Moderates*

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Abstract

Moderates are often overlooked in contemporary research on American voters. Many scholars who have examined moderates argue that these individuals are only classified as such due to a lack of political sophistication or conflicted views across issues. We develop a method to distinguish between three ways an individual might be classified as moderate: having genuinely moderate views across issues, being inattentive to politics or political surveys, or holding views poorly summarized by a single liberal-conservative dimension. We find that a single ideological dimension accurately describes most, but not all, Americans' policy views. Using the classifications from our model, we demonstrate that moderates and those whose views are not well explained by a single dimension are especially consequential for electoral selection and accountability. These results suggest a need for renewed attention to the middle of the American political spectrum.

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Recent scholarship on American political behavior has focused on strongly partisan Democrats and Republicans who express opposing views and disdain for one another (e.g., Hetherington and Rudolph, 2015; Abramowitz and Webster, 2016; Mason, 2018; Martherus et al., 2019; Iyengar et al., 2019). In this research, moderates, independents, and centrists have received less attention. Although Fiorina, Abrams, and Pope (2005) note that most Americans hold a mix of liberal and conservative positions on issues and Hill and Tausanovitch (2015) find no increase in the share of Americans with extreme policy ideologies from the 1950s to the 2010s, many have focused on understanding citizens at the ends of the ideological spectrum to the exclusion of those in the middle.

To the extent moderates have been discussed by political scientists, they are often described as politically unsophisticated, uninformed, or ideologically innocent (Kinder and Kalmoe, 2017; Freeder, Lenz, and Turney, 2019); secretly partisan (Dennis, 1992); ideologically cross-pressured (Treier and Hillygus, 2009); or extreme, with patterns of attitudes poorly described by a single ideological dimension (Broockman, 2016).

Measuring the nature and prevalence of centrist positions is difficult because different patterns of opinion can produce the appearance of ideological moderation. For example, if an opinion survey asks only one binary policy question, we can only classify respondents into three types, support, oppose, or missing. If we ask two binary policy questions, it is difficult to know if the respondents who give one liberal response and one conservative response actually hold centrist views, if they lack meaningful political opinions, if they aren't paying attention to the survey questions, or if they hold legitimate political attitudes not well summarized by a liberal-conservative dimension.

In this paper, we develop and estimate a statistical model to study the middle of the ideological distribution. Our model sorts survey respondents who are traditionally classified as moderate into three separate groups: those who have genuinely centrist views well-summarized by a single underlying ideological dimension, those who are inattentive to politics or our survey, and those who hold genuine views that are not well summarized by a single ideological dimension. Our mixture model uses response patterns to multiple policy questions to classify each survey respondent as one of the three types.

Our results clarify the importance of non-ideologues in American elections. First, we find that a large proportion of the American public is neither consistently liberal nor consistently conservative but that this inconsistency is not because their views are simply random or incoherent. Instead, we estimate that many of those who give a mix of liberal and conservative responses hold genuine views in the middle of the same dimension of policy ideology that explains the views of consistent liberals and consistent conservatives. A smaller number of survey respondents — but an important and compelling group — give a mix of liberal and conservative views, however, that are not well-described by the liberal-conservative dimension. Fewer still appear to be answering policy questions as if they were guessing or not paying attention.

Second, moderates appear to be central to electoral change and political accountability. The respondents we classify as moderate are more responsive to features of the candidates contesting elections than lever-pulling liberals and conservatives. We estimate that their vote choices in U.S. House elections are *four to five* times more responsive to the candidates' ideologies than the choices of liberals and conservatives, two to three times more responsive to incumbency, and two to three times more responsive to candidate experience.

These findings help resolve a puzzle. Research on aggregate electoral behavior (e.g., Ansolabehere, Snyder, and Stewart III, 2001; Canes-Wrone, Brady, and Cogan, 2002; Hall, 2015; Tausanovitch and Warshaw, 2018) shows that candidates benefit electorally from ideological moderation, yet many studies conclude that vote choices are highly partisan. We find that the moderate subset of the electorate responds to moderation and to candidate experience. As the old saying goes, ideologues may vote for a "blue dog" as long as that dog shares their views. But, the moderates in our analyses seem to care that the candidate is, in fact, a dog.

Because our results depend upon the mixture model we have developed, we present three analyses to demonstrate face validity of our estimates. First, we show that responses to a pair of minimum wage policy questions are consistent with what one should expect were our model differentiating respondents as intended. In Appendix C, we generalize this minimum wage analysis using all question pairs in a data set with 133 policy questions. Second, we use questions not included in our estimation to show that our classifications predict the likelihood of giving extreme liberal or extreme conservative responses. Third, we show that rates of support across different policy questions vary across our classifications as one would expect were the model differentiating respondents with views well-described by a single dimension from those with idiosyncratic preferences and those inattentive to the survey.

We present the validity analyses and several descriptive results first before turning to questions about electoral selection and accountability. Taken together, our analyses contribute to understanding of elections and public opinion and highlight the electoral importance of non-ideologues. We also hope that the continued application and adaptation of our measurement model will further improve our understanding of public opinion and voting behavior.

Background

Recent literature in political behavior and psychology gives the impression that many Americans identify strongly with political parties and political ideologies. Yet when asked in opinion surveys, roughly one in three typically self-identify as moderate and one in three as politically independent.[1] Some scholars argue that these self-identified moderates and independents are actually closet partisans, noting that they lean toward one party or another when nudged (Dennis, 1992; Keith et al., 1992). Others argue that because self-identified moderates are, on average, less educated, less informed, and less politically active, we should think of them as having no ideology (Kinder and Kalmoe, 2017).

[1] In the 2020 ANES time-series, 22.9 percent of respondents placed their ideology as "moderate or middle of the road" and another 17.1 percent responded that they hadn't thought much about ideology (using post-election full sample weights). Thirty-four percent responded "Independent or other party" to the first question of the party identification battery.

Instead of asking people to report their own ideology, other scholars assess ideology by aggregating responses to many questions on policy views (e.g., Ansolabehere, Rodden, and Snyder, 2006, 2008; Tausanovitch and Warshaw, 2013). These studies find that many people give a mix of liberal and conservative policy responses and conclude that the policy views of most Americans fall somewhere between the platforms of the major parties (e.g., Bafumi and Herron, 2010).

One limitation to methods that aggregate across multiple policy items is that there are different ways for an individual set of responses to appear moderate. People who are genuinely middle-of-the-road on most issues will be classified as moderates because they will give a mix of liberal and conservative responses on varying issues. For these genuine moderates, the pattern of responses will be predictable depending on how questions are asked and with what response options. For example, if genuine moderates were asked whether they would like to raise the federal minimum wage to $20/hour, they might give a "conservative" response opposing such a policy, while if they were asked whether they would like to lower the federal minimum wage to $5/hour, they might give the "liberal" response opposing such a policy.

But there are other kinds of individuals whose pattern of responses might also appear moderate after aggregation. For example, one might hold genuinely liberal and extreme positions on some issues and genuinely conservative and extreme positions on others. Such an individual, whom we would not classify as moderate, would give a mix of liberal and conservative responses and might be scored as a moderate just as a genuine centrist.

Still further problems arise if some survey respondents are simply inattentive, giving meaningless responses, perhaps because they're not paying attention to the survey or because they lack meaningful opinions (e.g., Zaller and Feldman, 1992). These people may likewise be inaccurately classified as moderates because they express a mix of liberal and conservative positions.

How serious a problem is this inability to disentangle different types of people who may get classified as moderates? Recent evidence suggests that there are many conflicted individuals with extreme views across issues poorly described by a single dimension of ideology (Ahler and Broockman, 2018; Broockman, 2016). Other research suggests a need to account for considerable heterogeneity among respondents in their patterns of survey responses (Baldassarri and Goldberg, 2014; Lauderdale, Hanretty, and Vivyan, 2018). What can be done, if anything, to better understand the composition of this significant group of Americans?

In this paper, we attempt to decompose apparent moderates into these three theoretical types by leveraging differences in patterns of survey responses. With enough policy items, the response patterns of genuine centrists will be more predictable than the response patterns of those who are inattentive or those who have idiosyncratic views. To estimate the distribution of three types using sets of response patterns to policy questions on different political surveys, we develop and implement a new mixture model that builds upon methods developed in the field of educational testing (e.g., Birnbaum, 1968).

Data and Measurement Model

Our method builds upon the conventional item-response theory (IRT) framework, which estimates a model of policy positions which arise from an underlying dimension of ideology (e.g., Clinton, Jackman, and Rivers, 2004). Instead of estimating an ideological location for each respondent as in the standard model, we estimate a mixture model where each respondent's pattern of responses is classified as coming from one of our three types. Among those who we classify as best described by the spatial model, we can calculate a most-likely ideal point given their pattern of responses. The model, however, does not use an individual ideal point when classifying each response pattern.

By embedding a conventional IRT model within a mixture model of survey responses, we estimate, for each respondent, a probability of being in each of three categories given their pattern of responses to the survey questions. Because no one has probability zero of having preferences consistent with the spatial model, we also calculate an a posteriori liberal-conservative ideology score for every respondent. Thus, our procedure gives us two substantively important quantities for each respondent. First, a trio of probabilities that responses come from (1) a spatial type, (2) an unsophisticated type, or (3) someone whose preferences are neither unsophisticated nor well-summarized by the spatial model; and second, an ideology score on the liberal-conservative dimension were the respondent to be a spatial type (#1 above). Both quantities are important in helping us decompose and understand public opinion.

Data

To estimate the IRT mixture model and classify individuals into these three types, we need data on policy positions across a range of issues for which people hold both liberal and conservative positions.

Our Monte Carlo simulations and out-of-sample tests reveal that we need at least 20 policy questions per respondent in order to obtain reliable estimates of type probability and ideal point (see Appendix B for details). Unfortunately, this means that we cannot apply our method to many political surveys of scholarly interest such as those analyzed by Broockman (2016).

Over the last decade or so, the Cooperative Congressional Election Study (CCES) has asked respondents an unusually large battery of policy questions. Therefore, we utilize data from all CCES common content surveys between 2012 and 2018, which include more than 280,000 respondents. We also analyze data from a 2010 CCES module (Stanford Team 3), which asked 133 different policy questions to 1,300 different respondents. Although the sample size of this module is small, the sheer number of policy questions allows us to more confidently characterize the positions of these respondents.

We focus on binary policy questions that are most easily accommodated in a statistical model. For example, many CCES questions ask respondents whether they support or oppose a particular policy or reform. If a policy question has multiple responses that are logically ordered, we turn it into a binary question by coding an indicator for whether a respondent's preferred position is above or below a particular cutoff.[2] Therefore, each observation of our data set is a respondent-question, where each respondent took one of two possible positions on each question.

Three Types of Respondents

Inspired by the literature on political preferences, we aim to classify respondents into three possible types. We note that these are stylized categories. No individual's policy positions will be perfectly described by an abstract model. However, to the extent that responses can be best explained and predicted by these different models of behavior, we hope to assess the substantive relevance of competing accounts in the literature. These classifications help us understand for whom and to what extent issue positions are meaningful and/or well-described by an underlying ideological dimension. Our model makes no a priori assumptions about the proportions of each type in the population.

Spatial or "Downsian" respondents: We refer to the first type of individuals as *Downsians* because of their relationship to the voters described in Downs (1957). These individuals have preferences across policy questions that are well-approximated by an ideal point on an underlying liberal-conservative ideological dimension (e.g., Bafumi and Herron, 2010; Hare, 2021; Jessee, 2012; Tausanovitch and Warshaw, 2013). We anticipate that there will be many liberal and conservative Downsians. Of greater interest here are moderate or centrist Downsians. Moderates will sometimes give liberal answers to policy questions and sometimes conservative answers, but the pattern of responses for Downsian moderates will be well-described by the same left-right dimension that explains responses of liberal and con-

[2] The selection of the cutoff to use is an arbitrary choice. We used our judgment in selecting the cutoff that we believed would be most informative about respondents' ideologies. We could have, alternatively, turned each of these questions into multiple binary items, but this would mechanically generate non-independence in the responses, which could make public opinion appear to be more structured than it is, so we instead turned each question into a single binary item.

servative Downsians.[3] In Appendix D, we present estimates from a two-dimensional model allowing Downsians to have two ideal points, one for each dimension.

We emphasize that a respondent need not literally conform to the Downsian model in order for our method to conclude that their positions are best described by this model. Indeed, we suspect that nobody answers policy questions by first recalling their ideological score and then mapping it onto the question, nor do we suspect that many people can articulate the ways in which their underlying values affect their positions across a range of issues. Nevertheless, it might be the case that the best way to predict and understand the policy positions of many individuals is by thinking of those individuals as having an underlying ideology that influences their positions across many political issues.

Furthermore, we should emphasize that our Downsian model allows for idiosyncratic variation in the way each individual answers each question. Previous research finds, for example, that we can better predict a respondent's policy position by using their response to the same question in the past than we can if we use their average ideology based on other responses (Lauderdale, Hanretty, and Vivyan, 2018). Similarly, experimental manipulation of a respondent's position on one question does not systematically appear to influence their position on other ideologically related questions (Coppock and Green, 2022). These studies demonstrate the existence of idiosyncratic variation in policy positions on single issues. Even so, the spatial model may better summarize one's full portfolio of issue positions relative to an alternative model.

Unsophisticated or "inattentive" respondents: A second set of respondents might choose responses to issue questions in an unsophisticated or meaningless way. Knowing how they answered one policy question will not help us predict how they answered other policy questions. We call these people *inattentive* respondents because it appears as though they

[3] The ideological locations of Downsians can be inferred using well-known statistical techniques and models first applied to inferring legislators' positions from roll call votes (for example, Poole and Rosenthal, 1985; Clinton, Jackman, and Rivers, 2004), and more recently to the mass public (for example, Gerber and Lewis, 2004; Jessee, 2012; Bafumi and Herron, 2010; Tausanovitch and Warshaw, 2013; Hill and Tausanovitch, 2015).

might not have policy preferences and therefore answer policy questions as if at random. Other respondents might be inattentive to the survey and select responses that do not necessarily coincide with their actual policy positions. For these respondents, the mix of liberal and conservative responses they give to survey questions does not reflect any stable feature of their preferences.

Idiosyncratic, unconstrained, or "Conversian" respondents: Unlike inattentives, the third set of respondents have expressed genuine positions. But, unlike Downsians, their positions are poorly-explained by an underlying left-right ideology. That is, their responses appear neither as-if generated at random nor do they follow a pattern well-summarized by an underlying liberal-conservative orientation. We call these individuals *Conversians* because they lack views well-explained by a single-dimensional model as in the argument made by Philip Converse that as "we move from the most sophisticated few ... the organization of more specific attitudes into wide-ranging belief systems is absent" (Converse, 1964, 30). These individuals might care only about a few issues (Hill, 2022) or might hold genuine preferences on multiple issues that are an idiosyncratic mix of liberal and conservative preferences (Broockman, 2016). Perhaps they support higher taxes to fund Social Security but believe the Medicare program should be repealed and are opposed to government regulation of business. These respondents are compelling in that they may not fit neatly within the confines of one of the two major parties. Their size and cross-pressure on issues makes them potentially important to election outcomes.

Our model of Conversian respondents is flexible and requires no assumptions about the logical or ideological connections between issues. In a sense, we can think of the Conversians as a category for the set of respondents who are neither giving a pattern of answers well explained by the spatial model nor a pattern that appears devoid of meaning.

A Simplified Example

To provide intuition for our subsequent statistical procedure and estimates, we present example patterns of survey responses for each of our three types. In Table 1, we consider a setting where individuals have reported their preference on each of three independent binary policy issues. Individuals either support the liberal (L) or conservative (C) position on each issue.

For exposition, we assume responses are perfect representations of preferences, i.e. no survey or measurement error. The issues have been ordered such that if a Downsian gives a conservative answer on issue one, he or she will necessarily give a conservative answer on issues two and three, and so on, such that the three questions divide Downsians at three points along the ideological spectrum. We have ordered the questions according to the popularity of the conservative response among Downsians—a quantity that will become important as we move through examples of each type. For the exposition, we have assumed we know the popularity of each issue. In our applications below, the model estimates popularity and relation to the liberal-conservative dimension for each issue.

With non-random responses and an ordering of policy positions from least to most conservative, we can use observed response patterns to identify individuals who are Downsians (well-represented by the spatial orientation of the issues) from individuals who are non-Downsians (not well-represented by the spatial orientation). In the left frame of Table 1, we enumerate the four possible Downsian response patterns for the three issues when ordered from least to most conservative. With perfect responding, the items make a Guttman scale (Guttman, 1944).

The patterns in the frame to the right are *inconsistent* with spatial preferences. The pattern in the first row has the respondent giving the liberal response on issues one and three and the conservative response on issue two. Likewise, the patterns in rows two, three, and four are inconsistent with individuals who hold spatial preferences on these issues.

Table 1 provides the basic intuition for how we distinguish Downsians from non-Downsians.

Table 1: Downsian versus non-Downsian response patterns with deterministic voting

Downsians					Non-Downsians				
		Issue					Issue		
Pattern	Description	1	2	3	Pattern	Description	1	2	3
1	Spatial liberal	L	L	L	5	Non-spatial	L	C	L
2	Spatial center-left	L	L	C	6	Non-spatial	C	L	C
3	Spatial center-right	L	C	C	7	Non-spatial	C	L	L
4	Spatial conservative	C	C	C	8	Non-spatial	C	C	L

Note: Issues numbered from least to most conservative support among Downsians.

We don't know, ex ante, how to order the questions ideologically (or which responses are liberal or conservative), but we can infer both from patterns of responses. If a respondent answers questions in a consistently liberal or conservative manner, they are likely a Downsian. If they give a mix of liberal or conservative responses, they could be either a Downsian or have non-Downsian preferences as described in the panels above. If there is a class of respondents who are neither consistently liberal nor consistently conservative but whose responses are well-classified by a Guttmann scale, they are more likely a Downsian moderate. The more a response profile conflicts with this Guttmann scale, the less likely they are to be Downsian.

Among these non-Downsians, we distinguish between two types: Conversian and inattentive types. An inattentive type should have a roughly equal probability of giving each response to each question. In contrast, Conversians discriminate between positions. Following this logic, we can calculate the relative likelihood that each non-Downsian response pattern was generated from a rate-0.5 Binomial distribution or from a set of preferences with rates not equal to 0.5. Conversian types are the residual category who do not appear to be responding randomly with probability 0.5 nor have a pattern of responses that maps well into the spatial dimension.

Measurement Model

Our statistical model uses patterns like those in Table 1 to estimate the item parameters of each policy question relative to an underlying ideological dimension. The model simultaneously estimates the probabilities that each respondent is Downsian, Conversian, or inattentive based upon how well-explained their issue responses are by the liberal-conservative dimension and how idiosyncratic their responses appear.[4] Our method then uses item parameters and individual response patterns to calculate the most likely ideal point on the ideological dimension that would have generated such a pattern of responses were the respondent a Downsian type.

Mixture model of issue opinion

Formally, we start with a set of respondents indexed $i = 1, \ldots, N$. Each of these respondents answers a (sub)set of binary issues questions indexed $j = 1, \ldots, J$. The likelihood of the ith respondent's answer to the jth question $y_{ij} \in \{0, 1\}$ depends on type $t = 1, 2, 3$.

For Downsian respondents, $t = 1$, we model their responses with the two-parameter IRT model described in Clinton, Jackman, and Rivers (2004). If respondent i is of type 1,

$$\Pr(y_{ij} = 1 | t = 1) = \Lambda(\beta_j(x_i - \alpha_j))$$

where Λ is the logistic cumulative distribution function, β_j and α_j are the so-called discrimination and cut-point parameters associated with the jth issue question, and x_i is the ideological position of the respondent. Assuming conditional independence across issue questions given the choice model, the Downsian likelihood of respondent i's vector of answers to the issue questions, $\boldsymbol{y}_{i\cdot}$ is

$$L_1(\boldsymbol{y}_{i\cdot}; \boldsymbol{\alpha}, \boldsymbol{\beta}) = \int \prod_{j \in \mathcal{J}_i} \Lambda\left(\beta_j(x - \alpha_j)\right)^{y_{ij}} \left(1 - \Lambda\left(\beta_j(x - \alpha_j)\right)\right)^{1 - y_{ij}} f(x) dx \qquad (1)$$

[4]Note that because each individual has a probability of each type, the combination of weights for Conversian and inattentive types can flexibly represent a variety of non-Downsian response patterns.

where $\mathcal{J}_i$ is the set of question indices corresponding to the issue questions answered by the ith respondent and f is the distribution of ideal points.[5] This approach of marginalizing over the ideal points was pioneered by Bock and Aitkin (1981) in the context of educational testing.[6] Marginalizing over the ideal points (x) allows us to estimate the probability of observing each vector of question responses conditional on the respondent i being of type 1 and, in turn, to apply Bayes rule to recover the probability that a respondent giving a particular set of responses is of type 1. We calculate an a posteriori ideal point for each respondent based on their issue question responses and estimates of α and β as described in Appendix A.

For inattentive respondents, $t = 2$,

$$Pr(y_{ij} = 1|t = 2) = 1/2$$

and the likelihood of the ith respondent's response pattern given that they are of the inattentive type is

$$L_3(\boldsymbol{y}_{i\cdot}) = (1/2)^{|\mathcal{J}_i|} \tag{2}$$

where $|\mathcal{J}_i|$ is the number of questions answered by the ith respondent.

For Conversian respondents, $t = 3$, responses are assumed to be independent across questions. Accordingly,

$$\Pr(y_{ij} = 1|t = 3) = \lambda_j$$

where λ_j is the probability that $y_{\cdot j}$ equals 1, equivalently the rate of support for response option one among Conversians. With independence across responses, the likelihood of indi-

[5] In some surveys that we consider, not every respondent is asked every issue question. Further, respondents may refrain from answering questions. We do not exclude these respondents from our analyses, and we consider all "missing" issue question responses to be missing at random (MAR) as is conventional in the empirical spatial voting literature (see Poole and Rosenthal, 2007, 273). A number of recent papers have evaluated the consequences of treating items as MAR (see, e.g., Goplerud, 2019; Rosas, Shomer, and Haptonstahl, 2015).

[6] The two-parameter Item Response Theory (IRT) model considered by Bock and Aitkin (1981) is equivalent to the model of voting described by Clinton, Jackman, and Rivers (2004) and employed here.

vidual i's vector of issue question answers given that they are Conversians is

$$L_2(\boldsymbol{y}_{i\cdot};\boldsymbol{\lambda}) = \prod_{j\in\mathcal{J}_i} {\lambda_j}^{y_{ij}}(1-\lambda_j)^{(1-y_{ij})}. \tag{3}$$

The marginal distribution of respondent i's vector of issue question responses across the three possible types is a mixture of the likelihoods of the three types and to estimating each respondent ideal point. In particular,

$$L(\boldsymbol{y}_{i\cdot};\boldsymbol{\alpha},\boldsymbol{\beta},\boldsymbol{\lambda},\bar{w}_1,\bar{w}_2,\bar{w}_3) = \bar{w}_1 L_1(\boldsymbol{y}_{i\cdot};\boldsymbol{\alpha},\boldsymbol{\beta}) + \bar{w}_2 L_2(\boldsymbol{y}_{i\cdot};\boldsymbol{\lambda}) + \bar{w}_3 L_3(\boldsymbol{y}_{i\cdot}) \tag{4}$$

where $\bar{w}_t$ is the fraction of the sample of type t and $\sum_t \bar{w}_t = 1$. Assuming independence across respondents, the overall likelihood is

$$L = \prod_i L(\boldsymbol{y}_{i\cdot};\boldsymbol{\alpha},\boldsymbol{\beta},\boldsymbol{\lambda},\bar{w}_1,\bar{w}_2,\bar{w}_3). \tag{5}$$

We maximize over all of the parameters using the usual EM approach to the estimation of finite mixture models as described in the Appendix.

Having estimated model parameters, we take an empirical Bayes approach to the estimation of the probability that each respondent is of each of the three types. In particular, using Bayes rule, the ith respondent's estimated probability of being of type t is

$$\hat{w}_{it} = \frac{\hat{\bar{w}}_t L_t(\boldsymbol{y}_{i\cdot};\hat{\boldsymbol{\alpha}},\hat{\boldsymbol{\beta}},\hat{\boldsymbol{\lambda}})}{\sum_{t'} \hat{\bar{w}}_{t'} L_{t'}(\boldsymbol{y}_{i\cdot};\hat{\boldsymbol{\alpha}},\hat{\boldsymbol{\beta}},\hat{\boldsymbol{\lambda}})}$$

where the hatted quantities represent estimates.

