of the time, the most appropriate model will be a lagged dependent variable model. Nevertheless, cross-sectional models can be used to show that particular issues had no influence on vote choice. Priming models, on the other hand, can be used as a conservative test of policy voting. Nevertheless, any inferences made using these models assume that there was no prior policy voting or persuasion in the opposite direction.

Others may want to compare cross-sectional models over time by showing that models from the most recent election have stronger coefficients than models from previous elections as Valentino, Wayne and Oceno (2018) and Sides, Tesler and Vavrek (2018) do in some of their analyses. Such comparisons can effectively rule out contemporaneous effects being due to prior behavior. They cannot, however, tell us whether results reflect policy voting or persuasion (Engelhardt et al. 2019; Lenz 2012). Determining which of these processes explains the results obtained from voting models requires that scholars think carefully about the models they use and the assumptions they make. It is my hope that producers and consumers of research on policy voting will from now on consider that conclusions about voters strongly reflect the models that are used.

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What Do Analyses of Elections Tell Us About Voters? Evaluating Election Models for Assessing Policy Voting

July 10, 2020

Contents

1 CCES Analyses

1.1 Issues

Table S1: Issues asked about in 2010-14 CSES Panel Study

	Issue	2010	2012	2014
1	Abortion (Abortion)	X	X	X
2	Affirmative Action (Affirmative)	X	X	X
3	Affordable Care Act (ACA)*	X	X	X
4	Allow Federal Funding of Stem Cell Research (Stem Cell)*	X	X	X
5	American Clean Energy and Security Act (Clean Energy)*	X	X	X
6	American Recovery and Reinvestment Act (Recovery)*	X	X	X
7	Appoint Elena Kagan to Supreme Court (Kagan)*	X	X	X
8	Birth Control Exemption (Birth Control)*		X	X
9	Climate Action (Climate)	X	X	X
10	Cut Domestic Spending (Domestic)	X	X	X
11	Deny Citizenship to Children of Illegal Immigrants (Citizenship)		X	X
12	End Don't Ask Don't Tell (Don't Ask)*	X	X	X
13	Environment more Important than Jobs (Environment)	X	X	X
14	Financial Reform Bill (Financial)*	X	X	
15	Fine Businesses that Hire Illegal Immigrants (Fine)	X	X	X
16	Foreign Intelligence Surveillance Act (Intelligence)*	X		
17	Gay Marriage Ban (Gay Marriage)	X	X	X
18	Gun Control (Gun Control)	X	X	X
19	Increase Border Patrols (Borders)	X	X	X
20	Keystone Pipeline (Keystone)*		X	X
21	Legal Status for Immigrants (Legal Status)	X	X	X
22	Middle Class Tax Cut* (Tax Cut)		X	X
23	Police Should Question Suspected Illegal Immigrants (Police)	X	X	X
24	Restore American Fiscal Stability Act (Fiscal)*		X	
25	Ryan Budget Bill (Ryan Budget)*		X	X
26	SCHIP (SCHIP)*	X	X	X
27	Simpson Bowles Budget Plan (Simpson-Bowles)*		X	X
28	Tax Hike Prevention (Tax Hike)*		X	X
29	Troubled Asset Relief Program (Troubled)*	X		
30	US-Korean FTA (Korean FTA)*		X	X

* indicates the question is about a roll-call vote.

I created a scale out of the four questions about immigration that were asked consistently across pre-election waves (Legal Status, Borders, Police, and Fine) by taking the mean of the four items. I also created a scale out of the three items that were asked about the environment in the three elections (Climate, Environment, and Clean Energy).