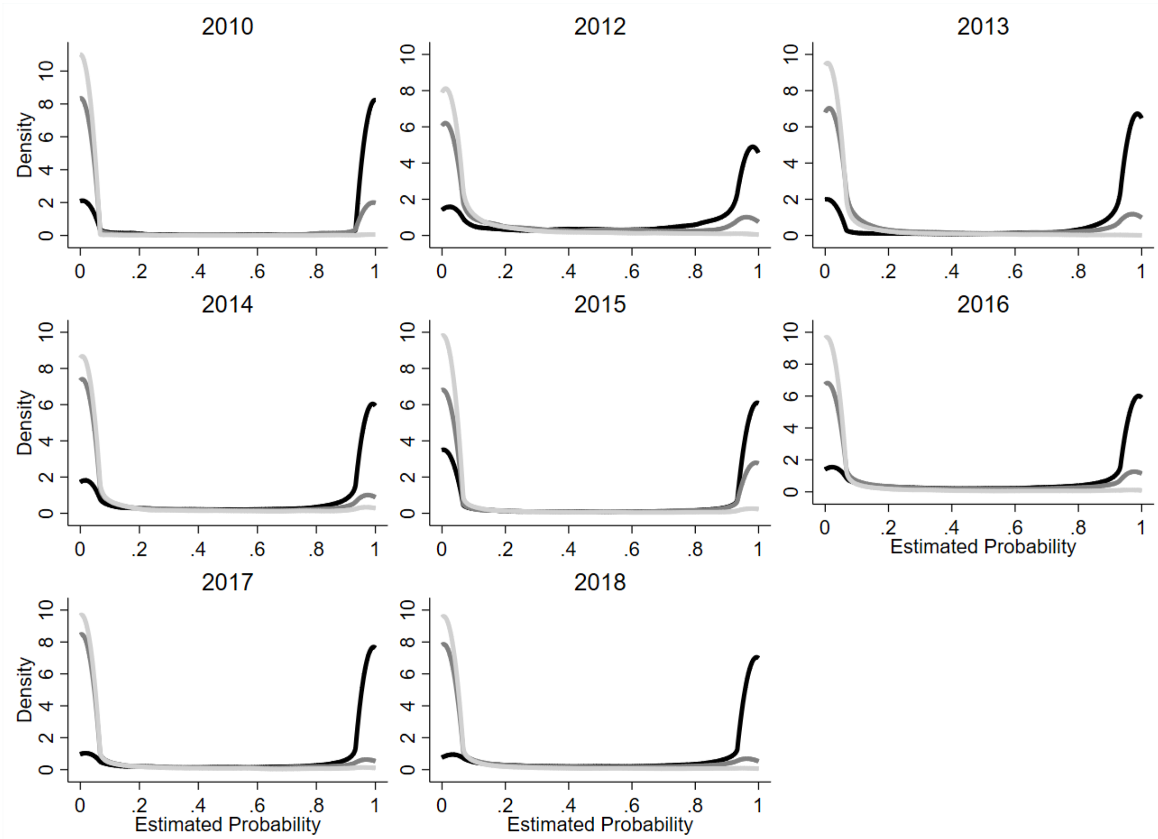
It is worth pointing out here that the algorithm does not proceed in stages by first identifying Downsians and then distinguishing Conversian and inattentive respondents. Our procedure estimates all parameters in an EM algorithm, finding: (1) estimated Conversian response rates λ for each question conditional on estimates of Conversian-type probability for each respondent, and (2) estimated population fraction of each type, given item response estimates α and β, Conversian rates λ, and observed data (pattern of responses for each respondent).

One potential concern is that respondents could be overfit into the Conversian or Downsian categories since each respondent's responses contribute to the estimated Conversian weights and the estimated Downsian cutpoints and discrimination parameters. However, because we have tens of thousands of respondents per survey, the contribution of any one individual to these estimates is negligible. Furthermore, because we have at least 20 questions per survey and because our Downsian model imposes relatively strong assumptions about how item parameters and ideal points map into response probabilities, an idiosyncratic response pattern is unlikely to be wrongly classified as Downsian. Our Monte Carlo simulations in the Appendix demonstrate that with a sufficient number of respondents and policy questions, our procedure does not meaningfully under- or over-estimate the shares of each group.

Estimated type probabilities

Figure 1 shows the Empirical Bayes estimated probabilities that each respondent is a Downsian (black), Conversian (dark gray), and inattentive (light gray) type after implementing our method for different data sets. We see that most respondents are classified into one of the three groups with high probability. Forty-eight percent of respondents have an estimated probability greater than .99, 66 percent exceed .95, and 74 percent exceed .9.

Figure 1: Distributions of Estimated Probabilities



The figure shows kernel density plots (bandwith = .03) of estimated probabilities that each respondent is a Downsian (black), Conversian (dark gray), and inattentive (light gray) type.

Descriptive Results: Who are the Genuine Moderates?

This section provides our descriptive results. First, we present several assessments of the validity of our estimates. Next, we discuss the response profiles of people in our three categories on several issue questions in the CCES survey data. Then, we provide descriptive results on the prevalence and characteristics of moderates. Finally, we discuss differences in electoral behavior across types.

Validating Our Estimates

The 2010 CCES module asked two questions about the minimum wage that elicit substantively meaningful variation in a policy view. Although these two questions were included in our mixture model estimation, they were but two of 133 questions for that module and so of only minor influence on results.

One question asked respondents whether they would support eliminating the minimum wage. A second question asked about support for raising the minimum wage to 15 dollars per hour. With two binary questions, each respondent could take one of four different positions: the most conservative position supporting eliminating the minimum wage and not raising it to 15 dollars, the most liberal position supporting the increase to 15 dollars and not eliminating it, a moderate position supporting neither change, or the incoherent position of supporting both the elimination of the minimum wage and its increase to 15 dollars.

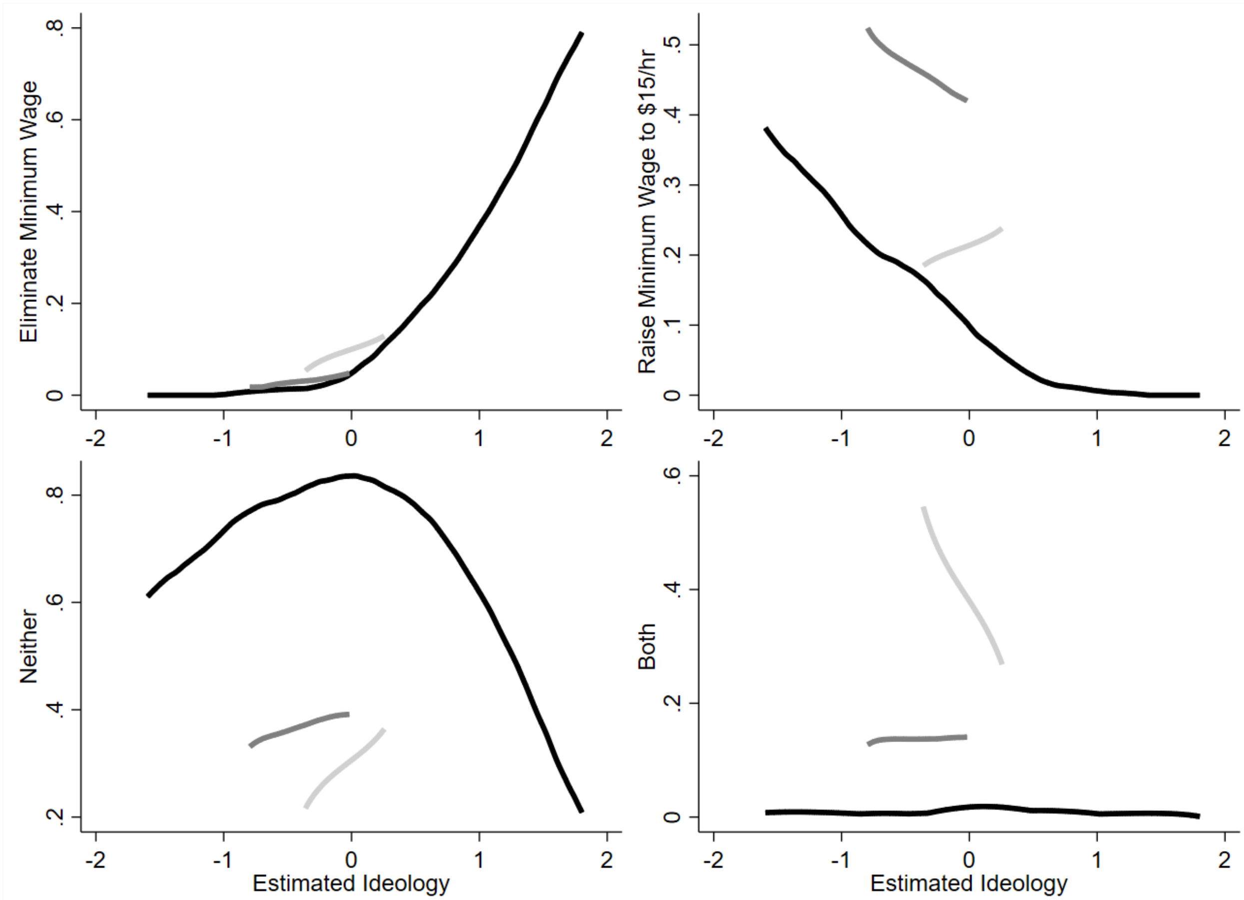
Figure 2 shows the probability that each type of respondent, as classified by the mixture model, took each possible set of positions. For each panel, we use kernel regression to estimate the probability of taking that minimum wage position (1=yes, 0=no) across estimated ideological scores for each type. Each respondent is classified according to their highest probability, Downsians in black, Conversians dark gray, and inattentives light gray.

As we would expect, the top-left panel of Figure 2 shows that Downsian conservatives are much more likely than other Downsians to support eliminating the minimum wage, and the top-right panel shows that Downsian liberals are much more likely to support raising the minimum wage to 15 dollars. If our method correctly identifies moderates, we should see that Downsians with moderate ideological scores are much more likely than other groups to support neither reform, which is exactly what we find in the bottom-left panel.

Conversians look like extreme liberals on this particular question. In fact, they are more likely to support a 15 dollar minimum wage than Downsian liberals. Of course, they are not liberal in all policy domains, otherwise, they would be classified as Downsian liberals. This illustrates that our mixture model does not require that Conversians be centrist on every policy.

Lastly, we would hope that the model would classify as inattentive those most likely to take the seemingly incoherent position that they would like to eliminate the minimum wage

Figure 2: Minimum wage positions across respondent types



Kernel regressions (bandwith = .03) of different positions on two minimum wage questions in the 2010 CCES module by a posteriori ideology. Separate plots are shown for Downsian (black), Conversian (dark gray), and inattentive (light gray) respondents. The top-left panel shows support for eliminating the minimum wage and not raising it to 15 dollars. The top-right panel shows support for an increase to 15 dollars and not eliminating. The bottom-left panel shows support for neither reform, and the bottom-right panel shows support for both reforms.

and raise it to 15 dollars. This is exactly what we find in the bottom-right panel of Figure 2. There are few inattentive respondents in this sample – 770 respondents answered both minimum wage questions and only 10 are classified as inattentive. Nevertheless, inattentive respondents are about equally likely to take any of the four positions. This is consistent with having either no meaningful position on minimum wage or answering survey questions without care.

We picked the minimum wage example for it's intuitive simplicity. In order to show that we have not cherry-picked this example, we conduct a similar analysis in Appendix C across the 133 questions and 13,225 question pairs. This analysis demonstrates a similar pattern to the minimum wage result.

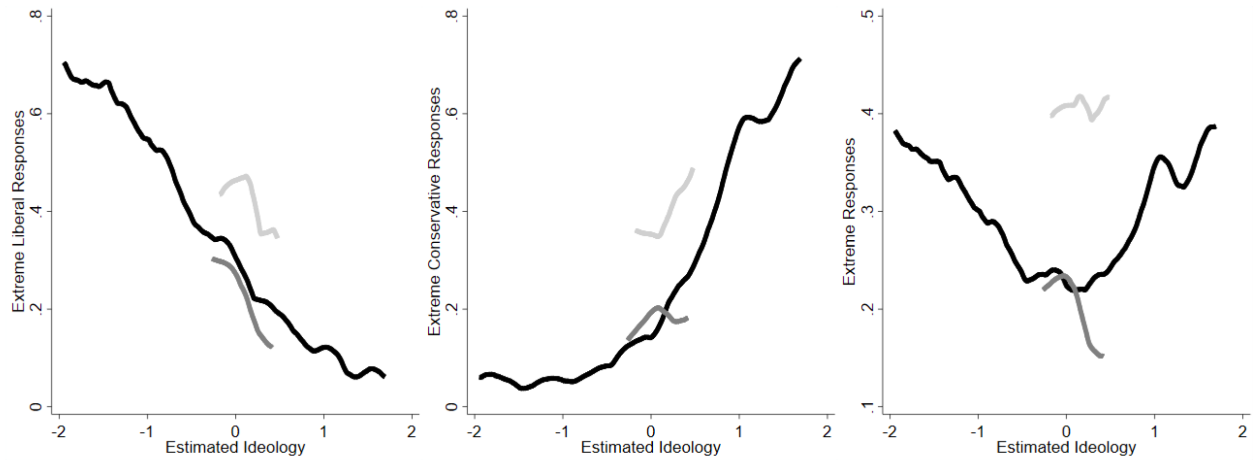
As a second validation for our estimates, and to assess the extent to which different respondent types hold extreme views, we examine responses to binary policy questions from the UCLA, UCSD, and MIT modules of the 2014 CCES. These modules contained a large number of binary policy questions but were asked to 2,584 out of 56,200 2014 CCES respondents. We did not use these items in the mixture model due to the small number of respondents so these responses provide an opportunity to evaluate out-of-sample validity of our estimates.

Our aim is to assess the frequency with which different types of individuals hold extreme policy positions. We classify a policy position as extreme if, in a binary question, that position was taken by less than 35 percent of all respondents. This classification is admittedly arbitrary. More stringent classifications would significantly reduce the sample of policy questions for which an extreme response is possible. Following Broockman (2016), we consider how the frequency of extreme positions varies across estimated ideologies. As before, we do this separately for Downsian, Conversian, and inattentive respondents, classifying each individual according to their highest posterior probability.

The left panel of Figure 3 presents kernel regressions of the proportion of extreme liberal positions taken by each respondent on questions for which an extreme liberal position was possible (meaning that the more liberal option was selected by less than 35 percent of respondents). The center panel shows the analogous plots for extreme conservative responses and the right panel the average of the two proportions from the other panels. This right panel measures the total frequency with which different respondents take extreme positions.[7]

[7]For our sample of policy questions and our definition of extreme positions, there are more questions for which an extreme conservative response is possible than questions for which an extreme liberal response is possible. This is why, in the right panel of Figure 3, we compute the average of the proportion of extreme liberal responses and the proportion of extreme conservative responses. If we had alternatively shown the

Figure 3: Extreme responses across respondent types



Kernel regressions (bandwith = .01) of extreme policy positions by estimated ideology using out-of-sample questions. Separate plots are shown for Downsian (black), Conversian (dark gray), and inattentive (light gray) types. Extreme positions are defined as responses to binary policy questions that are supported by less than 35 percent of respondents. The left panel examines the proportion of extreme liberal responses when such a response is possible. The center panel show the analogous proportion of extreme conservative responses. The right panel shows the sum of these two proportions.

As we would expect if our model correctly classifies respondents, liberal Downsians are more likely to hold extreme liberal positions, and conservative Downsians are more likely to hold extreme conservative positions. These results lend support to the model with out-of-sample policy questions.

Looking at the right panel, we find that moderate Downsians are, overall, much less likely to hold extreme positions than liberals or conservatives. This result contrasts with that of Broockman (2016) who finds that estimated ideology is uncorrelated with extreme positions. Our decomposition of moderates into the three types might explain these different results. By examining the inattentive respondents (light gray), we see they are are indeed more likely to provide extreme responses than even extreme liberal or conservative respondents. If we had not separately modeled these individuals as inattentive and instead classified them as moderate Downsians, we could overstate the extent to which people in the middle hold

overall proportion of extreme responses, it would appear that conservatives are more likely to hold extreme positions, but this would be an artifact of our sample of questions.

extreme positions.

Figure 3 also finds that Conversians are not especially likely to hold extreme positions for this particular set of questions. Therefore, although Conversians can hold outlying views, as we found with the minimum wage questions, they appear not to be conflicted extremists as a general matter (given the questions in this sample).

Issue Profiles of Respondents in Various Categories

To provide more validation and intuition for our estimates, we present differences across our categories on fourteen policy questions from the 2016, 2017, and 2018 CCES surveys. For simplicity, we put every respondent into one of five categories. First, we assign each respondent to their highest-probability type (Downsian, Conversian, or inattentive). Second, we break Downsians into thirds, most liberal, centrist, and most conservative.

We sort the fourteen policy items in Table 2 by the percentage of the public that supports the conservative option. The table shows that supermajorities of conservative and liberal Downsians select the conservative and liberal option on most questions. Downsian moderates are always somewhere between the liberal and conservative poles. On some questions, most moderates support the liberal response while on others, a majority of moderates support the conservative option.

In contrast, we find little consistent relationship between Conversian response patterns and either overall support for a position or the response patterns of liberal and conservative Downsians. For instance, Conversians give conservative answers on abortion and liberal answers on minimum wage.

Inattentive respondents are roughly equally likely to pick the liberal or conservative policy option regardless of overall population support. For instance, 48% support withdrawing from the Paris Climate Agreement, 48% support eliminating income taxes, and 54% oppose using Medicaid for abortion.

The descriptive statistics suggest that many of the Conversians we identify might be

Table 2: Issue Profiles Across Categories in 2016, 2017, and 2018 CCES. The table shows the share of respondents in each category giving the conservative response to each question.

		Downsian:				
Item	Overall	Conservative	Moderate	Liberal	Conversian	Inattentive
Three Strikes & Out Prison Sent.	.85	.95	.87	.72	.94	.39
Buy & Hire American	.75	.96	.93	.54	.46	.55
Ban Late-Term Abortion	.65	.89	.63	.31	.85	.42
Don't Publish Gun Owner Names	.59	.81	.58	.41	.58	.47
Don't Use Medicaid for Abortion	.58	.92	.53	.11	.93	.54
Repeal ACA	.50	.94	.48	.04	.57	.50
Eliminate Income Tax	.47	.67	.49	.22	.51	.48
Environmental Enforcement	.43	.94	.43	.03	.26	.55
Withdraw Paris Climate Agreement	.41	.97	.29	.01	.35	.48
Same-Sex Marriage	.39	.70	.22	.05	.55	.61
Assault Weapon Ban	.36	.74	.30	.07	.27	.64
Don't Increase Minimum Wage	.32	.74	.20	.04	.19	.39
Make Abortions Illegal	.18	.27	.07	.02	.35	.48
Body Cameras on Police	.12	.24	.10	.07	.07	.47

better summarized by two ideological dimensions. Perhaps many are liberal on economic policy and conservative on social policy. Indeed, when we implement a two-dimensional version of our mixture model (Appendix D), allowing Downsians to be described by ideal points in each of two dimensions, the estimated share of Conversians decreases. Rather than having completely idiosyncratic preferences, many of the respondents we classify as Conversian in a one-dimensional model have views that can be summarized by a spatial model with two ideological dimensions. This suggests public opinion might be more structured than the Conversian count implies.

The Prevalence of Moderates

Here we provide descriptive results on the prevalence and characteristics of our different respondent types. In total, we have estimates for 285,485 survey respondents (Table 3).[8] Pooling across all data sets, we estimate that 72.8 percent of respondents have positions well-

[8] We weight respondents according to the survey weights delivered with each data set with the goal of obtaining estimates for a nationally representative sample.

described by the spatial dimension — Downsians. Perhaps reassuringly, the one-dimensional ideological model that is standard in many empirical and theoretical literatures provides the best model of the views of more than 7 in 10 Americans across our samples.

Table 3: Average Estimates across Data Sources

Data Source	N	E[Downsian]	E[Conversian]	E[Inattentive]
CCES 2010 (module)	1,300	.771	.220	.009
CCES 2012	54,535	.683	.231	.085
CCES 2013	16,400	.752	.209	.039
CCES 2014	56,200	.707	.194	.099
CCES 2015	14,250	.621	.323	.056
CCES 2016	64,600	.716	.235	.049
CCES 2017	18,200	.815	.135	.050
CCES 2018	60,000	.791	.161	.048
Pooled	285,485	.728	.207	.065

Almost 3 in 10 Americans, however, are better described as Conversian or inattentive. We estimate that approximately 1 in 5 Americans expresses policy views that are neither well described by a single left-right ideological dimension nor best classified as random — Conversians. Other studies that assume that everyone is a Downsian miss this important and politically interesting group. Our method allows scholars to identify them using patterns of policy responses found in traditional political surveys.

Lastly, we find that 6.5 percent of CCES respondents are inattentive. Reassuringly for survey researchers, this number is small, but it would be inappropriate to assume that these respondents are moderate Downsians.

That said, we classify less than 1 percent of respondents as inattentive in the 2010 module where we have 133 policy questions. One possible interpretation is that the inattentive model does not accurately describe the behavior of many respondents and, as the number of questions increases, the share of individuals wrongly classified as inattentive shrinks. Another possibility is that the 2010 module, with its unusually large number of policy questions, changed the behavior of respondents.[9]

[9] We also considered the possibility that many of the people who would have been classified as inattentive

Next, we ask whether conventional inferences about the distribution of ideologies in the population are meaningfully biased because nearly 3 in 10 respondents are not well-described by the spatial model. Ansolabehere, Rodden, and Snyder (2006) argue that America is purple with a unimodal distribution of ideologies and with most of the public well between the positions of Democratic and Republican party leaders. But as Broockman (2016) points out, many survey respondents who appear to be moderate in the sense that they give a mix of liberal and conservative responses may be misclassified. Our decomposition method allows us to remove these individuals. Is America still "purple" if we focus only on the Downsians?

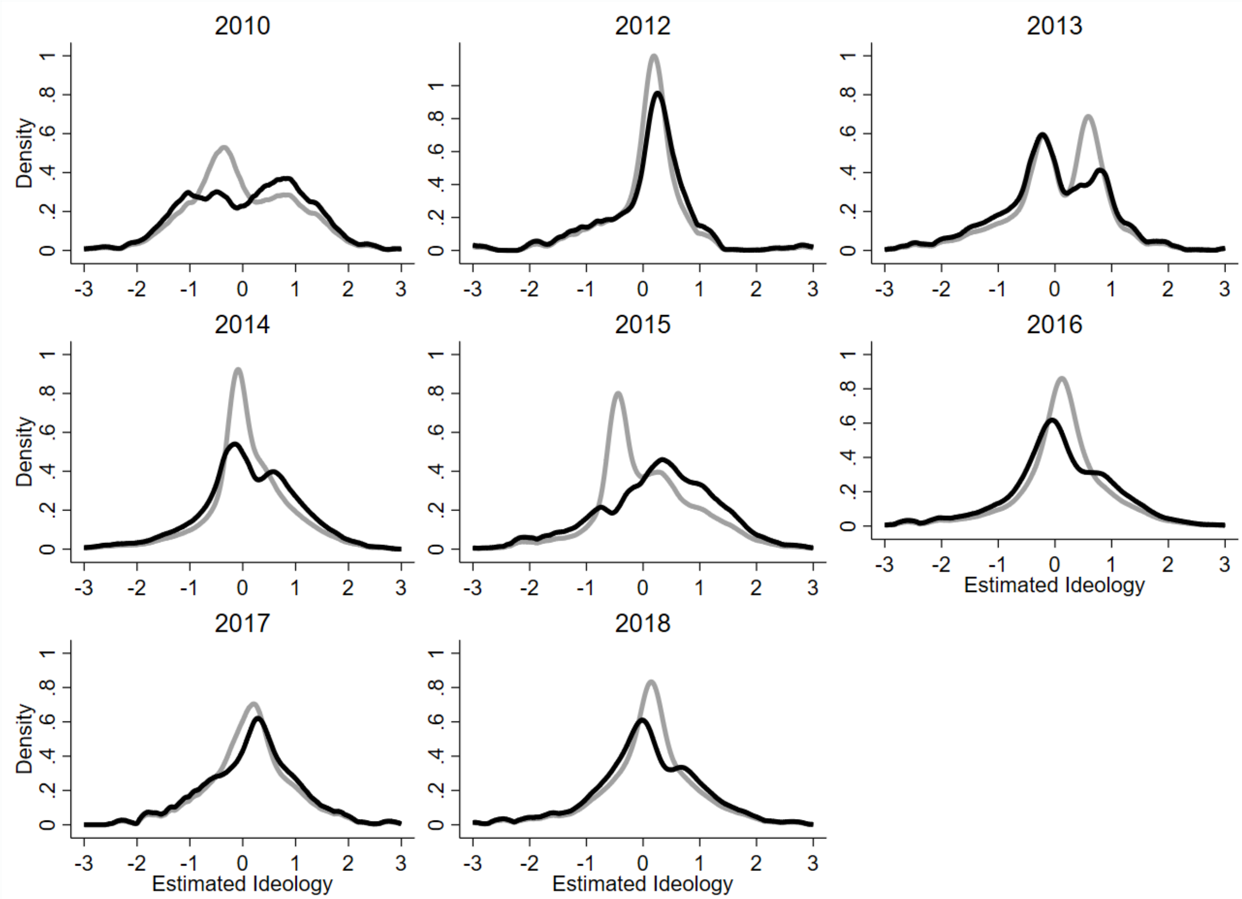
In Figure 4, we replicate the analyses of Ansolabehere, Rodden, and Snyder (2006). Figure 4 shows the distributions of estimated ideology in each of our data sets using kernel density plots (bandwidths set to 0.1). For each data set, we scale the estimated ideologies such that the mean is 0 and the standard deviation is 1. The gray curves show the distribution of estimated ideology across all respondents—as in Ansolabehere, Rodden, and Snyder (2006). The black curves estimate the distribution weighted by the probability of being a Downsian.

While America still looks purple when we discard the respondents who might be inaccurately characterized as moderates, there are important differences in the overall characterization of the population. Most notably, the naive analysis overstates moderation and understates extremism. When we focus on Downsians, we see relatively fewer respondents in the middle and relatively more in the tails. That said, the differences are not so dramatic as to make the population distribution look anything like the distribution of ideology in the United States Congress.

For those respondents who appear moderate based on their mix of liberal and conservative policy responses, how many are genuine Downsian moderates as we define them? Figure 5 presents kernel regressions of the proportion of respondents who are Downsian (black),

dropped out of this module because they didn't want to answer so many policy questions. However, if we apply our model to the CCES 2010 Common Content (which had too few policy questions to include in our other analyses), those who completed the module were not less likely than other respondents to be classified as inattentive.

Figure 4: Distributions of Ideology for All Respondents and for Downsians

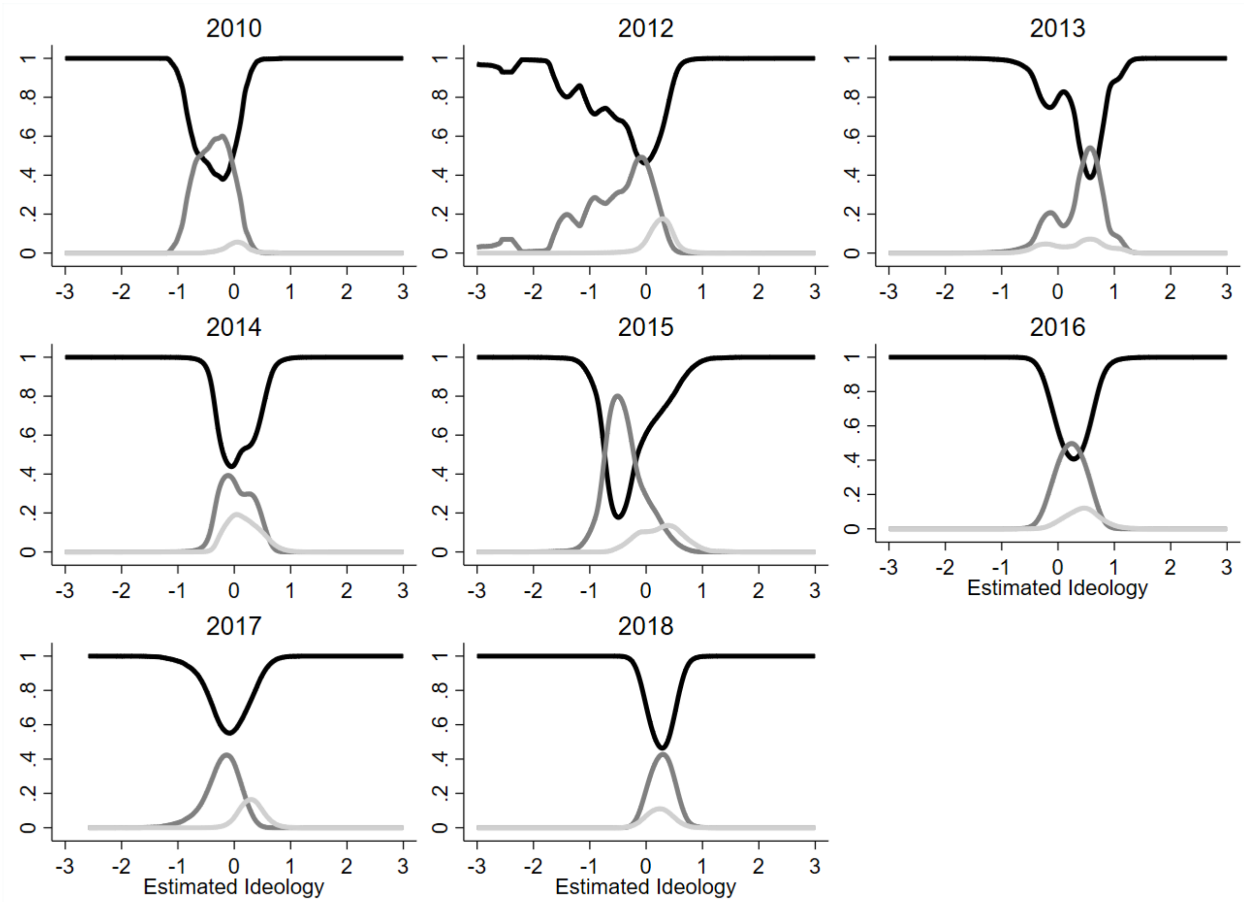


Kernel density plots (bandwith = 0.1) of estimated ideology for all respondents (gray) and for respondents weighted by their probability of being Downsian (black).

Conversian (dark gray), and inattentive (light gray) across estimated left-right scores for each of the data sets. Figure 5 shows that the probability of being a Downsian is very close to 1 for almost all respondents with estimated scores more than one standard deviation from the mean. This is not so much an empirical result as it is a mechanical implication of our assumptions.

If, however, we focus on estimated ideologies close to the mean, the average probability of being a Downsian remains above one-half for most ideal points in every data set. The probability of being a Conversian is just under one-half, and the probability of being inattentive is small. A large share—but by no means all—of those who appear moderate based

Figure 5: Respondent Type Probabilities by Estimated Ideology



Kernel regressions (bandwidth = 0.1) of Downsian (black), Conversian (dark gray), and inattentive (light gray) respondents across a posteriori Downsian ideologies.

on a left-right one-dimensional score are moderates with genuinely spatial preferences.

Differences in Electoral Attitudes and Behavior Across Types

To examine distinguishing features of moderates of all types, we focus on the 2016 CCES. This data set has a large sample size, a large number of policy questions, and several questions on electoral attitudes and behaviors of interest. In Figure 6, we plot kernel regressions of each attitude and behavior by estimated ideology separately for each type. We examine self-reported political interest, whether a respondent correctly identified the party controlling the House and Senate, whether they report reading a newspaper, voter registration, voter turnout in 2016, whether they report making a political donation, whether they report being contacted by a campaign or political group, whether they switched from supporting Obama in 2012 to Trump in 2016, whether they switched from supporting Romney in 2012 to Clinton in 2016, self-reported party identification, and self-reported ideology.

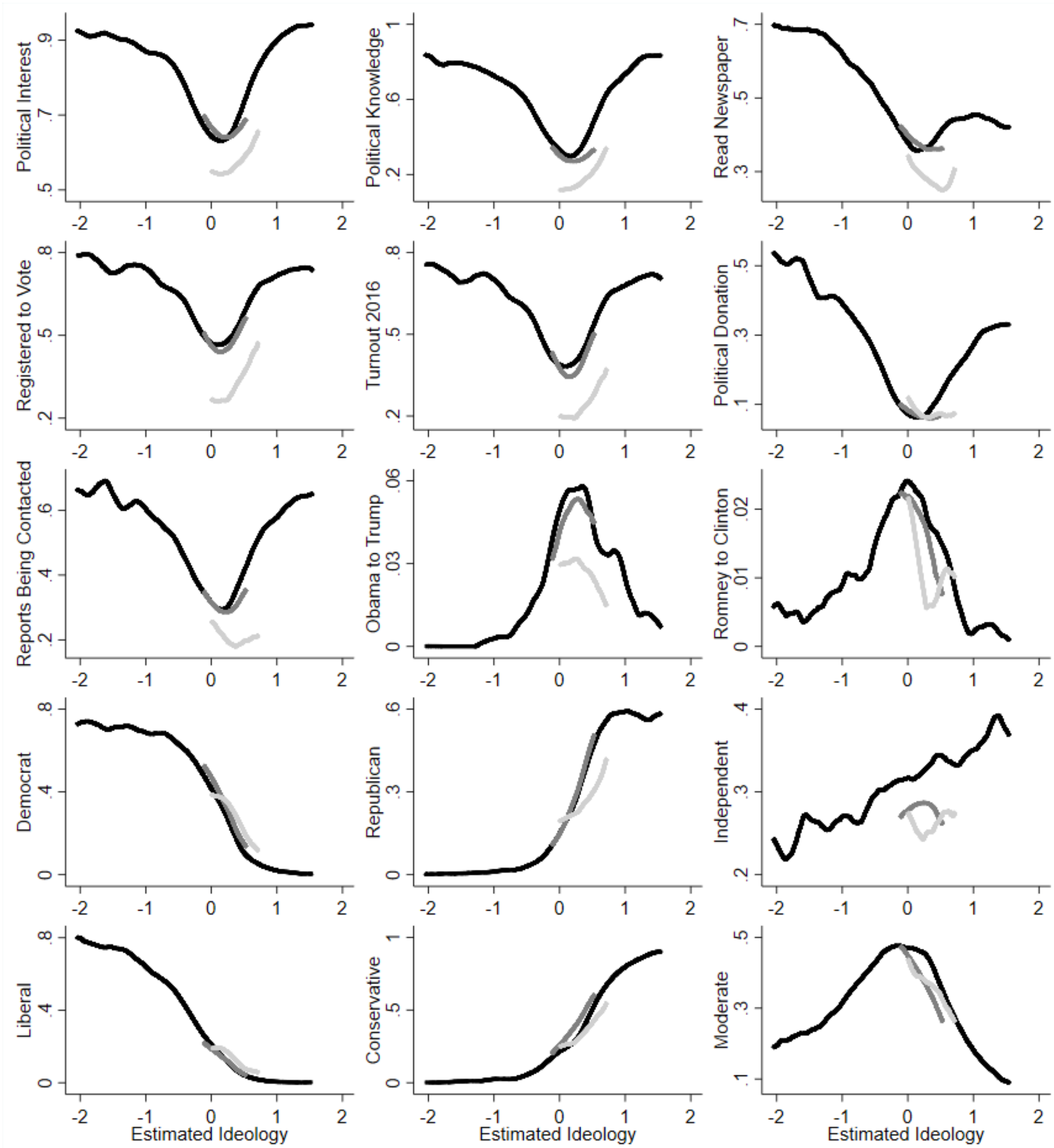
One caveat to these analyses is that if the inattentive respondents provide approximately meaningless responses to policy questions, perhaps they also provide meaningless responses to questions about their political behavior, knowledge, or identification. Survey researchers have found that factual recall questions are much easier for survey respondents than opinion or attitude questions (see, e.g., Tourangeau, Rips, and Rasinski, 2000), so careless answers to policy questions does not necessarily imply inaccurate answers to questions about, for example, vote choices or news consumption. That said, we advise caution in analyzing and interpreting the reported behaviors of inattentive respondents.

Ideologues, that is those who are Downsians with ideologies far from the mean, have higher levels of political interest and participation than all other types; and they are less likely to report having switched their party vote between 2012 and 2016. Downsian moderates have somewhat higher levels of political knowledge and participation and are more likely to have switched the party they voted for between 2012 and 2016 relative to Conversian or inattentive types. The inattentive respondents show the lowest levels of political participation and interest.

The results on vote switching are particularly important. Although few people change the party they support between presidential elections, those few who do may determine who wins elections. Downsian moderates make up a large share of this group. Among those who switched between the 2012 and 2016 presidential elections, 65 percent are Downsians with mostly moderate ideological scores, 32 percent Conversians, and 3 percent inattentive.

Finally, the last two rows of Figure 6 show that our estimates correspond with self-reported partisan leanings and ideologies. Estimated ideologies correspond strongly with the probability that a respondent self-identifies as a Democrat, Republican, liberal, or conserva-

Figure 6: Electoral Attitudes and Behavior across Types



Kernel regressions (bandwidth = .1) of electoral attitudes and behaviors across estimated ideologies for Downsian (black), Conversian (dark gray), and inattentive (light gray) respondents in the 2016 CCES.

tive. Those with moderate estimated ideologies are more likely to identify as independent or moderate. And providing some external validation of our estimates, among those who appear moderate, the Downsians are more likely to identify as independent or moderate than the Conversian or inattentive respondents.

In Appendix F, we show how our classifications and estimates relate to respondent demographics such as race, gender, age, income, education, and church attendance.

Who Drives Electoral Selection and Accountability?

Perhaps more important than the prevalence of moderates is the extent to which they are politically consequential. We saw in Figure 6 that those in the middle of the ideological spectrum were most likely to report changing their party support between the 2012 and 2016 presidential elections. Are moderates more responsive to the abilities, positions, and effort of candidates? If so, what are the implications for electoral selection and accountability?

Research Design

To address these questions, we merge our estimates for CCES respondents from 2012, 2014, 2016, and 2018 with information about the various U.S. House races in each respondent's district. We use data obtained from Gary Jacobson on incumbency status and the previous political experience of the major candidates (see, e.g., Jacobson, 2015). We also use estimates from Bonica (2014) that use campaign finance data to approximate the ideologies of the candidates running in each race (CF Scores).

As before, we group survey respondents into the five categories liberal, moderate, conservative, Conversian, and inattentive. Using the contextual variables about each House race, we estimate how each group responds to candidate experience and candidate ideology.

Our outcome is a variable that captures the self-reported vote choice of each respondent in their Congressional race. This variable takes a value of 1 if the respondent voted for the Democratic candidate, 0 if they voted for the Republican, and 0.5 if they abstained or supported a third-party candidate.

Because our independent variables could potentially influence turnout, we do not drop abstainers as this could induce bias. Instead, we code abstention and supporting a third-party candidate as being half way between voting for the Democratic and Republican candidates. We do this out of substantive interest because this trichotomous variable captures the extent to which each voter contributes to the vote margin or the two-party vote share. Therefore, our subsequent results tell us about the extent to which our independent variables ultimately influence election results through both turnout and vote choice. In Appendix E, we present results from additional analyses that utilize turnout and vote choice conditional on turnout as separate dependent variables.

To measure the ideological character of each contest, we compute the midpoint of the CF Scores (Bonica, 2014) of the two major candidates. Because higher CF Scores correspond to more conservative policy positions, a higher midpoint means that the Democrat is more centrist than normal, the Republican is more conservative than normal, or some combination of the two. If moderation is electorally beneficial for a party or candidate, we should see Democratic support increase as the midpoint increases. We re-scale midpoints so that the 5th percentile is 0 and the 95th percentile is 1 so that coefficients can be interpreted as the effect of shifting from a situation in which the candidate ideologies favor the Republican to a situation in which the ideologies favor the Democrat.

To capture the electoral advantage of a more experienced candidate and incumbency, we code an experience variable 1 if the Democratic candidate has previously held elective office but the Republican candidate has not, 0 if the Republican has held office but the Democrat has not, and 0.5 if neither or both have held office. We code an incumbency variable 1 if the Democratic candidate is an incumbent, 0 if the Republican candidate is an incumbent, and 0.5 for an open seat race.

To estimate heterogeneity in response to ideology, candidate experience, or incumbency by type, we regress the vote choice variable on indicators for each type, the contextual variable, and the interaction between contextual variable and the type indicators. Coefficients on the interaction terms tell us the extent to which that type responds differently relative to an omitted category.

Our simplest specification includes election-year fixed effects to account for the fact that some years are better for Democrats or Republicans. In a second specification, we add district fixed effects to account for the fact that some districts are generally more Democratic or Republican than others. In our most demanding specification, we include district-year fixed effects, which account for idiosyncratic differences across different Congressional contests that affect all types equally. District-year fixed effects subsume the main effect associated with ideology or experience, but we can still identify the interactive coefficients from cases where multiple respondents of different types answered a survey in the same district and year.

Results on Selection and Accountability

Table 4 presents the results of these analyses. To keep the table compact, we separate each contextual variable into trios of columns and indicate that contextual variable with an "X" in the rows. So, for column one, the X coefficient of 0.2 is the average effect of the ideological midpoint on vote choice for Liberals, because Liberals are the omitted category. The interaction coefficients tell us how much more or less each group responds to the ideological midpoint relative to Liberals.

We find that Downsian moderates and Conversians are notably more responsive to the ideological positions, candidate experience, and incumbency of candidates than those of the other three types. The point estimates indicate that Conversians are most responsive, followed closely by Downsian moderates.

Although inattentive respondents are less responsive than moderates and Conversians, we find that they are still more responsive than liberals and conservatives. This may be surprising for several reasons. First, if inattentive respondents are giving meaningless answers to policy questions, perhaps we should not trust them to honestly report their voting

Table 4: How Do Different Types Respond to Candidate Characteristics?

	DV = House Vote (Dem = 1, Rep = 0, Abstain/Other = .5)								
	X = Ideological Midpoint			X = Incumbency			X = Experience		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
X*Moderate	.057	.056	.057	.073	.074	.073	.070	.072	.071
	(.013)	(.012)	(.012)	(.008)	(.008)	(.008)	(.008)	(.009)	(.009)
X*Conversian	.080	.079	.082	.087	.085	.082	.084	.082	.079
	(.014)	(.013)	(.013)	(.008)	(.009)	(.009)	(.009)	(.009)	(.009)
X*Inattentive	.040	.035	.039	.053	.045	.039	.048	.040	.032
	(.020)	(.019)	(.019)	(.013)	(.013)	(.013)	(.013)	(.013)	(.013)
X*Conservative	.025	.024	.026	.015	.021	.020	.008	.016	.015
	(.014)	(.014)	(.015)	(.011)	(.012)	(.012)	(.012)	(.012)	(.013)
X	.020	-.017		.067	-.003		.070	-.012	
	(.009)	(.010)		(.006)	(.011)		(.007)	(.010)	
Moderate	-.354	-.347	-.347	-.333	-.331	-.329	-.333	-.331	-.330
	(.007)	(.007)	(.007)	(.006)	(.006)	(.006)	(.006)	(.006)	(.006)
Conversian	-.339	-.332	-.335	-.313	-.311	-.311	-.314	-.311	-.311
	(.008)	(.008)	(.008)	(.006)	(.006)	(.006)	(.006)	(.006)	(.006)
Inattentive	-.356	-.348	-.351	-.336	-.332	-.332	-.335	-.330	-.329
	(.011)	(.011)	(.011)	(.008)	(.008)	(.008)	(.009)	(.009)	(.009)
Conservative	-.707	-.694	-.694	-.657	-.653	-.651	-.655	-.651	-.649
	(.008)	(.008)	(.008)	(.007)	(.007)	(.007)	(.007)	(.008)	(.007)
Year FEs	✓	✓		✓	✓		✓	✓	
District FEs		✓			✓			✓	
District-Year FEs			✓			✓			✓
Observations	159,006	159,006	159,006	233,445	233,445	233,445	233,445	233,445	233,445

District-clustered standard errors in parentheses. Liberals are the omitted category.

behavior. Second, if these respondents are inattentive to political surveys, perhaps we would expect them to also be inattentive to the characteristics of political candidates. On the other hand, it may be easier for respondents to report how they voted than it is to answer policy questions. And just because someone is inattentive to policy questions in a survey, does not necessarily mean they are inattentive to politics in general or unable to utilize cues. Indeed, many political behavior scholars have argued that relatively unsophisticated voters observe candidate characteristics and performance and vote accordingly (see, e.g., Campbell et al., 1960; Wattenberg, 1991). These results suggest that, although some survey respondents give unpredictable answers to policy questions, many participate in elections and contribute to electoral selection and accountability.

Because nearly half of our respondents are classified as Conversians or moderates and because their vote choice is most responsive to candidate context, this suggests that in our current political landscape Conversians and moderates drive electoral selection and accountability. Previous work has found electoral returns in response to moderation for more centrist candidates (e.g., Ansolabehere, Snyder, and Stewart III, 2001; Canes-Wrone, Brady, and Cogan, 2002; Hall, 2015; Tausanovitch and Warshaw, 2018). Our results suggest it is centrist voters who drive the relative success of centrists, incumbents, and experienced candidates.

Our analysis accounts for the possibility that response to candidate characteristics operates through turnout because abstention is included in the coding of our outcome variable. That is, if potential voters stay home when presented with moderate or extreme candidates, or are more likely to come out and vote for candidates with experience, our results would reflect that responsiveness.

The differences we detect across groups are statistically significant and substantively large. For example, as we move from a contest with an experienced Republican facing an inexperienced Democrat to a contest with an inexperienced Republican facing an experienced Democrat, moderates and Conversians increase support for the Democratic candidate by 7-8 percentage points *more* than do liberals. Similarly, as we move from an election with a particularly moderate Republican and a particularly extreme Democrat to an election with an extreme Republican and moderate Democrat, moderates and Conversians increase their support for the Democratic candidate by 6-8 percentage points *more* than do liberals.

Conclusion

Conventional wisdom holds that American voters are polarized and hyper-partisan. Yet when scholars look at survey data, we find response patterns that look neither polarized nor hyper-partisan. Early in the 2000's, scholars noted that most Americans give a mix of liberal and conservative responses on surveys and few are consistently and firmly on one side of the aisle (e.g., Fiorina, Abrams, and Pope, 2005). Ten years later, Hill and Tausanovitch (2015) found no increase in the share of Americans with extreme policy ideology over time when scaling individuals using the approaches that have been used to scale candidates and elected officials.

One response to the evidence demonstrating a healthy group of centrist voters has been that surveys are notoriously error-prone and people look moderate because they are not paying close attention to the questions or don't know very much about politics (Kinder and Kalmoe, 2017). A second response is that public opinion is poorly-described by a single dimension (e.g., Treier and Hillygus, 2009). If some respondents are extreme liberals on half the issues and extreme conservatives on the other half, scaling techniques could wrongly conclude that these individuals are centrists (Broockman, 2016). These are surely possibilities, yet little work has quantitatively decomposed moderates using existing surveys to understand the meaning of a centrist classifications.

In this paper, we provide such a method. We take head-on the serious challenges to classifying moderates with survey data by separating respondents who are well described by a single-dimensional spatial model from those who might have no opinions and those who might hold idiosyncratic but real policy views. Our technique is applicable to any existing survey dataset with a relatively balanced collection of at least twenty issue questions. It allows us to paint a more vivid picture of respondents to political surveys that report moderate-looking policy views and to better understand how those who are not ideologues make sense of and influence our politics.

We find there are many genuine moderates in the American electorate. Nearly three in four survey respondents' issue positions are well-described by a single left-right dimension and most of those individuals have centrist views. Furthermore, these genuine moderates are a politically important group. Their votes are most responsive to the ideologies and qualities of political candidates.

We also find evidence that around one in five Americans have genuine policy preferences that are not well summarized by a single dimension. These individuals, too, contribute to electoral selection and accountability by responding to candidates in a similar manner as spatial moderates. Whether someone appears moderate because they are genuinely in the middle on most issues or because they hold an idiosyncratic mix of liberal and conservative positions, the implications for political outcomes are similar: non-liberals and non-conservatives are more responsive to candidate ideology and professional experience than their ideological counterparts.