1.2 Policy Voting

Figure S1: Policy Voting in 2012

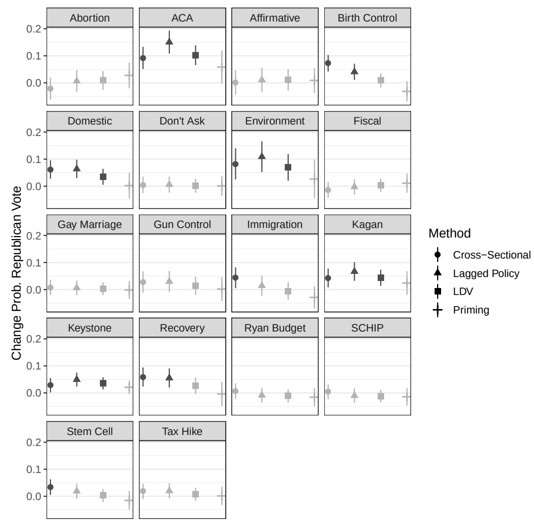
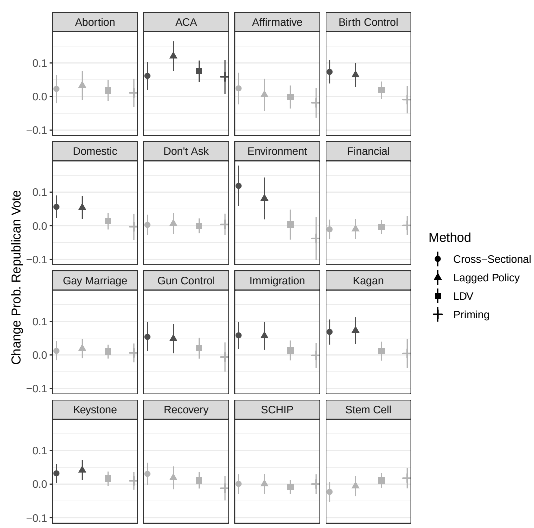


Figure S2: Policy Voting in 2014



1.3 Persuasion

Figure S3: Persuasion Between 2010 and 2012

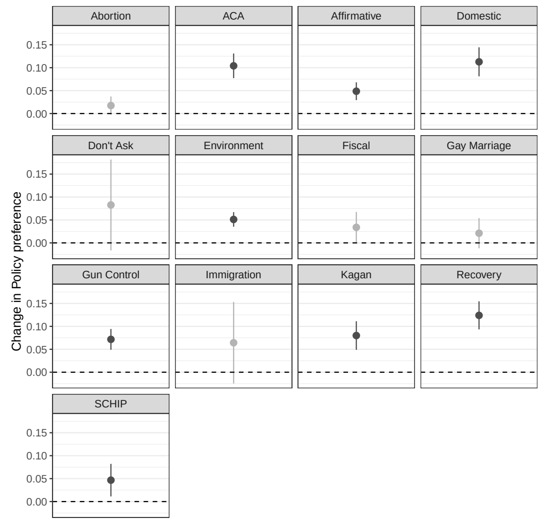
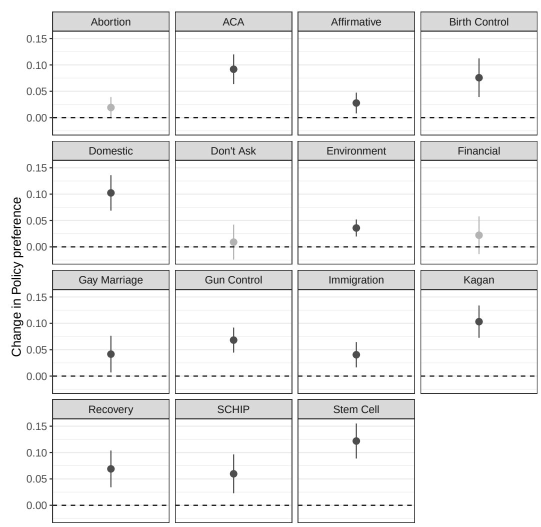


Figure S4: Persuasion Between 2012 and 2014



2 Simulations

Figure S5: Policy Voting Estimates from Lagged Policy Preference Model ($\beta_1 = 0.1$)