These Conversians, who have genuine policy preferences not well-summarized by the single dimension, merit further investigation. Future work might look to see how candidates and campaigns contact or attempt to persuade such voters. It may also be fruitful to try to estimate underlying patterns to Conversian policy views across issues. These voters might be particularly relevant for election-to-election shifts in outcomes as political context or party rhetoric pushes the balance of their conflicted policy considerations from supporting one party to the other. It will also be interesting to uncover how these voters interact with party politics such as participation in primary elections.

We estimate that a small number of survey respondents are providing answers that appear to come from no underlying pattern whatsoever. Future research may be able to use our approach to study these individuals in more detail. Perhaps survey methodology could be improved in order to minimize the share of inattentive respondents or understand whether these kinds of respondents lack meaningful positions or simply aren't paying attention to survey questions.

Our findings contribute to a growing literature suggesting that to the extent that elected officials are polarized, it is likely not attributable to mass voting behavior (e.g., Hall, 2019; Hill and Tausanovitch, 2015). We provide microfoundations for the finding that moderate and experienced candidates tend to perform better in Congressional elections, on average. We find that the electoral returns to moderation and experience are especially driven by Downsian moderates and Conversians.

Our analysis points to a need for renewed interest in and study of the middle in American politics and provides a method and framework for doing so. Many Americans are not partisan or ideologically extreme, and these individuals are especially important for political accountability and candidate selection. To best understand representation through elections in American politics, we must look to the moderates.

Data Transparency

Research documentation and data that support the findings in this study are openly available at the American Political Science Review Dataverse: `https://doi.org/10.7910/DVN/THU75A`.

Conflict of Interest

The authors declare no ethical issues or conflicts of interest in this research.

Human Subjects

The authors affirm that this research did not involve human subjects. This research was completed through secondary analyses of publicly available data.

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Supplementary Information for "Moderates"

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A EM algorithm for Issue Opinion Model Estimation

In this appendix, we describe the EM algorithm (Dempster, Laird, and Rubin, 1977) used to estimate the parameters of the likelihood function shown in Equation 5. Following the notation introduced in in the main text and for convenience letting $\theta = (\boldsymbol{\alpha}, \boldsymbol{\beta}, \boldsymbol{\lambda})$, we begin by forming the "complete data" log likelihood,

$$\ell(\theta) = \sum_i \sum_t v_{it} \log L_t(\boldsymbol{y}_{i\cdot}; \theta)$$

where $v_{it} = 1$ if the ith respondent is of type $t \in \{1, 2, 3\}$ and 0 otherwise. Note that $\sum_t v_{it} = 1$ for all respondents i. In the complete data problem, the type of each respondent is known and indicated by v. Of course, v is not observable. However, the EM algorithm is formed by iteratively maximizing the expected value of ℓ over the unknown values of v given estimates θ and the observed data.

In particular, we form the expectation of ℓ over v as

$$\begin{aligned} Q(\theta|\theta^{(s)}) &= \textstyle\sum_i \sum_t \mathrm{E}_{v_{it}|\boldsymbol{y_{i\cdot}}, \theta^{(s)}} \left(v_{it} \log L_t(\boldsymbol{y}_{i\cdot}; \theta) \right) \\ &= \textstyle\sum_i \sum_t \mathrm{E}_{v_{it}|\boldsymbol{y_{i\cdot}}, \theta^{(s)}} \left(v_{it} \right) \log L_t(\boldsymbol{y}_{i\cdot}; \theta) \\ &= \textstyle\sum_i \sum_t w_{it} \log L_t(\boldsymbol{y}_{i\cdot}; \theta) \end{aligned}$$

where

$$w_{it} = \frac{\bar{w}_t^{(s)} L_t(\boldsymbol{y}_{i\cdot}; \theta^{(s)})}{\sum_{t'} \bar{w}_{t'}^{(s)} L_{t'}(\boldsymbol{y}_{i\cdot}; \theta^{(s)})}$$

and $s = 0, 1, 2, \ldots$ indicates the current step of the EM algorithm.

A.1 The EM algorithm

The algorithm proceeds as follows:

1. The step counter, s, is set to zero and start values for $\theta^{(0)}$ and $\bar{w}_t^{(0)}$ for $t = 1, 2, 3$ are selected.

2. *E-Step*: w_{it} is formed for all i and t given $\theta^{(s)}$ and $\bar{w}_t^{(s)}$.

3. *M-Step*: Q is maximized in three parts yielding $\theta^{(s+1)}$ and $\bar{w}_t^{(s+1)}$ for $t = 1, 2, 3$. These three parts are as follows:

   a. For the parameters describing the issue opinions of respondents of type 1,

   $$\sum_i w_{i1} \log L_1(y_{i\cdot}; \boldsymbol{\alpha}, \boldsymbol{\beta})$$

   is maximized to update the estimates of $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$.

   b. The parameters describing the issue opinion of respondents of type 2 are updated as weighted means, $\lambda_j^{(s+1)} = \frac{\sum_{i \in \mathcal{N}_j} w_{i2} y_{ij}}{\sum_{i \in \mathcal{N}_j} w_{i2}}$ for $j = 1, \ldots, J$ where $\mathcal{N}_j$ is the set of respondents who answered question j.

   c. The sample proportions belonging to each type are updated as $\bar{w}_t^{(s+1)} = \sum_i w_{it}/N$ for $t = 1, 2, 3$.

4. s is incremented and the process repeated from (2) until convergence.

E-step details: As shown above, the calculation of w_{it}, requires the evaluation of L_1, L_2 and L_3. The likelihood of individual i's issue question responses if he is of type 3, $L_3(\boldsymbol{y}_{i\cdot})$, is simply a function of the number of responses given, does not depend on $\theta^{(s)}$, and is straightforward to calculate using Equation 2. Similarly, the calculation of the likelihood of individual i's issue question responses if she is of type 2, $L_2(\boldsymbol{y}_{i\cdot}, \boldsymbol{\lambda})$, requires only the straight-forward application of Equation 3.

The calculation of the likelihood of individual i's issue question responses if she is of type 1, $L_1(\boldsymbol{y}_{i\cdot}, \boldsymbol{\alpha}, \boldsymbol{\beta})$, is more complicated because it involves the calculation of the integral shown in Equation 1 as well as an estimate of the distribution of ideal points, f. We approximate f and the integral using Monte Carlo methods. In particular, we draw a sample from the current estimated ideal points, $\dot{x}_k$ for $k = 1, \ldots, M$, of size M. The sample is drawn independently and with replacement with sampling weights that are proportional to the current weights, w_{i1} for $i = 1, \ldots, N$. Because the estimated ideal points are drawn in proportion of the type 1 membership weights, the resulting sample is (approximately) drawn from f. Given this Monte Carlo draw from f, the integral in Equation 1 is approximated as

$$L_1(\boldsymbol{y}_{i\cdot}; \boldsymbol{\alpha}, \boldsymbol{\beta}) \approx \sum_{k=1}^{M} \prod_{j \in \mathcal{J}_i} \Lambda\left(\beta_j(\dot{x}_k - \alpha_j)\right)^{y_{ij}} \left(1 - \Lambda\left(\beta_j(\dot{x}_k - \alpha_j)\right)\right)^{1-y_{ij}}.$$

M-Step details: As part of the M-step, $\sum_i w_{i1} \log L_1(y_{i\cdot}; \boldsymbol{\alpha}, \boldsymbol{\beta})$ is maximized to update the estimates of $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$. These estimates are arrived at using a weighted version of the quadratic majorization approach of de Leeuw (2011b) where the weights are w_{i1} for $i = 1, \ldots, N$. Each ideal point is estimated as a fixed effect. Thus, the distribution of ideal points is estimated non-parametrically in this approach. This is also equivalent to a weighted version of the spatial voting model estimation method described in Imai, Lo, and Olmsted (2016).

B Power Simulations and Data Selection

The datasets that we use in this paper have very large numbers of respondents. However they have fewer policy questions than we would like, particularly for a model of this level of complexity. So it is important to assess the power of the model with respect to the number of items.

In Section B.1 of this appendix, we show two sets of simulations that examine how many items in a survey are necessary to accurately estimate both respondents' type and their spatial ideal points. Overall, this analysis leads us to conclude that about 20 policy items are necessary to accurately estimate all of the parameters in the model that we present in the main text.

If an analyst used less than 20 items:

- The respondents' one-dimensional ideal points would be estimated somewhat less accurately (see the left panels of Figures A1 and A2).

- More problematically, the respondents' types (Downsian, Conversion, Inattentive) would be estimated substantially less accurately when there are fewer than 20 items (see the middle panels of Figures A1 and A2), and estimates of the overall composition of the sample between these types would be greatly biased (right panels of Figures A1 and A2). Indeed, the accuracy of the estimated types and the overall composition of the sample between types increases dramatically at around 20 items.

In section B.2 of this appendix, we examine other features of the policy items that can increase the accuracy of the model parameters. Here too, we consistently find that the number of items is the most important predictor of model accuracy.

B.1 Simulations on effect of the number of policy items on model accuracy

There is no simple power calculation that will tell us how many items we need to get precise estimates of our model parameters. In the absence of such a formula we use simulations. We simulate our model two ways, both using actual data. First, we run the model on an existing data set, randomly selecting among the available items for each trial. We vary the number of items from 10 to the full number, in this case 32, conducting three trials for each number of items. In each trial we estimate the parameters of the model. We compare these estimates to the estimates we obtain using all 32 items.

Our second simulation method takes the estimated parameters from the full dataset and uses them to simulate new datasets. On each trial we randomly select a number of items M, doing this three times for each of M in 10 to 32, as before. Then we simulate a dataset using the estimated parameters from the full model for those items, and estimate our model on this simulated dataset. We continue to use the parameters estimated using all 32 items as our benchmark.

The first method has the advantage that it does not assume that our model is correctly specified. It simply takes a real dataset and estimates the parameters for various numbers of items. However this method is susceptible to the possibility that our conclusions will be affected by the idiosyncrasies of the dataset we choose. The second method assumes that our model *is* correctly specified. The data simply provide a set of plausible parameters to use for the simulations. The conclusions using this method are more generalizable in the sense that they should capture cases where there is similar heterogeneity in the parameters and the model is appropriate.

Among the datasets available to us, the 2014 CCES had the greatest number of items at the time of this simulation analysis.[1] The parameters of interest to us are the estimated type probabilities and ideal points for Downsian types. We want to know when we can make

[1] We later added the 2015, 2017 and 2018 CCES.

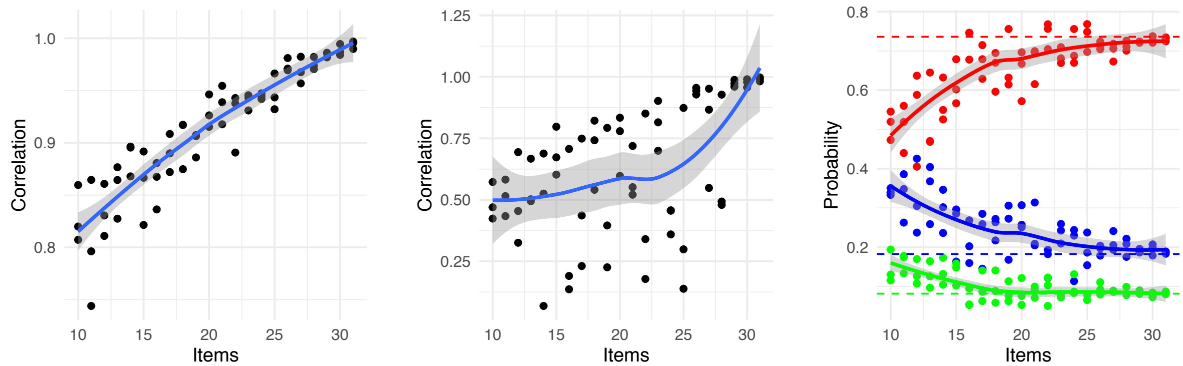
precise claims about which survey respondents have moderate ideal points, however defined. And we want to know when we can make precise claims about which respondents are very likely to be Downsians, as indicated by the size of the associated parameter. We also want to know how close our average estimates will be for all three parameters that indicate the fraction of the respondents that are Downsian, Conversian, and inattentive types.

Figure A1 shows the results for the first simulation method. The leftmost panel shows the correlation between the estimated ideal points in a given trial and the estimated ideal points using all 32 items on the y-axis. The x-axis is the number of used items in each trial. We fit a LOESS smoother to this relationship. With only 10 items this correlation hovers at a little over 0.8 on average but with correlations as low as .74. The relationship is close to linear. Twenty items are needed to consistently achieve correlations above .9, though of course more items are better.

The middle panel shows the correlation for the Downsian probabilities, w_1, estimated in each trial and the Downsian probabilities estimated with 32 items. This relationship is much noisier, but ranges from .5 in expectation with 10 items to very close to 1 with 32.

The last panel shows the averages for each set of probabilities along with a horizontal line for the averages when 32 item are used. Green indicates w_1, blue indicates w_2 and red indicates w_3. It is clear from this graph that these estimates are severely biased with only 10 items. w_1 and w_2 are biased upwards and w_3 is biased downwards. We suspect that this is part of a more general bias towards equality of the three probabilities in small samples. The bias ranges from almost .25 to close to 0, with the relationship flattening substantially around 20 items.

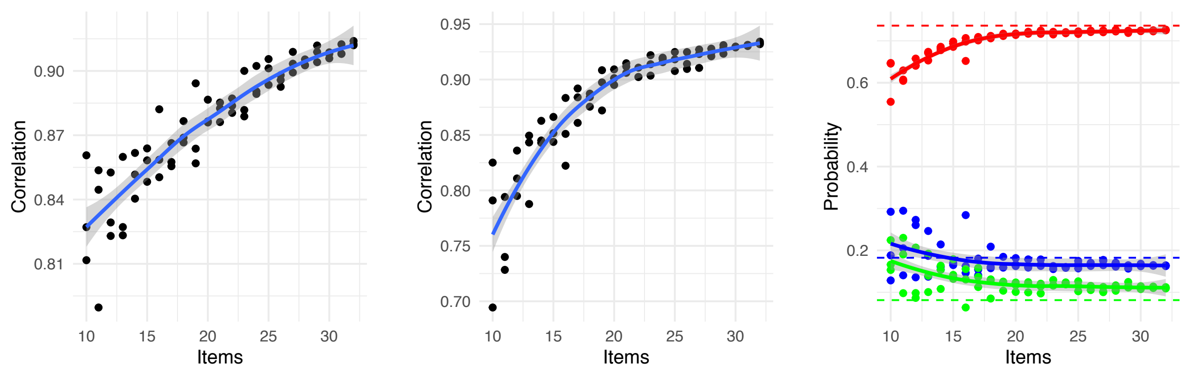
Figure A2 shows the results for the second simulation method. Assuming that our model is correctly specified substantially improves all of the metrics, particularly when few items are used. The association between the ideal points improves linearly in M from about .83 to about .91. The correlation in the probabilities improves rapidly from about .77 to about .94, flattening substantially around M=20. For the averages of the probabilities we see a



(a) Corr. ideal points (b) Corr. Pr($Downsian$) (c) Estimated composition

Figure A1: Results from Simulation 1

smaller but still substantial bias around M=10, which is mostly eliminated by M=20. In each case a small discrepancy remains between the benchmark parameters and the estimated parameters, reflecting a small degree of model misspecification.



(a) Corr. ideal points (b) Corr. Pr($Downsian$) (c) Estimated composition

Figure A2: Results from Simulation 2

There is no objective criteria for what threshold of items to use for precise estimation of these parameters. We consider the estimates using only 10 items to be clearly inadequate. It is clear from the graphs that greater numbers of items are better, and even greater than 32 would be preferable. However given the data available to us we choose to make do with datasets of 20 items or more. These estimates retain a small amount of bias against one of our central conclusions: that a low dimensional model is a good characterization of the preferences of most individuals. However they do not contain so much bias as to make type 2 errors very likely.

B.2 Other features of policy items that might improve model accuracy

So far we have only considered the number of items as an indicator of the power of a given dataset. However there are several other considerations that one might take into account in assessing power. The informativeness of a given dataset will depend on the unknown item parameters in complex ways. For instance, items that divide extreme liberals from moderate liberals are informative with respect to the parameters of those respondents but may not be very informative with respect to conservative respondents. So the position of the estimated cut points matter, and so does heterogeneity in these cut points. Items that are less discriminating will yield noisier estimates as well. In other words, "bad" items lead to "bad" estimates.

These factors are difficult to assess a priori. The margin of the survey question may be used as a rough indicator of where in the spectrum of ideal points the question is likely to be discriminating. In our case all survey questions are coded in what we believe to be the "conservative" direction. We can use the standard deviation of the margins as a measure of the coverage of these items. We evaluate whether the dispersion of the margins is an important factor in our simulated datasets, leaving a more thorough assessment of this methodological question to future work.

Table A1 shows the estimates from three models where the dependent variable is the correlation between the estimated w_1s from each simulation and the estimated w_1s using all 32 items from the CCES. These simulations are from our first method, described above. These models use three explanatory variables: the number of items, the standard deviation of the margins, and the interaction between those two factors. The number of items explains about a quarter of the variation in this correlation. However the standard deviation of the margins explains little if any variation, and only slightly improves upon a model using only the number of items.

Table A1: Effect of the number of items and standard deviation of the question margins on the correlation between the estimated w_1 and the benchmark w_1

	Dependent variable:		
	$corr_{w_1}$		
	(1)	(2)	(3)
# of items	0.021***		−0.054
	(0.004)		(0.050)
SD(margins) × # of items			0.560
			(0.371)
SD(margins)		1.832	−6.776
		(2.172)	(5.865)
Constant	0.204**	0.391	1.112
	(0.093)	(0.288)	(0.786)
Observations	66	66	66
R^2	0.265	0.011	0.299
Adjusted R^2	0.254	−0.004	0.266
Note:	*p<0.1; **p<0.05; ***p<0.01		

Table A2 shows estimates using the same independent variable, but here the dependent variable is the correlation between the simulated ideal points and the benchmark ideal points. This time the number of items explains 86% of the variance in the correlation. The standard deviation of the margins adds little if any explanatory power.

We take these models as evidence that, at least in this dataset, the number of items is a much more important factor than having a lot of dispersion in the margins. This may be because any random sample of the items available is sufficiently dispersed. However for our purposes we opt for a simple inclusion criterion and use all datasets where respondents answer at least 20 questions.

Table A2: Effect of the number of items and standard deviation of the question margins on the correlation between the estimated ideal points and the benchmark ideal points

	Dependent variable:		
	$corr_x$		
	(1)	(2)	(3)
# of items	0.009***		0.010**
	(0.0004)		(0.005)
SD(margins) × # of items			−0.013
			(0.038)
SD(margins)		0.186	0.286
		(0.494)	(0.595)
Constant	0.740***	0.890***	0.702***
	(0.009)	(0.066)	(0.080)
Observations	66	66	66
R^2	0.859	0.002	0.859
Adjusted R^2	0.856	−0.013	0.853
Note:			*p<0.1; **p<0.05; ***p<0.01

Table A3 shows the median number of responses to policy items for 11 large-sample surveys of political views: the 2006-2016 Cooperative Congressional Election Studies and the 2000 and 2004 National Annenberg Election Surveys. The surveys where the median respondent answers at least 20 policy questions are the 2012, 2013, 2014, 2015, 2016, 2017 and 2018 Cooperative Congressional Election Studies, the data sets represented in the paper.

Table A3: Number of policy items on large sample surveys

Survey	Median Policy Responses
CCES 2006	12
CCES 2007	13
CCES 2008	14
CCES 2009	11
CCES 2010	16
CCES 2011	13
CCES 2012	21
CCES 2013	22
CCES 2014	32
CCES 2015	33
CCES 2016	28
CCES 2017	31
CCES 2018	35
NAES 2000	17
NAES 2004	9

C Model Validation with the Stanford Module of the 2010 CCES

In this appendix, we show that the example given in Figure 2 of the main text generalizes. If we compare any two questions out of the 133 question asked on the 2010 CCES module, respondents classified as Downsian moderates are more likely to give spatially consistent responses. Downsian moderates become even more likely to give spatially consistent responses when the magnitude of any inconsistency would be large. Conversians are more likely to give spatially inconsistent responses and their likelihood of doing so depends less on the magnitude of the inconsistency. This validation exercise requires no knowledge of our model to understand.

Consider a 133-by-133 matrix where each row and column represents one of our 133 items. The rows are ordered by support for the liberal alternative such that the top row is the least popular liberal policy and the bottom row the most popular liberal policy. The columns are ordered by support for the conservative policy. In this arrangement, the bottom left of our graph represents item pairs where the liberal alternative is very popular for the item in the rows and the conservative alternative is very popular for the item in the column. As we ascend towards the top right of the matrix, the liberal alternative becomes less and less popular for the row item, and the conservative alternative becomes less and less popular for the column item.

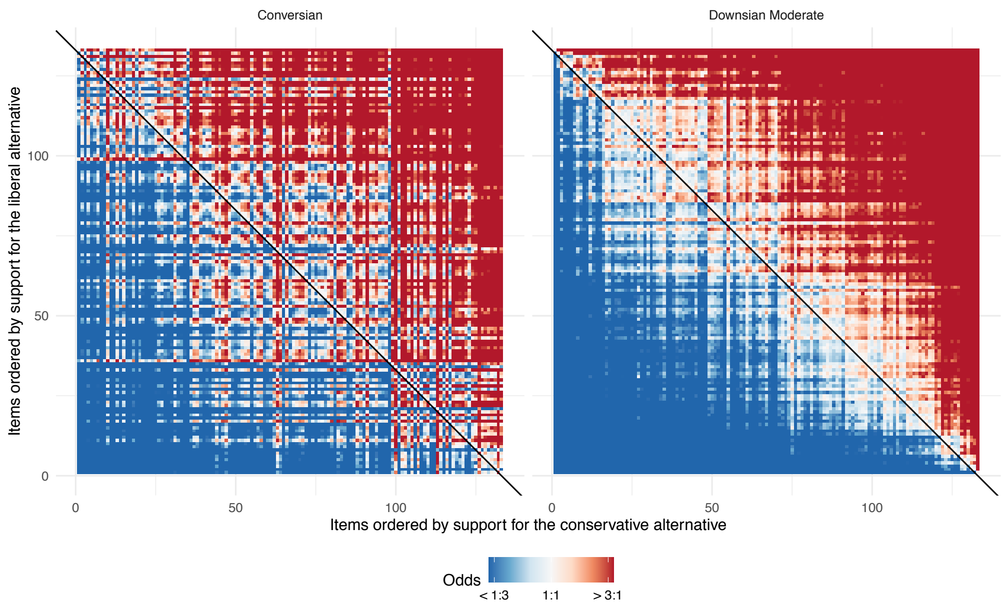
Without any statistical model, we want to try to capture the proportion of "spatial errors." If the items were perfectly Guttman scalable, then the margins would be sufficient. Consider a pair of items on the bottom left of our matrix, where the row item is R and the column item is C. Let 1 be a conservative response and 0 be a liberal response. Giving both liberal responses or both conservative responses will always be spatially consistent. For items on the bottom left, giving liberal responses to row items, $R = 0$, and conservative responses to column items, $C = 1$, is also spatially consistent, because these responses represent the majority of respondents. $R = 0$ and $C = 1$ is the moderate response to both questions. For the row item the conservative response is rare, and therefore relatively extreme, and for the column item the liberal response is rare, and therefore relatively extreme. So the response pattern $R = 1$, $C = 0$ gives the extreme conservative response on one question and the extreme liberal response on the other. This is a spatial error that suggests the respondent giving this answer pair has views not well summarized by a single dimension of policy ideology.

In the bottom left of the matrix, $(R = 0, C = 1)$ represents a spatially consistent choice and $(R = 1, C = 0)$ also represents a spatially inconsistent choice. As we move up the rows and to the left on the columns the margins of the questions get closer. At some point, the situation flips. Once majorities support the conservative side on the rows and the liberal side on the columns, then $(R = 1, C = 0)$ represents a spatially consistent choice and $(R = 0, C = 1)$ represents a spatially inconsistent choice. If these choices were perfectly Guttman scalable, than we would no longer observe the spatially inconsistent choice. In a random utility model, errors should become more common as the margins of the question become closer.

Figure A3 graphs the odds of choosing $(R = 1, C = 0)$ against $(R = 0, C = 1)$ for respondents who are classified as Conversian (left frame) and Downsian (right frame) moderates by our model. Moderate here indicates someone whose ideal point is in the middle third of the distribution with higher posterior probability Downsian than Conversian or inattentive. We focus on moderates to support the claims we make about moderates specifically in the paper.

Our expectation is that, for subjects whose views are well-explained by a single dimension of ideology, the odds should should be low on the bottom left, when $(R = 1, C = 0)$ is the spatially inconsistent choice, and high on the top right, when $(R = 1, C = 0)$ is the spatially consistent choice. The odds should approach 1:1 in the middle when the most spatially consistent choice is to respond in the same direction to both questions.

Figure A3: Odds of Spatially Consistent versus Spatially Inconsistent Choices



For each pair of 133 issues on the 2010 CCES, the color of each "pixel" represents the odds of a randomly selected respondent giving the conservative answer to the question indicated by the pixel's x-axis position and the liberal answer to the question indicated by the pixel's y-axis position from among those respondents giving one conservative and one liberal answer to that question pair. The questions are ordered by support for the conservative position on the x-axis and by support for the liberal position on the y-axis.

Under perfect one-dimensional spatial voting, the data would be Guttman scalable. In that case, these odds would be greater than 1:1 everywhere above the -45 degree line and less than 1:1 everywhere below the -45 degree line. Notice that for those respondents who we identify as Downsian moderate this is largely the case. On the other hand, for those respondents identified as Conversian, there is a great deal of red (odds greater than 1:1) below the -45 degree line and blue (odds less than 1:1) above the -45 degree line. It is clear from the graph that Conversians are much less constrained than are Downsian moderates.

This analysis provides descriptive nonparametric evidence that our model successfully separates ideologically consistent moderates (Downsians) from those whose responses are much less constrained by the ideological dimension (Conversians).

D Modeling Spatial Preferences in Two Dimensions

In the model presented in the main text, voters can either hold one-dimensional spatial preferences (with error) or hold issue opinions that are (across all such voters) independent across issues (Conversians and inattentives). An alternative approach would be to place all voters in a higher-dimensional preference space. Indeed, putting aside the small number of inattentive voters, it can be easily demonstrated that the mixture model that we advance can be represented as, and is isomorphic to, a standard two-dimensional model in which our Downsians have ideal points that fall on a single line and the Conversians fall on a single point that lies away from that line.[2] To see this, recall that, in the notation introduced in the main text, the probability that a Downsian respondent i answers issue question j in the affirmative ($y_{ij} = 1$) is

$$\Lambda\left(\beta_j(x_i - \alpha_j)\right).$$

If we extend this spatial choice function to two dimensions, the probability that $y_{ij} = 1$ becomes

$$\Lambda(\tilde{\alpha}_j + \tilde{\beta}_{j1}\tilde{x}_{i1} + \tilde{\beta}_{j2}\tilde{x}_{i2}).$$

While adding a second dimension to the usual quadratic spatial preference model increases the number of x and β parameters that characterize each choice, there is still only one α parameter (Clinton, Jackman, and Rivers, 2004, p. 365). The definition of $\tilde{\alpha}$ differs from its one-dimensional counterpart which is why we place a tilde over it (and the other parameters in the two-dimensional model). Note that $\tilde{\alpha}_j = -\alpha_j\beta_j$ in the one-dimensional case (in which $\tilde{\beta}_{j2} = 0$ for all j). Now, suppose that the data are generated according to the mixture model presented in the main text. We can represent the choice probabilities of Downsians in that model by setting $\tilde{\alpha}_j = -\alpha_j\beta_j$, $\tilde{\beta}_{j1} = \beta_j$, $\tilde{x}_{i1} = x_i$, and $\tilde{x}_{i2} = 0$ for all (Downsian) respondents

[2]We thank Ben Lauderdale for first pointing this out to us.

i and issue questions j because then

$$\Lambda(\tilde{\alpha}_j + \tilde{\beta}_{j1} x_i + \tilde{\beta}_{j2} \cdot 0)$$

equals

$$\Lambda\left(\beta_j(x_i - \alpha_j)\right).$$

Holding fixed these values of $\tilde{\alpha}$ and $\tilde{\beta}_{j1}$, we can accommodate the Conversian voters by setting their $\tilde{x}_{i1} = 0$ and their $\tilde{x}_{i2} = 1$ and choosing $\tilde{\beta}_{j2}$ to solve

$$\lambda_j = \Lambda(\tilde{\alpha}_j + \beta_j \cdot 0 + \tilde{\beta}_{j2} \cdot 1)$$

for all (Conversian) i and j. Rearranging we have

$$\Lambda^{-1}(\lambda_j) = \tilde{\alpha}_j + \tilde{\beta}_{j2} \cdot 1$$

or

$$\tilde{\beta}_{j2} = \Lambda^{-1}(\lambda_j) - \tilde{\alpha}_j.$$

Adding the inattentive voter type to the mix breaks the isomorphism of the two models, but given that few respondents of this type are estimated to exist in the data, the two models are close to isomorphic in this application.[3] Because spatial models in two dimensions are invariant to translations, dilations, reflections, and rotations of the ideal point space (see Clinton, Jackman, and Rivers, 2004, p. 365–366), there is a continuum of ways in which the model presented in the main text (leaving out the inattentives) can be made isomorphic to a (restricted) two-dimensional spatial model. However, all of these isomorphic two-dimensional models have the Downsians falling on a single line through the two-dimensional space and

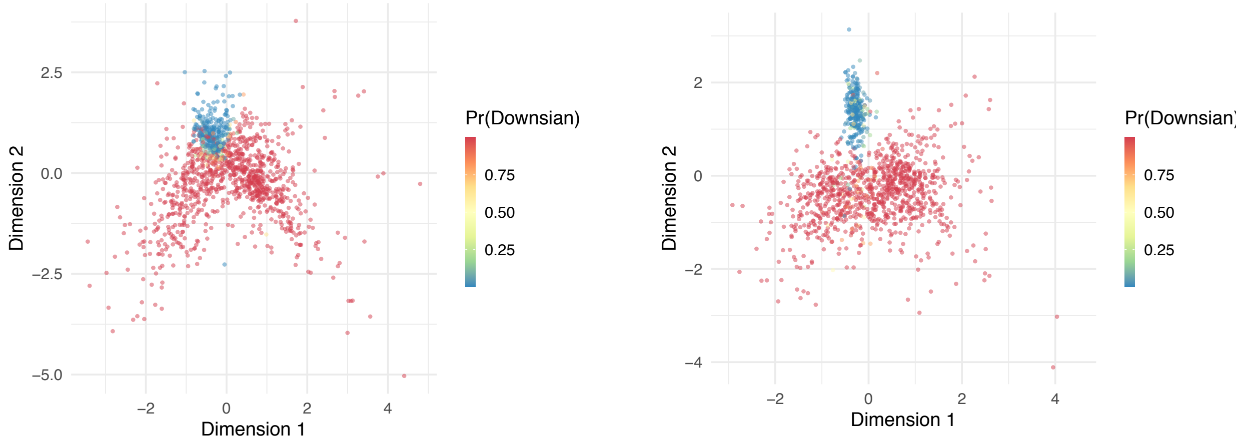
[3] Adding a third spatial dimension would be sufficient to recreate the isomorphism with inattentives included.

the Conversians falling on a point that does not (in general) lie on that line.[4]

In this Appendix, we allow for the possibility that (some) voters have two-dimensional spatial preferences. We focus this exploration on the same 133-question dataset drawn from the 2010 CCES that we employ in Appendix C, the 2010 CCES module dataset. The large number of issue items found in this dataset relative to the other datasets presented in the text gives us the best opportunity to explore preferences in more than one dimension. We also present estimates of the out-of-sample fit of various alternative preference models considered for all of the datasets analyzed in the text.

We first apply a standard two-dimensional IRT-like model (Clinton, Jackman, and Rivers, 2004) to the 2010 CCES module dataset. Panel (a) of Figure A4 plots the resulting estimated ideal points. The points are colored according to the estimated probability that a respondent is a Downsian as estimated by the mixture model employed in the text. This plot does not reveal a single line of Downsians and a single point of Conversians that falls away from that line. However, the deviation from that pattern is perhaps less stark than it might appear. First, we see that the Conversians are concentrated in a small area of the graph. Second, because there is a stochastic component to the voters' preferences and because their locations are determined by no more than 133 questions (91.9 on average), each ideal point is estimated with error. Therefore, even if the true ideal points all fell on a single line in the space, we would expect the estimates to form a cloud around that line. To demonstrate this, Panel (b) of Figure A4 shows the estimated results when the same two-dimensional spatial model is applied to a simulated data set produced according to our mixture model calibrated to the CCES 2010 module data. Here we see that despite the mixture model holding exactly in the data, the Conversians are clustered, but do not fall on a single point nor do the

[4] If, in the parameterization presented, $\Lambda^{-1}(\lambda_j) = \tilde{\alpha}_j$ for all j then $\tilde{\beta}_{j2} = 0$ for all j and Conversians would be located at $\tilde{x}_i = (0, 0)$ which is a point on the line containing the Downsians. Of course, in this case Conversians cannot be empirically distinguished from Downsians because their choice probabilities would be identical to those of Downsians for whom $x_i = 0$. Note that in this knife-edged case where there is only one-dimension of choice, the values of $\tilde{\beta}_{j2}$ and $\tilde{x}_{i2}$ are not separately identified because $\tilde{\beta}_{j2} = 0$ for all j with $\tilde{x}_{i2} \in (-\infty, \infty)$ for all i and $\tilde{x}_{i2} = 0$ for all i with $\tilde{\beta}_{j2} \in (-\infty, \infty)$ for all j yield equivalent choice probabilities.



(a) Estimated (b) Simulated

Figure A4: Estimating respondent preferences in two spatial dimensions. *Panel (a) shows the locations of 2010 CCES module respondents as estimated by a standard two-dimensional spatial model. The points are shaded to reflect the probability that each respondent is of the Downsian type as estimated by the model presented in the main text. Panel (b) shows the same plot based on simulated data that is calibrated to the 2010 CCES module dataset under the assumptions of the model presented in the main text.*

estimated locations of the Downsians fall on a single line. The general pattern shown in the two panels is similar though the locations of the Conversians is more strongly differentiated in the simulated data and there appears to be more structure to the second dimension in the empirical data. Given that there is no second dimension of spatial preference in the simulated data, this is not surprising. Though there is apparent structure in the second dimension of the empirical data, the first and second dimension locations are far from independent calling into question the degree to which there is an important distinct second dimension of preference manifest in the issue question responses.

Indeed, the empirical estimates reveal the horseshoe pattern often found when two-dimensional scaling models are applied in situations in which a single underlying dimension is expected (see Diaconis, Goel, and Holmes, 2008). In such cases, the recovered second dimension can be accounting for some misspecification of the functional form of the stochastic spatial preference, choice or distance function rather than a distinct second dimension (for example, in our context, distinct "economic" and "social" policy preference dimensions)

(Kendall, 1970; Shepard, 1974; Hill and Gauch, 1980; Diaconis, Goel, and Holmes, 2008; de Leeuw, 2011*a*).

Because there may be a distinct second dimension of spatial preference or the assumed functional form of the one-dimensional spatial preference model may be driving our results, we next consider how the inclusion of a second dimension into the mixture model affects our estimates of the fraction of Downsians and Conversians in the population. To do this, we fit an extended version of our mixture model to the CCES 2010 module dataset that allows the Downsians to have preferences over two spatial dimensions.

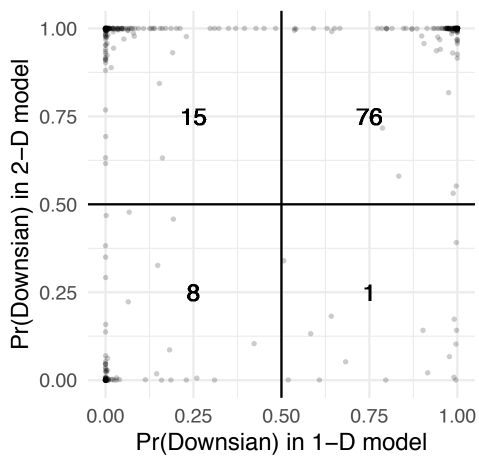


Figure A5: Estimated probabilities of each respondent being of the Downsian type.

For each respondent in the 2010 CCES module data, the x-axis shows the probability that a given respondent is of the Downsian type when one-dimensional spatial preferences are assumed. The y-axis shows the probability that a given respondent is of the Downsian type when two-dimensional spatial preferences are assumed. The quadrants partition respondents predicted to be Downsian from those predicted to be non-Downsian in either model or both. The numbers indicate the percentage of the sample that is estimated to fall into each quadrant. For example, 76 percent of the sample is estimated to be of the Downsian type in both one and two dimensions, while one percent of the sample is estimated to be Downsian when one spatial dimension is assumed, but non-Downsian when two spatial dimensions are assumed.

Figure A5 shows the estimated probability of being a Downsian for each survey respondent under the one-dimensional and two-dimensional mixture models. The four quadrants of the plot contain voters who are estimated to be (moving clockwise from the upper left): Downsian in the two-dimensional model, but Conversian in the one-dimensional model; Downsian in both models; Downsian in the one-dimensional model and Conversian in the two-dimensional model; and Conversian in both models. Whereas the one-dimensional model estimates about 23 percent of the sample to be Conversian, the two-dimensional model places only 9 percent of the sample in that category. Fifteen percent of the sample moves from Conversian to Downsian when a second dimension is available whereas only one percent moves from Downsian to Conversian. As noted in the main text, this suggests that some of the voters identified as Conversian moderates in the main text may hold preferences that, while not easily reconciled with a single spatial dimension, can be made reconcilable with spatial preferences when a second spatial dimension is added. Thus, our characterization of the fraction of "moderates" who actually have spatial preferences is perhaps understated.

Another related question is whether the addition of a second spatial dimension substantially improves the fidelity of the model with the data. To answer that question, we need a measure of (out of sample) fit. Table A4 reports the in-sample log likelihood as well as the out-of-sample perplexity associated with each model when applied to the 2010 CCES module dataset. The out-of-sample perplexity is approximated via a five-fold cross validation. Under the "null" model, across the entire sample, preferences are assumed to be independent across choices (in effect, all voters are assumed to be Conversians). The "1-D (mix.)" is the model presented in the main text that considers a mixture of Downsian, Conversian, and inattentive respondents. The "2-D (no mix.)" is the standard two-dimensional model used to produce the estimates in Figure A4. It does not include Conversian and inattentive types. The "2-D (Mix.)" is a version of the model used in the main text in which Downsians are given preferences over two spatial dimensions rather than one, and includes Conversian and inattentive types. Given the large number of data points (1,300 respondents answering on average 91.9 issue questions), it is not surprising that the differences between each pair of log likelihoods are statistically significant (p values not shown). That is, a statistically significant increase in data fit is afforded by each increase in model complexity.

Model	Log-likelihood	Perplexity
Null	-72675	1.84
1-D (mix.)	-53049	1.58
2-D (no mix.)	-51978	1.57
2-D (mix.)	-51383	1.56

Table A4: Model log likelihood and perplexity, 2010 CCES module dataset. *Shows the estimated model log likelihoods and estimated average (per item) perplexities across four possible models of preference. Each model is fit to the same 1,300 respondents answering an average of 91.9 issue questions). Each row of the table presents the estimated fit for a given model. The rows are organized in increasing order of model complexity. The log likelihood is estimated in sample. Perplexity is estimated out of sample using five-fold cross validation. The differences in log likelihood are highly statistically significant though the reductions in perplexity as model complexity increases are modest (except when comparing the null model to the others). Each model is described in the text.*

However, the perplexity differences among the various spatial models are modest particularly in comparison to the null model. Perplexity can be understood as the average number of bits per issue item required to compactly represent the responses of a single respondent. The higher the likelihood the model assigns to each observed pattern of the data the lower the perplexity (the perplexity is the average of the inverse of the geometric mean probability of the responses given by each respondent). If every respondent were an inattentive type, perplexity would be 2, which is the theoretical maximum (the maximally entropic data generating process). On the other hand, if every respondent expressed one of only two patterns across items, the perplexity would approach 0 (1 over the number of items) because a single bit would be sufficient to label the two observed patterns. As with the log likelihood, the value of perplexity is a function of both the nature of the data and the fidelity of the model. Because the perplexity is calculated using cross-validation, the observed reduction in the estimated perplexity as model complexity increases is not a mechanical result.

In fact, only small improvements in model fit result from the addition of a second spatial dimension. The inclusion of the Conversian and inattentive types appears to increase the fit of the two-dimensional model. However, the differences in fit among the various models that include a spatial component are very small (less than 1 percent differences in perplexity

		Log likelihood				Perplexity			
				2-D				2-D	
Survey	Avg. no. of items	Null	1-D Mix.	No mix.	Mix.	Null	1-D Mix.	No mix.	Mix.
2012	18.6	-661043	-550889	-551832	-550929	1.93	1.74	1.75	1.74
2013	21.8	-226870	-194338	-193809	-193867	1.89	1.74	1.74	1.74
2014	31.6	-1156518	-960685	-956933	-949695	1.92	1.74	1.73	1.72
2015	32.5	-292295	-230744	-227953	-226884	1.89	1.66	1.66	1.65
2016	28.8	-1137878	-972217	-973954	-971166	1.86	1.71	1.71	1.71
2017	30.9	-358915	-269839	-269580	-267369	1.90	1.64	1.64	1.63
2018	33.1	-1274454	-973250	-975855	-968311	1.91	1.66	1.67	1.66

Table A5: Model log likelihood and perplexity, 2012–2018 CCES datasets. *Shows the estimated model log likelihoods and estimated average (per item) perplexities across four possible models of issue preference. Each model is fit to the same respondents to each survey. The average number of responses to each survey is given in the table. Each row of the table presents estimated model fits for a given survey. The differences in log likelihood are statistically significant across the models for each survey though the reductions in perplexity as model complexity increases are very small (except when comparing the null model to the others). Each model is described in the text.*

per issue item). Table A5 shows the log likelihoods and perplexities associated with the Null, 1-D (with mixture), 2-D (without mixture), and 2-D (with mixture) models described above when applied to the CCES datasets from 2012 to 2018 analyzed in the text. As with the 2010 CCES module dataset, adding model complexity increases fit in a statistically significant way (the log likelihoods differ by more than chance would allow). However the degree of additional (out of sample) fit is minimal (often zero to two decimal places).

E Additional Results on Selection and Accountability

Table 4 in the text assessed the extent to which the voting behavior of different types of individuals responds to candidate ideology and experience. To assess the extent to which each group contributes to election results, we utilized a trichotomous dependent variable that takes a value of 1 if the respondent voted for the Democratic candidate, 0 if the respondent voted for the Republican candidate, and 0.5 if the respondent abstained or voted for a third-party candidate.

For readers interested in the extent to which those previous results were explained by voter turnout versus vote choice, we replicate those analyses but utilize alternative dependent variables. Table A6 excludes those who abstained or supported a third-party candidate and utilizes a binary dependent variable indicating support for the Democratic candidate. This analysis suffers from the potential concern that the independent variables of interest could affect turnout, which could induce bias. However, if we assume that candidate ideology and experience do not influence turnout, we can interpret these results as the differential effects of ideology and experience for those who voted.

If anything, the interactive coefficients in Table A6 are greater than those in Table 4. In other words, if we condition on those who voted, moderate, Conversian, and inattentive individuals are even more likely than liberals and conservatives to change their partisan vote choices in response to candidate ideology and experience. Of course, moderate, Conversian, and especially inattentive individuals are less likely to vote than liberal and conservative individuals, so these estimates overstate the extent to which these groups contribute to election results. But these results show that among those who vote, the non-ideologues are especially likely to contribute to electoral selection and accountability.

Additionally, Table A7 shows the same analyses but utilizes abstention as the dependent variable of interest. Consistent with our previous results, we find that moderate, Conversian, and inattentive individuals are more likely to abstain than liberals and conservatives.

The first three columns show that the extent to which these groups differentially abstain does not meaningfully vary as the ideologies of the candidates shift from favoring the Republican candidate to favoring the Democratic candidate.

However, we do find that the participation differences do vary across candidate experience in ways that we might expect. As the experience gap between the Democratic and Republican candidate increases, conservatives become much more likely to abstain relative

Table A6: Excluding Abstainers

	DV = House Vote (Dem = 1, Rep = 0)								
	X = Ideological Midpoint			X = Incumbency			X = Experience		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
X*Moderate	.107	.102	.101	.219	.214	.210	.225	.221	.215
	(.021)	(.020)	(.020)	(.013)	(.013)	(.013)	(.013)	(.013)	(.013)
X*Conversian	.157	.146	.150	.253	.242	.233	.257	.248	.237
	(.024)	(.024)	(.024)	(.015)	(.015)	(.015)	(.016)	(.016)	(.015)
X*Inattentive	.106	.096	.098	.250	.229	.221	.251	.228	.219
	(.051)	(.046)	(.046)	(.031)	(.029)	(.029)	(.031)	(.029)	(.029)
X*Conservative	.011	.007	.010	.001	.014	.016	.002	.018	.017
	(.012)	(.013)	(.014)	(.008)	(.010)	(.011)	(.009)	(.010)	(.011)
X	.042	-.012		.066	-.039		.065	-.059	
	(.009)	(.012)		(.005)	(.013)		(.005)	(.012)	
Moderate	-.492	-.480	-.479	-.513	-.505	-.498	-.523	-.515	-.506
	(.011)	(.011)	(.011)	(.008)	(.008)	(.008)	(.008)	(.008)	(.008)
Conversian	-.460	-.448	-.451	-.474	-.467	-.462	-.484	-.477	-.471
	(.014)	(.014)	(.014)	(.010)	(.009)	(.009)	(.010)	(.010)	(.010)
Inattentive	-.520	-.509	-.511	-.558	-.549	-.543	-.563	-.553	-.547
	(.029)	(.026)	(.026)	(.019)	(.018)	(.018)	(.019)	(.018)	(.018)
Conservative	-.917	-.894	-.892	-.890	-.878	-.866	-.891	-.879	-.866
	(.006)	(.007)	(.007)	(.005)	(.005)	(.006)	(.005)	(.006)	(.006)
Year FEs	✓	✓		✓	✓		✓	✓	
District FEs		✓			✓			✓	
District-Year FEs			✓			✓			✓
Observations	102,350	102,350	102,350	143,715	143,715	143,715	143,715	143,715	143,715

District-clustered standard errors in parentheses. Liberals are the omitted category.

to liberals, and moderates, Conversians, and inattentive individuals are somewhere in between. In other words, an experience advantage for the Republican (Democratic) candidate motivates conservative (liberal) individuals to participate relative to liberal (conservative) individuals. Interestingly, the estimated differences between conservatives and moderates are greater than those between liberals and moderates. One potential explanation is that conservative abstention is more responsive to candidate experience than liberal abstention or that moderate abstention more closely matches that of liberals.

Table A8 replicates the analyses in Table 4 but adds in controls for party identification. Specifically, all regressions include fixed effects for each possible category of the seven-point party identification scale. On one hand, these controls might increase precision since party identifcation is strongly correlated with vote choice. On the other hand, controlling for party identification could induce bias because the ideology and experiences of congressional candi-

Table A7: Analyzing Abstention

	DV = House Abstention (Abstain/Other = 1, Dem/Rep = 0)								
	X = Ideological Midpoint			X = Incumbency			X = Experience		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
X*Moderate	-.026	-.033	-.033	.028	.030	.031	.031	.035	.035
	(.016)	(.016)	(.016)	(.012)	(.012)	(.012)	(.012)	(.012)	(.012)
X*Conversian	-.011	-.014	-.010	.040	.042	.038	.041	.044	.043
	(.020)	(.019)	(.019)	(.012)	(.012)	(.012)	(.013)	(.012)	(.012)
X*Inattentive	-.009	-.025	-.019	.044	.042	.039	.071	.069	.068
	(.029)	(.029)	(.029)	(.019)	(.019)	(.019)	(.020)	(.020)	(.020)
X*Conservative	-.008	-.015	-.014	.118	.133	.129	.125	.144	.140
	(.017)	(.017)	(.017)	(.016)	(.015)	(.015)	(.016)	(.016)	(.016)
X	.036	.017		-.051	-.056		-.060	-.065	
	(.014)	(.015)		(.011)	(.016)		(.012)	(.017)	
Moderate	.242	.236	.234	.205	.196	.194	.203	.193	.191
	(.009)	(.009)	(.009)	(.008)	(.008)	(.008)	(.008)	(.008)	(.008)
Conversian	.263	.250	.243	.225	.208	.204	.223	.205	.201
	(.011)	(.010)	(.010)	(.008)	(.008)	(.008)	(.009)	(.009)	(.009)
Inattentive	.353	.345	.341	.319	.302	.300	.304	.287	.284
	(.017)	(.017)	(.018)	(.013)	(.013)	(.013)	(.014)	(.014)	(.014)
Conservative	-.049	-.056	-.055	-.096	-.107	-.104	-.103	-.116	-.113
	(.009)	(.009)	(.009)	(.008)	(.008)	(.008)	(.009)	(.008)	(.008)
Year FEs	✓	✓		✓	✓		✓	✓	
District FEs		✓			✓			✓	
District-Year FEs			✓			✓			✓
Observations	159,006	159,006	159,006	233,445	233,445	233,445	233,445	233,445	233,445

District-clustered standard errors in parentheses. Liberals are the omitted category.

dates could potentially influence the reported party identification of respondents. Because of this potential bias, we believe analyses that exclude partisanship controls are more reliable.