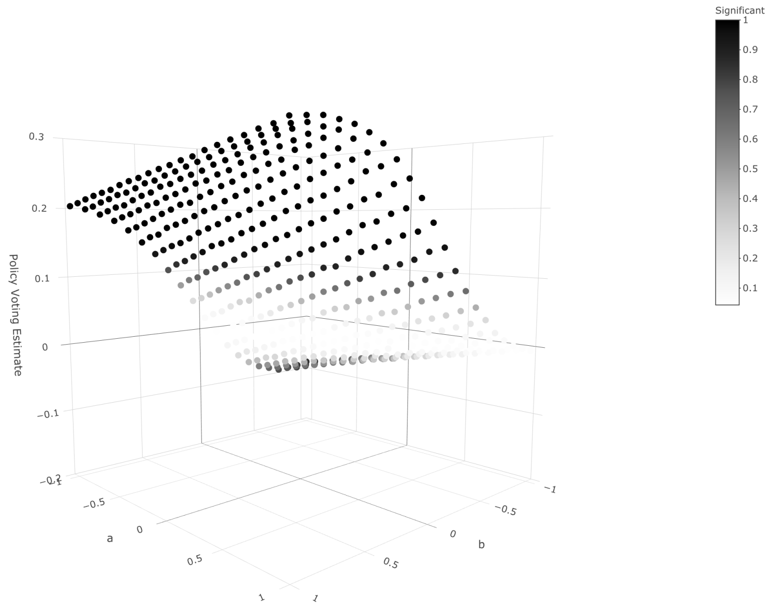


Figure S6: Policy Voting Estimates from Priming Model ($\beta_1 = 0.1$)

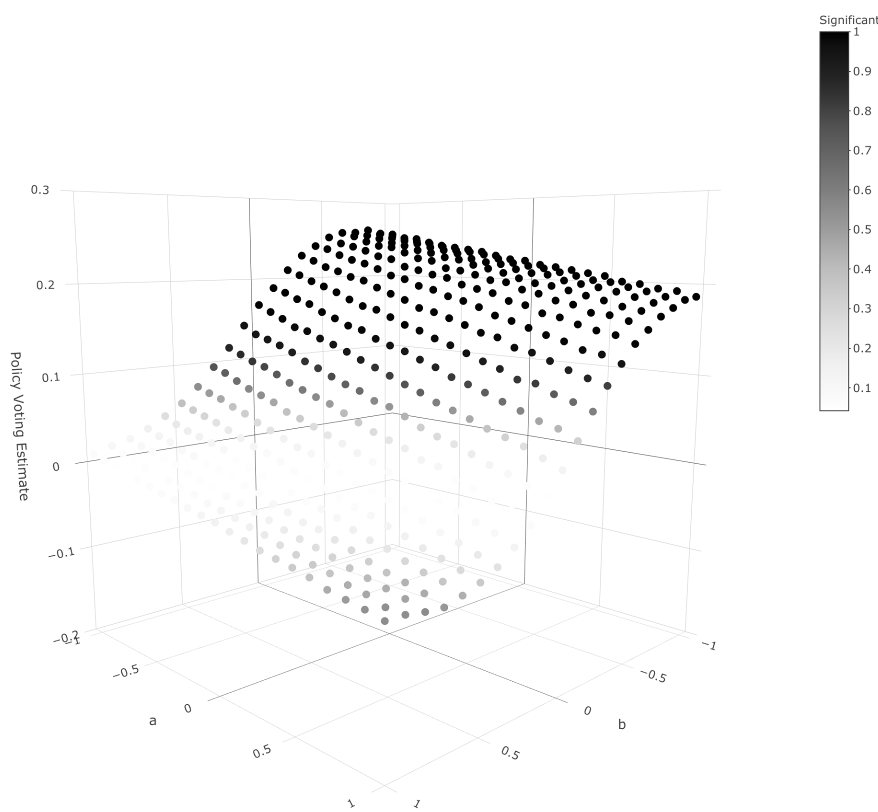


Figure S7: Policy Voting Estimates from Lagged Policy Preference Model ($\beta_1 = 0$)