When we control for party identification, the estimated interactive effects of interest in Table A8 are similar to those in Table 4 although slightly attenuated. This could follow from the relative appeal of Democratic and Republican congressional candidates affecting reports of party identification. Nevertheless, even when we control for party, the results are qualitatively similar.

We might also want to know how the ideological types we identify interact with party identification. Because party identification is strongly correlated with vote choice, we would expect, for example, liberal Democrats to behave differently than liberal independents. To assess this possibility, we coded indicators for every potential combination of our ideological types (liberal, moderate, conservative, Conversian, and inattentive) and three-point party

Table A8: Controlling for Party ID

	DV = House Vote (Dem = 1, Rep = 0, Abstain/Other = .5)								
	X = Ideological Midpoint			X = Incumbency			X = Experience		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
X*Moderate	.036	.037	.039	.044	.046	.045	.043	.045	.044
	(.010)	(.010)	(.010)	(.007)	(.007)	(.007)	(.007)	(.007)	(.007)
X*Conversian	.040	.043	.046	.048	.049	.046	.044	.045	.042
	(.012)	(.012)	(.011)	(.007)	(.007)	(.007)	(.008)	(.008)	(.008)
X*Inattentive	.015	.016	.018	.022	.020	.013	.016	.014	.005
	(.017)	(.017)	(.017)	(.012)	(.012)	(.012)	(.012)	(.012)	(.012)
X*Conservative	.024	.024	.026	.015	.018	.017	.007	.010	.009
	(.013)	(.013)	(.014)	(.011)	(.011)	(.012)	(.012)	(.012)	(.012)
X	.017	-.007		.057	.015		.061	.005	
	(.008)	(.008)		(.007)	(.010)		(.007)	(.010)	
Moderate	-.188	-.185	-.186	-.183	-.181	-.180	-.183	-.181	-.180
	(.006)	(.006)	(.006)	(.005)	(.005)	(.005)	(.005)	(.005)	(.005)
Conversian	-.176	-.173	-.176	-.168	-.165	-.166	-.167	-.164	-.165
	(.007)	(.007)	(.006)	(.005)	(.005)	(.005)	(.005)	(.005)	(.005)
Inattentive	-.184	-.180	-.183	-.180	-.177	-.176	-.178	-.174	-.172
	(.010)	(.009)	(.009)	(.008)	(.008)	(.008)	(.008)	(.008)	(.008)
Conservative	-.371	-.367	-.368	-.350	-.348	-.348	-.347	-.345	-.345
	(.007)	(.007)	(.007)	(.006)	(.006)	(.006)	(.007)	(.007)	(.007)
Year FEs	✓	✓		✓	✓		✓	✓	
District FEs		✓			✓			✓	
District-Year FEs			✓			✓			✓
Party ID FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	152,616	152,616	152,616	224,047	224,047	224,047	224,047	224,047	224,047

District-clustered standard errors in parentheses. Liberals are the omitted category.

identification (Democrat, independent, and Republican). We then replicated the methodology used in Table 4 but separately examined each of these categories. The results of this analysis are in Table A9.

As expected, both our ideological classifications and party identification are important for explaining voting behavior and the contributions of different voters to selection and accountability, and there are interesting interactions between ideology and party identification.

Among liberals, Republicans (a very small share of liberals) are more responsive to candidate ideology and experience than Democrats. Conversely, among conservatives, Democrats are more responsive than Republicans. Similarly, among Democrats, conservatives are more responsive than liberals, and among Republicans, liberals are more responsive than conservatives. These results are consistent with the possibility that party identification is another proxy for ideology. For example, liberal Republicans are likely more ideologically moderate than liberal Democrats, and since more ideologically moderate individuals are likely more responsive to candidate ideology and experience, we find that the former group is more responsive.

Interestingly, among moderates, independents are not necessarily more responsive to candidate ideology and experience than partisans. Moderate Democrats and moderate Republicans are among the most responsive groups. Similarly, Conversian Republicans are also very responsive to candidate ideology and experience.

The results in Table A9 suggest that if you want to understand the extent to which different people contribute to electoral selection and accountability, their ideological classification are more informative than their party identification. To be sure, independents are generally more responsive than partisans, but moderates and Conversians are much more responsive than liberals and conservatives. Furthermore, moderate and Conversian partisans appear to be more responsive than independent liberals and conservatives.

Table A9: Ideological Type by Party Identification

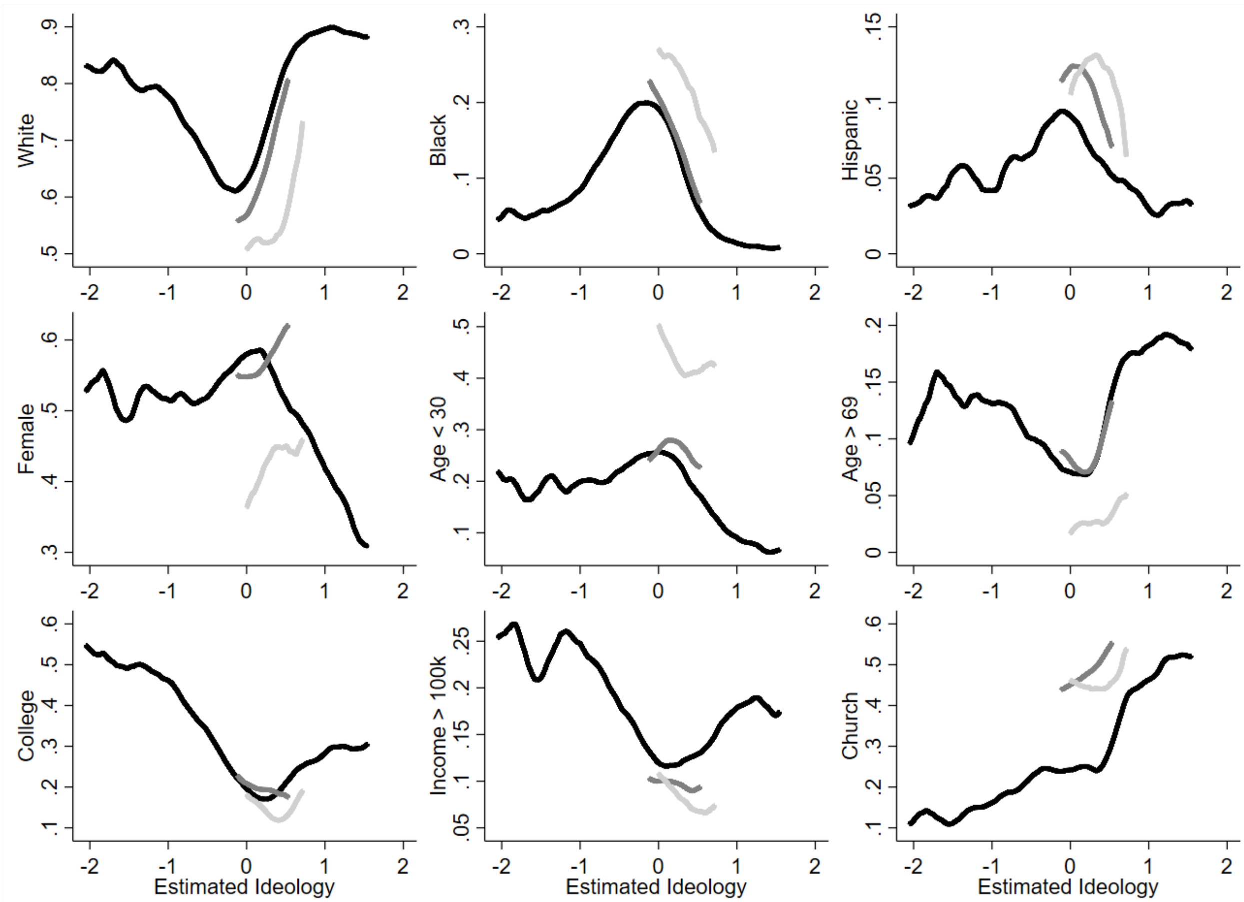
	DV = House Vote (Dem = 1, Rep = 0, Abstain/Other = .5)								
	X = Ideological Midpoint			X = Incumbency			X = Experience		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
X*Liberal Independent	.013	.012	.014	-.004	-.002	-.000	-.001	.001	.002
	(.013)	(.013)	(.013)	(.009)	(.009)	(.009)	(.009)	(.009)	(.009)
X*Liberal Republican	.030	.030	.021	.084	.090	.082	.105	.108	.096
	(.046)	(.045)	(.048)	(.036)	(.036)	(.036)	(.037)	(.037)	(.037)
X*Moderate Democrat	.048	.051	.055	.052	.051	.052	.055	.056	.057
	(.015)	(.015)	(.015)	(.010)	(.010)	(.009)	(.009)	(.009)	(.009)
X*Moderate Independent	.029	.028	.029	.024	.028	.026	.020	.023	.021
	(.013)	(.013)	(.013)	(.009)	(.009)	(.010)	(.010)	(.010)	(.010)
X*Moderate Republican	.051	.051	.051	.059	.066	.065	.058	.065	.064
	(.020)	(.020)	(.020)	(.014)	(.014)	(.014)	(.014)	(.014)	(.014)
X*Conservative Democrat	.062	.067	.069	.043	.046	.040	.066	.070	.067
	(.070)	(.065)	(.066)	(.035)	(.034)	(.034)	(.035)	(.034)	(.033)
X*Conservative Independent	.046	.045	.045	.027	.029	.027	.025	.026	.023
	(.018)	(.018)	(.019)	(.014)	(.014)	(.014)	(.014)	(.014)	(.014)
X*Conservative Republican	.017	.016	.020	.008	.014	.015	-.000	.006	.007
	(.015)	(.015)	(.016)	(.012)	(.013)	(.013)	(.013)	(.013)	(.013)
X*Conversian Democrat	.020	.021	.020	.038	.038	.034	.040	.039	.035
	(.016)	(.015)	(.015)	(.010)	(.009)	(.009)	(.010)	(.010)	(.010)
X*Conversian Independent	.063	.062	.065	.040	.040	.037	.035	.035	.033
	(.018)	(.017)	(.017)	(.010)	(.010)	(.010)	(.010)	(.010)	(.010)
X*Conversian Republican	.071	.075	.084	.070	.076	.075	.064	.072	.071
	(.020)	(.020)	(.020)	(.015)	(.015)	(.016)	(.015)	(.016)	(.016)
X*Inattentive Democrat	.007	.014	.023	.017	.016	.008	.013	.010	.001
	(.031)	(.030)	(.030)	(.019)	(.019)	(.019)	(.020)	(.019)	(.019)
X*Inattentive Independent	.061	.056	.050	.019	.019	.010	.007	.007	-.004
	(.022)	(.022)	(.021)	(.015)	(.015)	(.015)	(.015)	(.015)	(.015)
X*Inattentive Conservative	.003	.000	.007	.052	.050	.046	.054	.053	.048
	(.038)	(.037)	(.037)	(.025)	(.025)	(.025)	(.026)	(.026)	(.026)
X	.013	-.011		.060	.013		.061	.003	
	(.009)	(.010)		(.007)	(.011)		(.007)	(.011)	
Liberal Independent	-.096	-.094	-.095	-.081	-.084	-.084	-.083	-.085	-.085
	(.008)	(.008)	(.008)	(.007)	(.006)	(.006)	(.007)	(.007)	(.007)
Liberal Republican	-.340	-.334	-.328	-.355	-.353	-.350	-.366	-.363	-.358
	(.028)	(.028)	(.029)	(.023)	(.023)	(.023)	(.025)	(.024)	(.025)
Moderate Democrat	-.185	-.183	-.185	-.182	-.179	-.178	-.185	-.182	-.182
	(.009)	(.009)	(.009)	(.007)	(.007)	(.006)	(.007)	(.007)	(.006)
Moderate Independent	-.384	-.378	-.378	-.354	-.353	-.352	-.352	-.351	-.350
	(.008)	(.008)	(.008)	(.007)	(.007)	(.007)	(.007)	(.007)	(.007)
Moderate Republican	-.640	-.632	-.630	-.599	-.598	-.596	-.601	-.599	-.596
	(.011)	(.011)	(.011)	(.009)	(.009)	(.008)	(.009)	(.009)	(.009)
Conservative Democrat	-.455	-.448	-.450	-.420	-.417	-.411	-.431	-.428	-.424
	(.032)	(.031)	(.031)	(.023)	(.022)	(.021)	(.023)	(.022)	(.022)
Conservative Independent	-.724	-.717	-.716	-.666	-.665	-.664	-.667	-.664	-.663
	(.010)	(.010)	(.010)	(.008)	(.008)	(.008)	(.009)	(.009)	(.009)
Conservative Republican	-.771	-.762	-.763	-.720	-.718	-.717	-.717	-.715	-.714
	(.009)	(.009)	(.009)	(.008)	(.008)	(.008)	(.008)	(.009)	(.009)
Conversian Democrat	-.160	-.158	-.159	-.159	-.157	-.157	-.161	-.158	-.158
	(.010)	(.010)	(.010)	(.007)	(.007)	(.007)	(.007)	(.007)	(.007)
Conversian Independent	-.375	-.369	-.371	-.339	-.337	-.336	-.338	-.335	-.335
	(.009)	(.009)	(.009)	(.007)	(.007)	(.007)	(.007)	(.007)	(.007)
Conversian Republican	-.630	-.623	-.627	-.580	-.578	-.578	-.580	-.579	-.578
	(.011)	(.011)	(.011)	(.009)	(.009)	(.009)	(.009)	(.010)	(.010)
Inattentive Democrat	-.201	-.201	-.205	-.201	-.200	-.200	-.200	-.197	-.196
	(.020)	(.019)	(.019)	(.014)	(.014)	(.014)	(.015)	(.015)	(.014)
Inattentive Independent	-.402	-.393	-.391	-.361	-.358	-.356	-.356	-.353	-.349
	(.012)	(.012)	(.012)	(.010)	(.010)	(.010)	(.010)	(.010)	(.010)
Inattentive Conservative	-.584	-.574	-.579	-.557	-.551	-.551	-.559	-.553	-.553
	(.019)	(.019)	(.019)	(.014)	(.014)	(.014)	(.014)	(.015)	(.015)
Year FEs	✓	✓		✓	✓		✓	✓	
District FEs		✓			✓			✓	
District-Year FEs			✓			✓			✓
Observations	159,006	159,006	159,006	233,445	233,445	233,445	233,445	233,445	233,445

District-clustered standard errors in parentheses. Liberal Democrats are the omitted category.

F Demographics of Ideological Types

In this section, we assess the descriptive characteristics of the different types of respondents we identify. Figure A6 shows the same kinds of analyses utilized in Figure 6 in the text but for various demographic and social characteristics of interest.

Figure A6: Demographics across Types



The figure shows kernel regressions (bandwidth = .1) of demographic characteristics across estimated ideologies for Downsians (black), Conversians (dark gray), and inattentive (light gray) respondents in the 2016 CCES.

Generally speaking, liberals and conservatives are more likely to be white, male, older, college educated and high income than Downsian moderates, Conversians, and inattentive respondents are. Also as expected, conservatives are more likely to attend church, while liberals are especially more likely to be young or have a college degree.

Focusing on non-ideologues with moderate estimated ideologies, Downsian moderates are more likely to be white, more likely to be high income, and less likely to attend church. Inattentive respondents are more likely than other groups to be Black or young.

Although demographics are correlated with our classifications, demographics would not necessarily allow one to accurately predict a respondent's type. For example, among our 2016 respondents, approximately 2.8 percent of those who are 30 years of age or older are classified as inattentive, while approximately 8.1 percent of those under 30 are classified as inattentive. So young people are much more likely to be inattentive, but only a small minority of young voters are inattentive. For these reasons, we would caution against researchers utilizing demographics as a proxy for whether survey respondents are Downsian, Conversian, or inattentive, as this would likely result in many misclassifications.

G Stability of Estimates

In this section we assess the stability of our estimates using data from the 2010-2014 Cooperative Congressional Election Panel Study (Schaffner and Ansolabehere, 2015). This data includes panel re-interviews for 9,500 respondents in the 2010, 2012, and 2014 waves of the Cooperative Congressional Election Studies. These respondents were asked the same questions as the respondents in our main results. We re-estimated our model for each of these three waves separately, and compared the estimates for each of these groups.

We are interested in the degree to which respondents retain the same "type" from wave to wave, particularly the degree to which respondents who are estimated to be Downsians in one wave are also classified as Downsians in other waves. Although we don't have a strong prediction for how often respondents should change types, we take stability as evidence of for the validity of the measurement. We are also interested in the degree to which respondent ideal points are stable. In particular, if our types are meaningful then the ideal points of Downsians should be more stable than the ideal points of non-Downsians.

Table A10 shows the percentage of respondents who are classified as Downsian or non-Downsian in 2010 and 2012. It shows that 82% of respondents are classified as Downsians in both years; and 94% of respondents classified as Downsian in 2010 are still classified as Downsian in 2012. Table A11 shows the same numbers for 2012 and 2014: 84% of respondents are classified as Downsian in both years, and among Downsians in 2012, 93% are still classified as Downsians in 2014. Our estimates across these years appear to be quite consistent when it comes to respondents classified as Downsians.

Table A10: Percent of respondents classified as Downsian in 2010 and 2012

	Downsian in 2012	Not Downsian in 2012
Downsian in 2010	82.2%	8.3%
Not Downsian in 2010	5.2%	4.3%

Table A11: Percent of respondents classified as Downsian in 2012 and 2014

	Downsian in 2014	Not Downsian in 2014
Downsian in 2012	84.4%	6.1%
Not Downsian in 2012	4.2%	5.3%

Figure A7 plots the estimated ideal points of non-Downsians and Downsians in 2012 and 2014. For non-Downsians, the correlation across these two time periods is 0.62. For Downsians, the correlation is 0.86. Doubtless some of this has to with the range of estimated ideal points, which is very compressed for non-Downsians. However the high degree of stability of the estimated ideal points of Downsians across two years is reassuring evidence that Downsians have meaningful policy views.

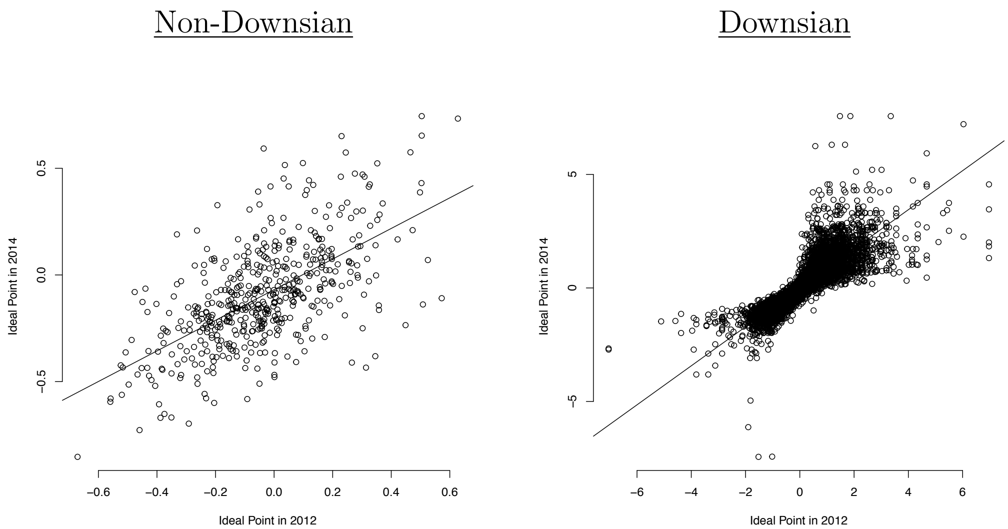


Figure A7: Stability of Estimated Ideal Points

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Supplementary Information for "Moderates"

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A EM algorithm for Issue Opinion Model Estimation

In this appendix, we describe the EM algorithm (Dempster, Laird, and Rubin, 1977) used to estimate the parameters of the likelihood function shown in Equation 5. Following the notation introduced in in the main text and for convenience letting $\theta = (\boldsymbol{\alpha}, \boldsymbol{\beta}, \boldsymbol{\lambda})$, we begin by forming the "complete data" log likelihood,

$$\ell(\theta) = \sum_i \sum_t v_{it} \log L_t(\boldsymbol{y}_{i\cdot}; \theta)$$

where $v_{it} = 1$ if the ith respondent is of type $t \in \{1, 2, 3\}$ and 0 otherwise. Note that $\sum_t v_{it} = 1$ for all respondents i. In the complete data problem, the type of each respondent is known and indicated by v. Of course, v is not observable. However, the EM algorithm is formed by iteratively maximizing the expected value of ℓ over the unknown values of v given estimates θ and the observed data.

In particular, we form the expectation of ℓ over v as

$$\begin{aligned} Q(\theta|\theta^{(s)}) &= \textstyle\sum_i \sum_t \mathrm{E}_{v_{it}|\boldsymbol{y}_{i\cdot}, \theta^{(s)}} \left(v_{it} \log L_t(\boldsymbol{y}_{i\cdot}; \theta) \right) \\ &= \textstyle\sum_i \sum_t \mathrm{E}_{v_{it}|\boldsymbol{y}_{i\cdot}, \theta^{(s)}} \left(v_{it} \right) \log L_t(\boldsymbol{y}_{i\cdot}; \theta) \\ &= \textstyle\sum_i \sum_t w_{it} \log L_t(\boldsymbol{y}_{i\cdot}; \theta) \end{aligned}$$

where

$$w_{it} = \frac{\bar{w}_t^{(s)} L_t(\boldsymbol{y}_{i\cdot}; \theta^{(s)})}{\sum_{t'} \bar{w}_{t'}^{(s)} L_{t'}(\boldsymbol{y}_{i\cdot}; \theta^{(s)})}$$

and $s = 0, 1, 2, \ldots$ indicates the current step of the EM algorithm.

A.1 The EM algorithm

The algorithm proceeds as follows:

1. The step counter, s, is set to zero and start values for $\theta^{(0)}$ and $\bar{w}_t^{(0)}$ for $t = 1, 2, 3$ are selected.

2. *E-Step*: w_{it} is formed for all i and t given $\theta^{(s)}$ and $\bar{w}_t^{(s)}$.

3. *M-Step*: Q is maximized in three parts yielding $\theta^{(s+1)}$ and $\bar{w}_t^{(s+1)}$ for $t = 1, 2, 3$. These three parts are as follows:

   a. For the parameters describing the issue opinions of respondents of type 1,

   $$\sum_i w_{i1} \log L_1(y_{i\cdot}; \boldsymbol{\alpha}, \boldsymbol{\beta})$$

   is maximized to update the estimates of $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$.

   b. The parameters describing the issue opinion of respondents of type 2 are updated as weighted means, $\lambda_j^{(s+1)} = \frac{\sum_{i \in \mathcal{N}_j} w_{i2} y_{ij}}{\sum_{i \in \mathcal{N}_j} w_{i2}}$ for $j = 1, \ldots, J$ where $\mathcal{N}_j$ is the set of respondents who answered question j.

   c. The sample proportions belonging to each type are updated as $\bar{w}_t^{(s+1)} = \sum_i w_{it}/N$ for $t = 1, 2, 3$.

4. s is incremented and the process repeated from (2) until convergence.

E-step details: As shown above, the calculation of w_{it}, requires the evaluation of L_1, L_2 and L_3. The likelihood of individual i's issue question responses if he is of type 3, $L_3(\boldsymbol{y}_{i\cdot})$, is simply a function of the number of responses given, does not depend on $\theta^{(s)}$, and is straightforward to calculate using Equation 2. Similarly, the calculation of the likelihood of individual i's issue question responses if she is of type 2, $L_2(\boldsymbol{y}_{i\cdot}, \boldsymbol{\lambda})$, requires only the straight-forward application of Equation 3.

The calculation of the likelihood of individual i's issue question responses if she is of type 1, $L_1(\boldsymbol{y}_{i\cdot}, \boldsymbol{\alpha}, \boldsymbol{\beta})$, is more complicated because it involves the calculation of the integral shown in Equation 1 as well as an estimate of the distribution of ideal points, f. We approximate f and the integral using Monte Carlo methods. In particular, we draw a sample from the current estimated ideal points, $\dot{x}_k$ for $k = 1, \ldots, M$, of size M. The sample is drawn independently and with replacement with sampling weights that are proportional to the current weights, w_{i1} for $i = 1, \ldots, N$. Because the estimated ideal points are drawn in proportion of the type 1 membership weights, the resulting sample is (approximately) drawn from f. Given this Monte Carlo draw from f, the integral in Equation 1 is approximated as

$$L_1(\boldsymbol{y}_{i\cdot}; \boldsymbol{\alpha}, \boldsymbol{\beta}) \approx \sum_{k=1}^{M} \prod_{j \in \mathcal{J}_i} \Lambda\left(\beta_j(\dot{x}_k - \alpha_j)\right)^{y_{ij}} \left(1 - \Lambda\left(\beta_j(\dot{x}_k - \alpha_j)\right)\right)^{1-y_{ij}}.$$

M-Step details: As part of the M-step, $\sum_i w_{i1} \log L_1(y_{i\cdot}; \boldsymbol{\alpha}, \boldsymbol{\beta})$ is maximized to update the estimates of $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$. These estimates are arrived at using a weighted version of the quadratic majorization approach of de Leeuw (2011b) where the weights are w_{i1} for $i = 1, \ldots, N$. Each ideal point is estimated as a fixed effect. Thus, the distribution of ideal points is estimated non-parametrically in this approach. This is also equivalent to a weighted version of the spatial voting model estimation method described in Imai, Lo, and Olmsted (2016).

B Power Simulations and Data Selection

The datasets that we use in this paper have very large numbers of respondents. However they have fewer policy questions than we would like, particularly for a model of this level of complexity. So it is important to assess the power of the model with respect to the number of items.

In Section B.1 of this appendix, we show two sets of simulations that examine how many items in a survey are necessary to accurately estimate both respondents' type and their spatial ideal points. Overall, this analysis leads us to conclude that about 20 policy items are necessary to accurately estimate all of the parameters in the model that we present in the main text.

If an analyst used less than 20 items:

- The respondents' one-dimensional ideal points would be estimated somewhat less accurately (see the left panels of Figures A1 and A2).

- More problematically, the respondents' types (Downsian, Conversion, Inattentive) would be estimated substantially less accurately when there are fewer than 20 items (see the middle panels of Figures A1 and A2), and estimates of the overall composition of the sample between these types would be greatly biased (right panels of Figures A1 and A2). Indeed, the accuracy of the estimated types and the overall composition of the sample between types increases dramatically at around 20 items.

In section B.2 of this appendix, we examine other features of the policy items that can increase the accuracy of the model parameters. Here too, we consistently find that the number of items is the most important predictor of model accuracy.

B.1 Simulations on effect of the number of policy items on model accuracy

There is no simple power calculation that will tell us how many items we need to get precise estimates of our model parameters. In the absence of such a formula we use simulations. We simulate our model two ways, both using actual data. First, we run the model on an existing data set, randomly selecting among the available items for each trial. We vary the number of items from 10 to the full number, in this case 32, conducting three trials for each number of items. In each trial we estimate the parameters of the model. We compare these estimates to the estimates we obtain using all 32 items.

Our second simulation method takes the estimated parameters from the full dataset and uses them to simulate new datasets. On each trial we randomly select a number of items M, doing this three times for each of M in 10 to 32, as before. Then we simulate a dataset using the estimated parameters from the full model for those items, and estimate our model on this simulated dataset. We continue to use the parameters estimated using all 32 items as our benchmark.

The first method has the advantage that it does not assume that our model is correctly specified. It simply takes a real dataset and estimates the parameters for various numbers of items. However this method is susceptible to the possibility that our conclusions will be affected by the idiosyncrasies of the dataset we choose. The second method assumes that our model *is* correctly specified. The data simply provide a set of plausible parameters to use for the simulations. The conclusions using this method are more generalizable in the sense that they should capture cases where there is similar heterogeneity in the parameters and the model is appropriate.

Among the datasets available to us, the 2014 CCES had the greatest number of items at the time of this simulation analysis.[1] The parameters of interest to us are the estimated type probabilities and ideal points for Downsian types. We want to know when we can make

[1] We later added the 2015, 2017 and 2018 CCES.

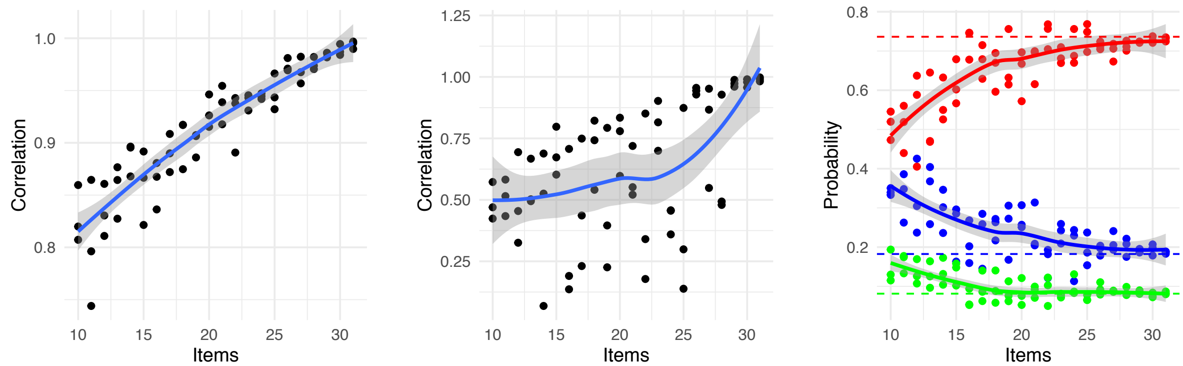
precise claims about which survey respondents have moderate ideal points, however defined. And we want to know when we can make precise claims about which respondents are very likely to be Downsians, as indicated by the size of the associated parameter. We also want to know how close our average estimates will be for all three parameters that indicate the fraction of the respondents that are Downsian, Conversian, and inattentive types.

Figure A1 shows the results for the first simulation method. The leftmost panel shows the correlation between the estimated ideal points in a given trial and the estimated ideal points using all 32 items on the y-axis. The x-axis is the number of used items in each trial. We fit a LOESS smoother to this relationship. With only 10 items this correlation hovers at a little over 0.8 on average but with correlations as low as .74. The relationship is close to linear. Twenty items are needed to consistently achieve correlations above .9, though of course more items are better.

The middle panel shows the correlation for the Downsian probabilities, w_1, estimated in each trial and the Downsian probabilities estimated with 32 items. This relationship is much noisier, but ranges from .5 in expectation with 10 items to very close to 1 with 32.

The last panel shows the averages for each set of probabilities along with a horizontal line for the averages when 32 item are used. Green indicates w_1, blue indicates w_2 and red indicates w_3. It is clear from this graph that these estimates are severely biased with only 10 items. w_1 and w_2 are biased upwards and w_3 is biased downwards. We suspect that this is part of a more general bias towards equality of the three probabilities in small samples. The bias ranges from almost .25 to close to 0, with the relationship flattening substantially around 20 items.

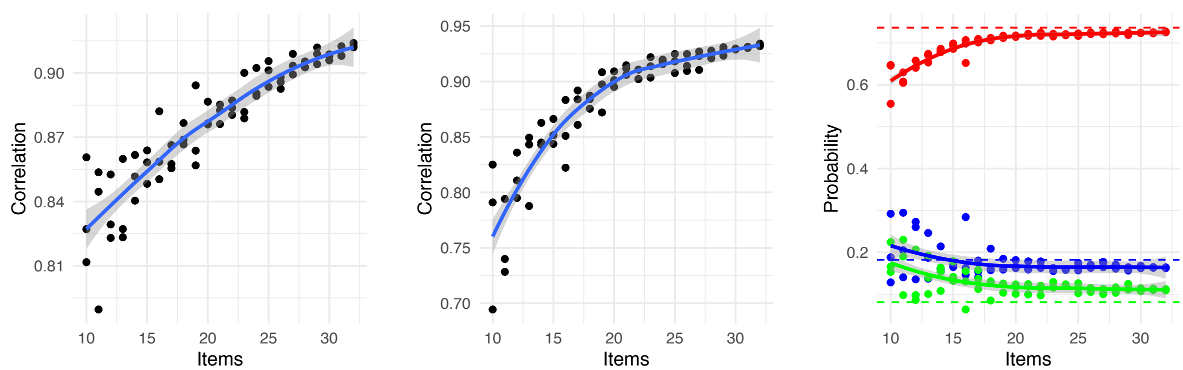
Figure A2 shows the results for the second simulation method. Assuming that our model is correctly specified substantially improves all of the metrics, particularly when few items are used. The association between the ideal points improves linearly in M from about .83 to about .91. The correlation in the probabilities improves rapidly from about .77 to about .94, flattening substantially around M=20. For the averages of the probabilities we see a



(a) Corr. ideal points (b) Corr. Pr(*Downsian*) (c) Estimated composition

Figure A1: Results from Simulation 1

smaller but still substantial bias around M=10, which is mostly eliminated by M=20. In each case a small discrepancy remains between the benchmark parameters and the estimated parameters, reflecting a small degree of model misspecification.



(a) Corr. ideal points (b) Corr. Pr(*Downsian*) (c) Estimated composition

Figure A2: Results from Simulation 2

There is no objective criteria for what threshold of items to use for precise estimation of these parameters. We consider the estimates using only 10 items to be clearly inadequate. It is clear from the graphs that greater numbers of items are better, and even greater than 32 would be preferable. However given the data available to us we choose to make do with datasets of 20 items or more. These estimates retain a small amount of bias against one of our central conclusions: that a low dimensional model is a good characterization of the preferences of most individuals. However they do not contain so much bias as to make type 2 errors very likely.

B.2 Other features of policy items that might improve model accuracy

So far we have only considered the number of items as an indicator of the power of a given dataset. However there are several other considerations that one might take into account in assessing power. The informativeness of a given dataset will depend on the unknown item parameters in complex ways. For instance, items that divide extreme liberals from moderate liberals are informative with respect to the parameters of those respondents but may not be very informative with respect to conservative respondents. So the position of the estimated cut points matter, and so does heterogeneity in these cut points. Items that are less discriminating will yield noisier estimates as well. In other words, "bad" items lead to "bad" estimates.

These factors are difficult to assess a priori. The margin of the survey question may be used as a rough indicator of where in the spectrum of ideal points the question is likely to be discriminating. In our case all survey questions are coded in what we believe to be the "conservative" direction. We can use the standard deviation of the margins as a measure of the coverage of these items. We evaluate whether the dispersion of the margins is an important factor in our simulated datasets, leaving a more thorough assessment of this methodological question to future work.

Table A1 shows the estimates from three models where the dependent variable is the correlation between the estimated w_1s from each simulation and the estimated w_1s using all 32 items from the CCES. These simulations are from our first method, described above. These models use three explanatory variables: the number of items, the standard deviation of the margins, and the interaction between those two factors. The number of items explains about a quarter of the variation in this correlation. However the standard deviation of the margins explains little if any variation, and only slightly improves upon a model using only the number of items.

Table A1: Effect of the number of items and standard deviation of the question margins on the correlation between the estimated w_1 and the benchmark w_1

	Dependent variable:		
	$corr_{w_1}$		
	(1)	(2)	(3)
# of items	0.021***		−0.054
	(0.004)		(0.050)
SD(margins) × # of items			0.560
			(0.371)
SD(margins)		1.832	−6.776
		(2.172)	(5.865)
Constant	0.204**	0.391	1.112
	(0.093)	(0.288)	(0.786)
Observations	66	66	66
R^2	0.265	0.011	0.299
Adjusted R^2	0.254	−0.004	0.266
Note:	*p<0.1; **p<0.05; ***p<0.01		

Table A2 shows estimates using the same independent variable, but here the dependent variable is the correlation between the simulated ideal points and the benchmark ideal points. This time the number of items explains 86% of the variance in the correlation. The standard deviation of the margins adds little if any explanatory power.

We take these models as evidence that, at least in this dataset, the number of items is a much more important factor than having a lot of dispersion in the margins. This may be because any random sample of the items available is sufficiently dispersed. However for our purposes we opt for a simple inclusion criterion and use all datasets where respondents answer at least 20 questions.

Table A2: Effect of the number of items and standard deviation of the question margins on the correlation between the estimated ideal points and the benchmark ideal points

	Dependent variable:		
	$corr_x$		
	(1)	(2)	(3)
# of items	0.009***		0.010**
	(0.0004)		(0.005)
SD(margins) × # of items			−0.013
			(0.038)
SD(margins)		0.186	0.286
		(0.494)	(0.595)
Constant	0.740***	0.890***	0.702***
	(0.009)	(0.066)	(0.080)
Observations	66	66	66
R^2	0.859	0.002	0.859
Adjusted R^2	0.856	−0.013	0.853
Note:	*p<0.1; **p<0.05; ***p<0.01		

Table A3 shows the median number of responses to policy items for 11 large-sample surveys of political views: the 2006-2016 Cooperative Congressional Election Studies and the 2000 and 2004 National Annenberg Election Surveys. The surveys where the median respondent answers at least 20 policy questions are the 2012, 2013, 2014, 2015, 2016, 2017 and 2018 Cooperative Congressional Election Studies, the data sets represented in the paper.

Table A3: Number of policy items on large sample surveys

Survey	Median Policy Responses
CCES 2006	12
CCES 2007	13
CCES 2008	14
CCES 2009	11
CCES 2010	16
CCES 2011	13
CCES 2012	21
CCES 2013	22
CCES 2014	32
CCES 2015	33
CCES 2016	28
CCES 2017	31
CCES 2018	35
NAES 2000	17
NAES 2004	9

C Model Validation with the Stanford Module of the 2010 CCES

In this appendix, we show that the example given in Figure 2 of the main text generalizes. If we compare any two questions out of the 133 question asked on the 2010 CCES module, respondents classified as Downsian moderates are more likely to give spatially consistent responses. Downsian moderates become even more likely to give spatially consistent responses when the magnitude of any inconsistency would be large. Conversians are more likely to give spatially inconsistent responses and their likelihood of doing so depends less on the magnitude of the inconsistency. This validation exercise requires no knowledge of our model to understand.

Consider a 133-by-133 matrix where each row and column represents one of our 133 items. The rows are ordered by support for the liberal alternative such that the top row is the least popular liberal policy and the bottom row the most popular liberal policy. The columns are ordered by support for the conservative policy. In this arrangement, the bottom left of our graph represents item pairs where the liberal alternative is very popular for the item in the rows and the conservative alternative is very popular for the item in the column. As we ascend towards the top right of the matrix, the liberal alternative becomes less and less popular for the row item, and the conservative alternative becomes less and less popular for the column item.

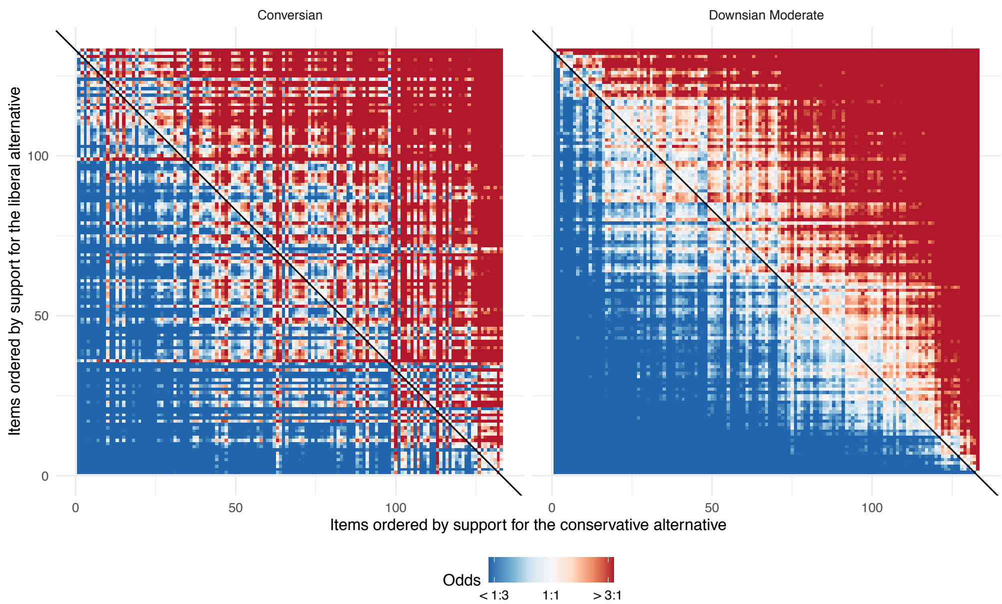
Without any statistical model, we want to try to capture the proportion of "spatial errors." If the items were perfectly Guttman scalable, then the margins would be sufficient. Consider a pair of items on the bottom left of our matrix, where the row item is R and the column item is C. Let 1 be a conservative response and 0 be a liberal response. Giving both liberal responses or both conservative responses will always be spatially consistent. For items on the bottom left, giving liberal responses to row items, $R = 0$, and conservative responses to column items, $C = 1$, is also spatially consistent, because these responses represent the majority of respondents. $R = 0$ and $C = 1$ is the moderate response to both questions. For the row item the conservative response is rare, and therefore relatively extreme, and for the column item the liberal response is rare, and therefore relatively extreme. So the response pattern $R = 1$, $C = 0$ gives the extreme conservative response on one question and the extreme liberal response on the other. This is a spatial error that suggests the respondent giving this answer pair has views not well summarized by a single dimension of policy ideology.

In the bottom left of the matrix, $(R = 0, C = 1)$ represents a spatially consistent choice and $(R = 1, C = 0)$ also represents a spatially inconsistent choice. As we move up the rows and to the left on the columns the margins of the questions get closer. At some point, the situation flips. Once majorities support the conservative side on the rows and the liberal side on the columns, then $(R = 1, C = 0)$ represents a spatially consistent choice and $(R = 0, C = 1)$ represents a spatially inconsistent choice. If these choices were perfectly Guttman scalable, than we would no longer observe the spatially inconsistent choice. In a random utility model, errors should become more common as the margins of the question become closer.

Figure A3 graphs the odds of choosing $(R = 1, C = 0)$ against $(R = 0, C = 1)$ for respondents who are classified as Conversian (left frame) and Downsian (right frame) moderates by our model. Moderate here indicates someone whose ideal point is in the middle third of the distribution with higher posterior probability Downsian than Conversian or inattentive. We focus on moderates to support the claims we make about moderates specifically in the paper.

Our expectation is that, for subjects whose views are well-explained by a single dimension of ideology, the odds should should be low on the bottom left, when $(R = 1, C = 0)$ is the spatially inconsistent choice, and high on the top right, when $(R = 1, C = 0)$ is the spatially consistent choice. The odds should approach 1:1 in the middle when the most spatially consistent choice is to respond in the same direction to both questions.

Figure A3: Odds of Spatially Consistent versus Spatially Inconsistent Choices



For each pair of 133 issues on the 2010 CCES, the color of each "pixel" represents the odds of a randomly selected respondent giving the conservative answer to the question indicated by the pixel's x-axis position and the liberal answer to the question indicated by the pixel's y-axis position from among those respondents giving one conservative and one liberal answer to that question pair. The questions are ordered by support for the conservative position on the x-axis and by support for the liberal position on the y-axis.

Under perfect one-dimensional spatial voting, the data would be Guttman scalable. In that case, these odds would be greater than 1:1 everywhere above the -45 degree line and less than 1:1 everywhere below the -45 degree line. Notice that for those respondents who we identify as Downsian moderate this is largely the case. On the other hand, for those respondents identified as Conversian, there is a great deal of red (odds greater than 1:1) below the -45 degree line and blue (odds less than 1:1) above the -45 degree line. It is clear from the graph that Conversians are much less constrained than are Downsian moderates.

This analysis provides descriptive nonparametric evidence that our model successfully separates ideologically consistent moderates (Downsians) from those whose responses are much less constrained by the ideological dimension (Conversians).

D Modeling Spatial Preferences in Two Dimensions

In the model presented in the main text, voters can either hold one-dimensional spatial preferences (with error) or hold issue opinions that are (across all such voters) independent across issues (Conversians and inattentives). An alternative approach would be to place all voters in a higher-dimensional preference space. Indeed, putting aside the small number of inattentive voters, it can be easily demonstrated that the mixture model that we advance can be represented as, and is isomorphic to, a standard two-dimensional model in which our Downsians have ideal points that fall on a single line and the Conversians fall on a single point that lies away from that line.[2] To see this, recall that, in the notation introduced in the main text, the probability that a Downsian respondent i answers issue question j in the affirmative ($y_{ij} = 1$) is

$$\Lambda\left(\beta_j(x_i - \alpha_j)\right).$$

If we extend this spatial choice function to two dimensions, the probability that $y_{ij} = 1$ becomes

$$\Lambda(\tilde{\alpha}_j + \tilde{\beta}_{j1}\tilde{x}_{i1} + \tilde{\beta}_{j2}\tilde{x}_{i2}).$$

While adding a second dimension to the usual quadratic spatial preference model increases the number of x and β parameters that characterize each choice, there is still only one α parameter (Clinton, Jackman, and Rivers, 2004, p. 365). The definition of $\tilde{\alpha}$ differs from its one-dimensional counterpart which is why we place a tilde over it (and the other parameters in the two-dimensional model). Note that $\tilde{\alpha}_j = -\alpha_j\beta_j$ in the one-dimensional case (in which $\tilde{\beta}_{j2} = 0$ for all j). Now, suppose that the data are generated according to the mixture model presented in the main text. We can represent the choice probabilities of Downsians in that model by setting $\tilde{\alpha}_j = -\alpha_j\beta_j$, $\tilde{\beta}_{j1} = \beta_j$, $\tilde{x}_{i1} = x_i$, and $\tilde{x}_{i2} = 0$ for all (Downsian) respondents

[2]We thank Ben Lauderdale for first pointing this out to us.

i and issue questions j because then

$$\Lambda(\tilde{\alpha}_j + \tilde{\beta}_{j1} x_i + \tilde{\beta}_{j2} \cdot 0)$$

equals

$$\Lambda\left(\beta_j (x_i - \alpha_j)\right).$$

Holding fixed these values of $\tilde{\alpha}$ and $\tilde{\beta}_{j1}$, we can accommodate the Conversian voters by setting their $\tilde{x}_{i1} = 0$ and their $\tilde{x}_{i2} = 1$ and choosing $\tilde{\beta}_{j2}$ to solve

$$\lambda_j = \Lambda(\tilde{\alpha}_j + \beta_j \cdot 0 + \tilde{\beta}_{j2} \cdot 1)$$

for all (Conversian) i and j. Rearranging we have

$$\Lambda^{-1}(\lambda_j) = \tilde{\alpha}_j + \tilde{\beta}_{j2} \cdot 1$$

or

$$\tilde{\beta}_{j2} = \Lambda^{-1}(\lambda_j) - \tilde{\alpha}_j.$$

Adding the inattentive voter type to the mix breaks the isomorphism of the two models, but given that few respondents of this type are estimated to exist in the data, the two models are close to isomorphic in this application.[3] Because spatial models in two dimensions are invariant to translations, dilations, reflections, and rotations of the ideal point space (see Clinton, Jackman, and Rivers, 2004, p. 365–366), there is a continuum of ways in which the model presented in the main text (leaving out the inattentives) can be made isomorphic to a (restricted) two-dimensional spatial model. However, all of these isomorphic two-dimensional models have the Downsians falling on a single line through the two-dimensional space and

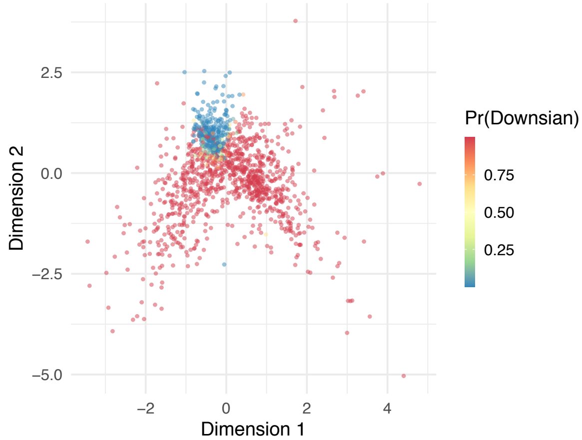
[3]Adding a third spatial dimension would be sufficient to recreate the isomorphism with inattentives included.

the Conversians falling on a point that does not (in general) lie on that line.[4]

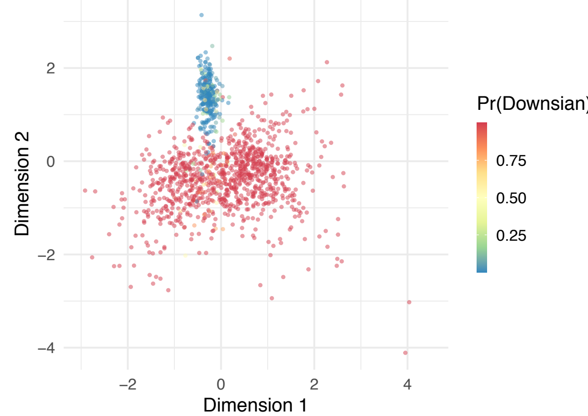
In this Appendix, we allow for the possibility that (some) voters have two-dimensional spatial preferences. We focus this exploration on the same 133-question dataset drawn from the 2010 CCES that we employ in Appendix C, the 2010 CCES module dataset. The large number of issue items found in this dataset relative to the other datasets presented in the text gives us the best opportunity to explore preferences in more than one dimension. We also present estimates of the out-of-sample fit of various alternative preference models considered for all of the datasets analyzed in the text.