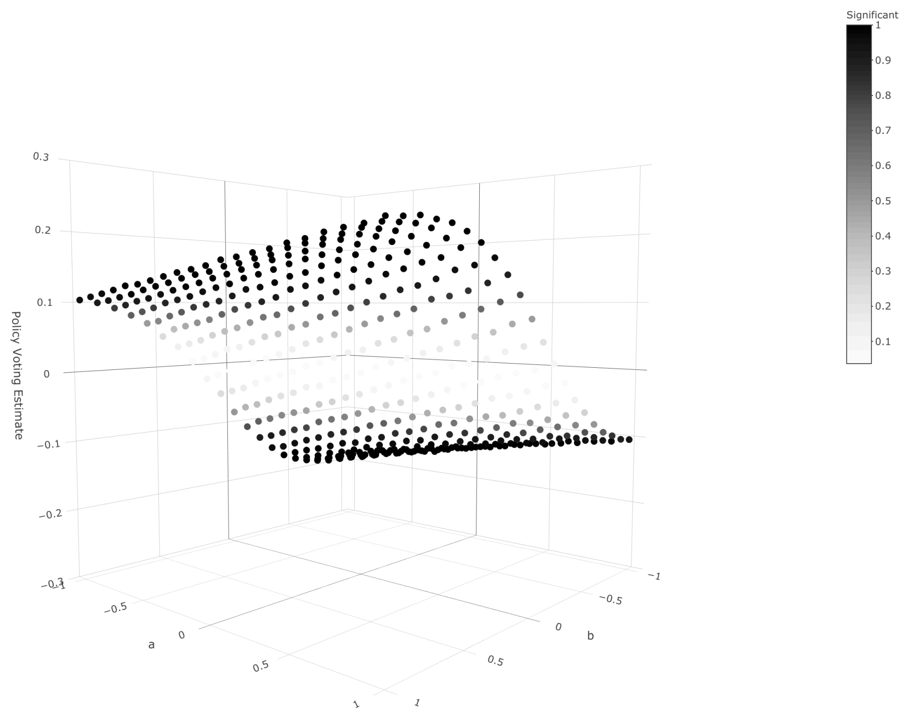
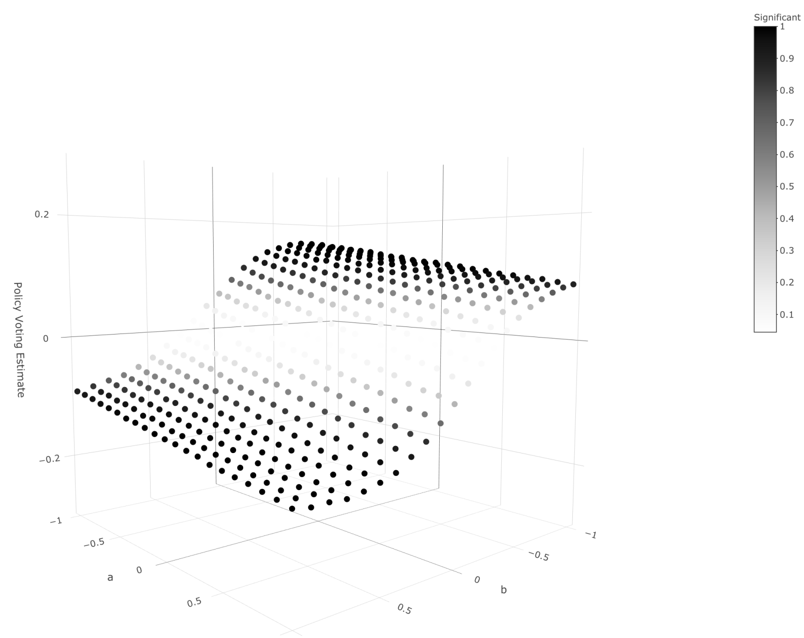


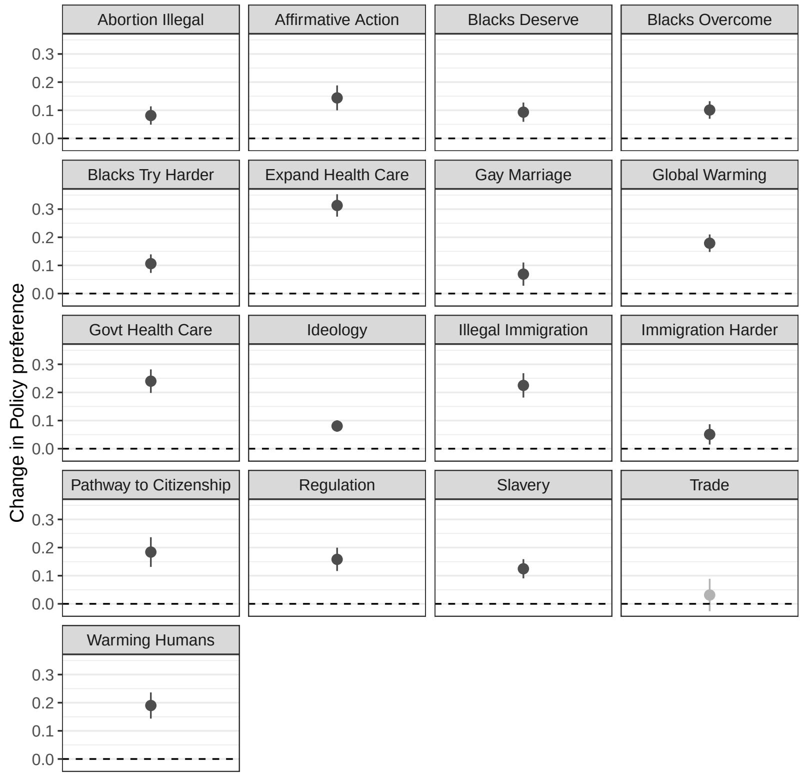
Figure S8: Policy Voting Estimates from Priming Model ($\beta_1 = 0$)



3 Results of Persuasion Models from VOTER Survey

Policy preferences are from 2011 and 2016. All are coded so that higher values indicate more conservative positions and are coded from 0 to 1. All policy preference questions that were asked in both years are included. The independent variable is a dummy variable indicating that the respondent voted for the Republican candidate in 2012 (Romney).

Figure S9: Models of Persuasion Using VOTER Survey (2011-2016)



4 List of Vote Intention/Choice Questions

The vote intention/choice variables included in the Republican vote propensity scale for the 2012 model are: 2010 House voting intentions, 2010 House vote, 2010 Senate voting intentions, 2010 Senate vote, 2010 gubernatorial voting intentions, 2010 gubernatorial vote, 2012 Senate voting intentions, 2012 gubernatorial voting intentions, 2008 vote choice (asked in 2010, pre-election), and 2008 vote choice (asked in 2012, pre-election).

The vote intention/choice variables included in the Republican vote propensity scale for the 2014 model are: 2010 House voting intentions, 2010 House vote, 2010 Senate voting intentions, 2010 Senate vote, 2010 gubernatorial voting intentions, 2010 gubernatorial vote, 2012 Senate voting intentions, 2012 gubernatorial voting intentions, 2008 vote choice (asked in 2010, pre-election), and 2008 vote choice (asked in 2012, pre-election), the sum of all the vote dummies included in the 2012 scale in addition to dummies for 2012 House vote choice, 2012 Senate vote choice, 2012 gubernatorial vote choice, 2014 Senate voting intentions, 2014 gubernatorial voting intentions, and 2012 presidential vote.