We first apply a standard two-dimensional IRT-like model (Clinton, Jackman, and Rivers, 2004) to the 2010 CCES module dataset. Panel (a) of Figure A4 plots the resulting estimated ideal points. The points are colored according to the estimated probability that a respondent is a Downsian as estimated by the mixture model employed in the text. This plot does not reveal a single line of Downsians and a single point of Conversians that falls away from that line. However, the deviation from that pattern is perhaps less stark than it might appear. First, we see that the Conversians are concentrated in a small area of the graph. Second, because there is a stochastic component to the voters' preferences and because their locations are determined by no more than 133 questions (91.9 on average), each ideal point is estimated with error. Therefore, even if the true ideal points all fell on a single line in the space, we would expect the estimates to form a cloud around that line. To demonstrate this, Panel (b) of Figure A4 shows the estimated results when the same two-dimensional spatial model is applied to a simulated data set produced according to our mixture model calibrated to the CCES 2010 module data. Here we see that despite the mixture model holding exactly in the data, the Conversians are clustered, but do not fall on a single point nor do the

[4] If, in the parameterization presented, $\Lambda^{-1}(\lambda_j) = \tilde{\alpha}_j$ for all j then $\tilde{\beta}_{j2} = 0$ for all j and Conversians would be located at $\tilde{x}_i = (0, 0)$ which is a point on the line containing the Downsians. Of course, in this case Conversians cannot be empirically distinguished from Downsians because their choice probabilities would be identical to those of Downsians for whom $x_i = 0$. Note that in this knife-edged case where there is only one-dimension of choice, the values of $\tilde{\beta}_{j2}$ and $\tilde{x}_{i2}$ are not separately identified because $\tilde{\beta}_{j2} = 0$ for all j with $\tilde{x}_{i2} \in (-\infty, \infty)$ for all i and $\tilde{x}_{i2} = 0$ for all i with $\tilde{\beta}_{j2} \in (-\infty, \infty)$ for all j yield equivalent choice probabilities.



(a) Estimated



(b) Simulated

Figure A4: Estimating respondent preferences in two spatial dimensions. *Panel (a) shows the locations of 2010 CCES module respondents as estimated by a standard two-dimensional spatial model. The points are shaded to reflect the probability that each respondent is of the Downsian type as estimated by the model presented in the main text. Panel (b) shows the same plot based on simulated data that is calibrated to the 2010 CCES module dataset under the assumptions of the model presented in the main text.*

estimated locations of the Downsians fall on a single line. The general pattern shown in the two panels is similar though the locations of the Conversians is more strongly differentiated in the simulated data and there appears to be more structure to the second dimension in the empirical data. Given that there is no second dimension of spatial preference in the simulated data, this is not surprising. Though there is apparent structure in the second dimension of the empirical data, the first and second dimension locations are far from independent calling into question the degree to which there is an important distinct second dimension of preference manifest in the issue question responses.

Indeed, the empirical estimates reveal the horseshoe pattern often found when two-dimensional scaling models are applied in situations in which a single underlying dimension is expected (see Diaconis, Goel, and Holmes, 2008). In such cases, the recovered second dimension can be accounting for some misspecification of the functional form of the stochastic spatial preference, choice or distance function rather than a distinct second dimension (for example, in our context, distinct “economic” and “social” policy preference dimensions)

(Kendall, 1970; Shepard, 1974; Hill and Gauch, 1980; Diaconis, Goel, and Holmes, 2008; de Leeuw, 2011*a*).

Because there may be a distinct second dimension of spatial preference or the assumed functional form of the one-dimensional spatial preference model may be driving our results, we next consider how the inclusion of a second dimension into the mixture model affects our estimates of the fraction of Downsians and Conversians in the population. To do this, we fit an extended version of our mixture model to the CCES 2010 module dataset that allows the Downsians to have preferences over two spatial dimensions.

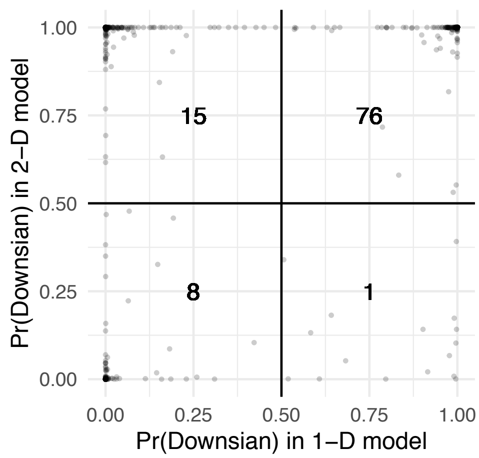


Figure A5: Estimated probabilities of each respondent being of the Downsian type.

For each respondent in the 2010 CCES module data, the x-axis shows the probability that a given respondent is of the Downsian type when one-dimensional spatial preferences are assumed. The y-axis shows the probability that a given respondent is of the Downsian type when two-dimensional spatial preferences are assumed. The quadrants partition respondents predicted to be Downsian from those predicted to be non-Downsian in either model or both. The numbers indicate the percentage of the sample that is estimated to fall into each quadrant. For example, 76 percent of the sample is estimated to be of the Downsian type in both one and two dimensions, while one percent of the sample is estimated to be Downsian when one spatial dimension is assumed, but non-Downsian when two spatial dimensions are assumed.

Figure A5 shows the estimated probability of being a Downsian for each survey respondent under the one-dimensional and two-dimensional mixture models. The four quadrants of the plot contain voters who are estimated to be (moving clockwise from the upper left): Downsian in the two-dimensional model, but Conversian in the one-dimensional model; Downsian in both models; Downsian in the one-dimensional model and Conversian in the two-dimensional model; and Conversian in both models. Whereas the one-dimensional model estimates about 23 percent of the sample to be Conversian, the two-dimensional model places only 9 percent of the sample in that category. Fifteen percent of the sample moves from Conversian to Downsian when a second dimension is available whereas only one percent moves from Downsian to Conversian. As noted in the main text, this suggests that some of the voters identified as Conversian moderates in the main text may hold preferences that, while not easily reconciled with a single spatial dimension, can be made reconcilable with spatial preferences when a second spatial dimension is added. Thus, our characterization of the fraction of "moderates" who actually have spatial preferences is perhaps understated.

Another related question is whether the addition of a second spatial dimension substantially improves the fidelity of the model with the data. To answer that question, we need a measure of (out of sample) fit. Table A4 reports the in-sample log likelihood as well as the out-of-sample perplexity associated with each model when applied to the 2010 CCES module dataset. The out-of-sample perplexity is approximated via a five-fold cross validation. Under the "null" model, across the entire sample, preferences are assumed to be independent across choices (in effect, all voters are assumed to be Conversians). The "1-D (mix.)" is the model presented in the main text that considers a mixture of Downsian, Conversian, and inattentive respondents. The "2-D (no mix.)" is the standard two-dimensional model used to produce the estimates in Figure A4. It does not include Conversian and inattentive types. The "2-D (Mix.)" is a version of the model used in the main text in which Downsians are given preferences over two spatial dimensions rather than one, and includes Conversian and inattentive types. Given the large number of data points (1,300 respondents answering on average 91.9 issue questions), it is not surprising that the differences between each pair of log likelihoods are statistically significant (p values not shown). That is, a statistically significant increase in data fit is afforded by each increase in model complexity.

Model	Log-likelihood	Perplexity
Null	-72675	1.84
1-D (mix.)	-53049	1.58
2-D (no mix.)	-51978	1.57
2-D (mix.)	-51383	1.56

Table A4: Model log likelihood and perplexity, 2010 CCES module dataset. *Shows the estimated model log likelihoods and estimated average (per item) perplexities across four possible models of preference. Each model is fit to the same 1,300 respondents answering an average of 91.9 issue questions). Each row of the table presents the estimated fit for a given model. The rows are organized in increasing order of model complexity. The log likelihood is estimated in sample. Perplexity is estimated out of sample using five-fold cross validation. The differences in log likelihood are highly statistically significant though the reductions in perplexity as model complexity increases are modest (except when comparing the null model to the others). Each model is described in the text.*

However, the perplexity differences among the various spatial models are modest particularly in comparison to the null model. Perplexity can be understood as the average number of bits per issue item required to compactly represent the responses of a single respondent. The higher the likelihood the model assigns to each observed pattern of the data the lower the perplexity (the perplexity is the average of the inverse of the geometric mean probability of the responses given by each respondent). If every respondent were an inattentive type, perplexity would be 2, which is the theoretical maximum (the maximally entropic data generating process). On the other hand, if every respondent expressed one of only two patterns across items, the perplexity would approach 0 (1 over the number of items) because a single bit would be sufficient to label the two observed patterns. As with the log likelihood, the value of perplexity is a function of both the nature of the data and the fidelity of the model. Because the perplexity is calculated using cross-validation, the observed reduction in the estimated perplexity as model complexity increases is not a mechanical result.

In fact, only small improvements in model fit result from the addition of a second spatial dimension. The inclusion of the Conversian and inattentive types appears to increase the fit of the two-dimensional model. However, the differences in fit among the various models that include a spatial component are very small (less than 1 percent differences in perplexity

Survey	Avg. no. of items	Log likelihood				Perplexity			
				2-D				2-D	
		Null	1-D Mix.	No mix.	Mix.	Null	1-D Mix.	No mix.	Mix.
2012	18.6	-661043	-550889	-551832	-550929	1.93	1.74	1.75	1.74
2013	21.8	-226870	-194338	-193809	-193867	1.89	1.74	1.74	1.74
2014	31.6	-1156518	-960685	-956933	-949695	1.92	1.74	1.73	1.72
2015	32.5	-292295	-230744	-227953	-226884	1.89	1.66	1.66	1.65
2016	28.8	-1137878	-972217	-973954	-971166	1.86	1.71	1.71	1.71
2017	30.9	-358915	-269839	-269580	-267369	1.90	1.64	1.64	1.63
2018	33.1	-1274454	-973250	-975855	-968311	1.91	1.66	1.67	1.66

Table A5: Model log likelihood and perplexity, 2012–2018 CCES datasets. *Shows the estimated model log likelihoods and estimated average (per item) perplexities across four possible models of issue preference. Each model is fit to the same respondents to each survey. The average number of responses to each survey is given in the table. Each row of the table presents estimated model fits for a given survey. The differences in log likelihood are statistically significant across the models for each survey though the reductions in perplexity as model complexity increases are very small (except when comparing the null model to the others). Each model is described in the text.*

per issue item). Table A5 shows the log likelihoods and perplexities associated with the Null, 1-D (with mixture), 2-D (without mixture), and 2-D (with mixture) models described above when applied to the CCES datasets from 2012 to 2018 analyzed in the text. As with the 2010 CCES module dataset, adding model complexity increases fit in a statistically significant way (the log likelihoods differ by more than chance would allow). However the degree of additional (out of sample) fit is minimal (often zero to two decimal places).

E Additional Results on Selection and Accountability

Table 4 in the text assessed the extent to which the voting behavior of different types of individuals responds to candidate ideology and experience. To assess the extent to which each group contributes to election results, we utilized a trichotomous dependent variable that takes a value of 1 if the respondent voted for the Democratic candidate, 0 if the respondent voted for the Republican candidate, and 0.5 if the respondent abstained or voted for a third-party candidate.

For readers interested in the extent to which those previous results were explained by voter turnout versus vote choice, we replicate those analyses but utilize alternative dependent variables. Table A6 excludes those who abstained or supported a third-party candidate and utilizes a binary dependent variable indicating support for the Democratic candidate. This analysis suffers from the potential concern that the independent variables of interest could affect turnout, which could induce bias. However, if we assume that candidate ideology and experience do not influence turnout, we can interpret these results as the differential effects of ideology and experience for those who voted.

If anything, the interactive coefficients in Table A6 are greater than those in Table 4. In other words, if we condition on those who voted, moderate, Conversian, and inattentive individuals are even more likely than liberals and conservatives to change their partisan vote choices in response to candidate ideology and experience. Of course, moderate, Conversian, and especially inattentive individuals are less likely to vote than liberal and conservative individuals, so these estimates overstate the extent to which these groups contribute to election results. But these results show that among those who vote, the non-ideologues are especially likely to contribute to electoral selection and accountability.

Additionally, Table A7 shows the same analyses but utilizes abstention as the dependent variable of interest. Consistent with our previous results, we find that moderate, Conversian, and inattentive individuals are more likely to abstain than liberals and conservatives.

The first three columns show that the extent to which these groups differentially abstain does not meaningfully vary as the ideologies of the candidates shift from favoring the Republican candidate to favoring the Democratic candidate.

However, we do find that the participation differences do vary across candidate experience in ways that we might expect. As the experience gap between the Democratic and Republican candidate increases, conservatives become much more likely to abstain relative

Table A6: Excluding Abstainers

	DV = House Vote (Dem = 1, Rep = 0)								
	X = Ideological Midpoint			X = Incumbency			X = Experience		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
X*Moderate	.107	.102	.101	.219	.214	.210	.225	.221	.215
	(.021)	(.020)	(.020)	(.013)	(.013)	(.013)	(.013)	(.013)	(.013)
X*Conversian	.157	.146	.150	.253	.242	.233	.257	.248	.237
	(.024)	(.024)	(.024)	(.015)	(.015)	(.015)	(.016)	(.016)	(.015)
X*Inattentive	.106	.096	.098	.250	.229	.221	.251	.228	.219
	(.051)	(.046)	(.046)	(.031)	(.029)	(.029)	(.031)	(.029)	(.029)
X*Conservative	.011	.007	.010	.001	.014	.016	.002	.018	.017
	(.012)	(.013)	(.014)	(.008)	(.010)	(.011)	(.009)	(.010)	(.011)
X	.042	-.012		.066	-.039		.065	-.059	
	(.009)	(.012)		(.005)	(.013)		(.005)	(.012)	
Moderate	-.492	-.480	-.479	-.513	-.505	-.498	-.523	-.515	-.506
	(.011)	(.011)	(.011)	(.008)	(.008)	(.008)	(.008)	(.008)	(.008)
Conversian	-.460	-.448	-.451	-.474	-.467	-.462	-.484	-.477	-.471
	(.014)	(.014)	(.014)	(.010)	(.009)	(.009)	(.010)	(.010)	(.010)
Inattentive	-.520	-.509	-.511	-.558	-.549	-.543	-.563	-.553	-.547
	(.029)	(.026)	(.026)	(.019)	(.018)	(.018)	(.019)	(.018)	(.018)
Conservative	-.917	-.894	-.892	-.890	-.878	-.866	-.891	-.879	-.866
	(.006)	(.007)	(.007)	(.005)	(.005)	(.006)	(.005)	(.006)	(.006)
Year FEs	✓	✓		✓	✓		✓	✓	
District FEs		✓			✓			✓	
District-Year FEs			✓			✓			✓
Observations	102,350	102,350	102,350	143,715	143,715	143,715	143,715	143,715	143,715

District-clustered standard errors in parentheses. Liberals are the omitted category.

to liberals, and moderates, Conversians, and inattentive individuals are somewhere in between. In other words, an experience advantage for the Republican (Democratic) candidate motivates conservative (liberal) individuals to participate relative to liberal (conservative) individuals. Interestingly, the estimated differences between conservatives and moderates are greater than those between liberals and moderates. One potential explanation is that conservative abstention is more responsive to candidate experience than liberal abstention or that moderate abstention more closely matches that of liberals.

Table A8 replicates the analyses in Table 4 but adds in controls for party identification. Specifically, all regressions include fixed effects for each possible category of the seven-point party identification scale. On one hand, these controls might increase precision since party identifcation is strongly correlated with vote choice. On the other hand, controlling for party identification could induce bias because the ideology and experiences of congressional candi-

Table A7: Analyzing Abstention

	DV = House Abstention (Abstain/Other = 1, Dem/Rep = 0)								
	X = Ideological Midpoint			X = Incumbency			X = Experience		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
X*Moderate	-.026	-.033	-.033	.028	.030	.031	.031	.035	.035
	(.016)	(.016)	(.016)	(.012)	(.012)	(.012)	(.012)	(.012)	(.012)
X*Conversian	-.011	-.014	-.010	.040	.042	.038	.041	.044	.043
	(.020)	(.019)	(.019)	(.012)	(.012)	(.012)	(.013)	(.012)	(.012)
X*Inattentive	-.009	-.025	-.019	.044	.042	.039	.071	.069	.068
	(.029)	(.029)	(.029)	(.019)	(.019)	(.019)	(.020)	(.020)	(.020)
X*Conservative	-.008	-.015	-.014	.118	.133	.129	.125	.144	.140
	(.017)	(.017)	(.017)	(.016)	(.015)	(.015)	(.016)	(.016)	(.016)
X	.036	.017		-.051	-.056		-.060	-.065	
	(.014)	(.015)		(.011)	(.016)		(.012)	(.017)	
Moderate	.242	.236	.234	.205	.196	.194	.203	.193	.191
	(.009)	(.009)	(.009)	(.008)	(.008)	(.008)	(.008)	(.008)	(.008)
Conversian	.263	.250	.243	.225	.208	.204	.223	.205	.201
	(.011)	(.010)	(.010)	(.008)	(.008)	(.008)	(.009)	(.009)	(.009)
Inattentive	.353	.345	.341	.319	.302	.300	.304	.287	.284
	(.017)	(.017)	(.018)	(.013)	(.013)	(.013)	(.014)	(.014)	(.014)
Conservative	-.049	-.056	-.055	-.096	-.107	-.104	-.103	-.116	-.113
	(.009)	(.009)	(.009)	(.008)	(.008)	(.008)	(.009)	(.008)	(.008)
Year FEs	✓	✓		✓	✓		✓	✓	
District FEs		✓			✓			✓	
District-Year FEs			✓			✓			✓
Observations	159,006	159,006	159,006	233,445	233,445	233,445	233,445	233,445	233,445

District-clustered standard errors in parentheses. Liberals are the omitted category.

dates could potentially influence the reported party identification of respondents. Because of this potential bias, we believe analyses that exclude partisanship controls are more reliable.

When we control for party identification, the estimated interactive effects of interest in Table A8 are similar to those in Table 4 although slightly attenuated. This could follow from the relative appeal of Democratic and Republican congressional candidates affecting reports of party identification. Nevertheless, even when we control for party, the results are qualitatively similar.

We might also want to know how the ideological types we identify interact with party identification. Because party identification is strongly correlated with vote choice, we would expect, for example, liberal Democrats to behave differently than liberal independents. To assess this possibility, we coded indicators for every potential combination of our ideological types (liberal, moderate, conservative, Conversian, and inattentive) and three-point party

Table A8: Controlling for Party ID

	DV = House Vote (Dem = 1, Rep = 0, Abstain/Other = .5)								
	X = Ideological Midpoint			X = Incumbency			X = Experience		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
X*Moderate	.036	.037	.039	.044	.046	.045	.043	.045	.044
	(.010)	(.010)	(.010)	(.007)	(.007)	(.007)	(.007)	(.007)	(.007)
X*Conversian	.040	.043	.046	.048	.049	.046	.044	.045	.042
	(.012)	(.012)	(.011)	(.007)	(.007)	(.007)	(.008)	(.008)	(.008)
X*Inattentive	.015	.016	.018	.022	.020	.013	.016	.014	.005
	(.017)	(.017)	(.017)	(.012)	(.012)	(.012)	(.012)	(.012)	(.012)
X*Conservative	.024	.024	.026	.015	.018	.017	.007	.010	.009
	(.013)	(.013)	(.014)	(.011)	(.011)	(.012)	(.012)	(.012)	(.012)
X	.017	-.007		.057	.015		.061	.005	
	(.008)	(.008)		(.007)	(.010)		(.007)	(.010)	
Moderate	-.188	-.185	-.186	-.183	-.181	-.180	-.183	-.181	-.180
	(.006)	(.006)	(.006)	(.005)	(.005)	(.005)	(.005)	(.005)	(.005)
Conversian	-.176	-.173	-.176	-.168	-.165	-.166	-.167	-.164	-.165
	(.007)	(.007)	(.006)	(.005)	(.005)	(.005)	(.005)	(.005)	(.005)
Inattentive	-.184	-.180	-.183	-.180	-.177	-.176	-.178	-.174	-.172
	(.010)	(.009)	(.009)	(.008)	(.008)	(.008)	(.008)	(.008)	(.008)
Conservative	-.371	-.367	-.368	-.350	-.348	-.348	-.347	-.345	-.345
	(.007)	(.007)	(.007)	(.006)	(.006)	(.006)	(.007)	(.007)	(.007)
Year FEs	✓	✓		✓	✓		✓	✓	
District FEs		✓			✓			✓	
District-Year FEs			✓			✓			✓
Party ID FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	152,616	152,616	152,616	224,047	224,047	224,047	224,047	224,047	224,047

District-clustered standard errors in parentheses. Liberals are the omitted category.

identification (Democrat, independent, and Republican). We then replicated the methodology used in Table 4 but separately examined each of these categories. The results of this analysis are in Table A9.

As expected, both our ideological classifications and party identification are important for explaining voting behavior and the contributions of different voters to selection and accountability, and there are interesting interactions between ideology and party identification.

Among liberals, Republicans (a very small share of liberals) are more responsive to candidate ideology and experience than Democrats. Conversely, among conservatives, Democrats are more responsive than Republicans. Similarly, among Democrats, conservatives are more responsive than liberals, and among Republicans, liberals are more responsive than conservatives. These results are consistent with the possibility that party identification is another proxy for ideology. For example, liberal Republicans are likely more ideologically moderate than liberal Democrats, and since more ideologically moderate individuals are likely more responsive to candidate ideology and experience, we find that the former group is more responsive.

Interestingly, among moderates, independents are not necessarily more responsive to candidate ideology and experience than partisans. Moderate Democrats and moderate Republicans are among the most responsive groups. Similarly, Conversian Republicans are also very responsive to candidate ideology and experience.

The results in Table A9 suggest that if you want to understand the extent to which different people contribute to electoral selection and accountability, their ideological classification are more informative than their party identification. To be sure, independents are generally more responsive than partisans, but moderates and Conversians are much more responsive than liberals and conservatives. Furthermore, moderate and Conversian partisans appear to be more responsive than independent liberals and conservatives.

Table A9: Ideological Type by Party Identification

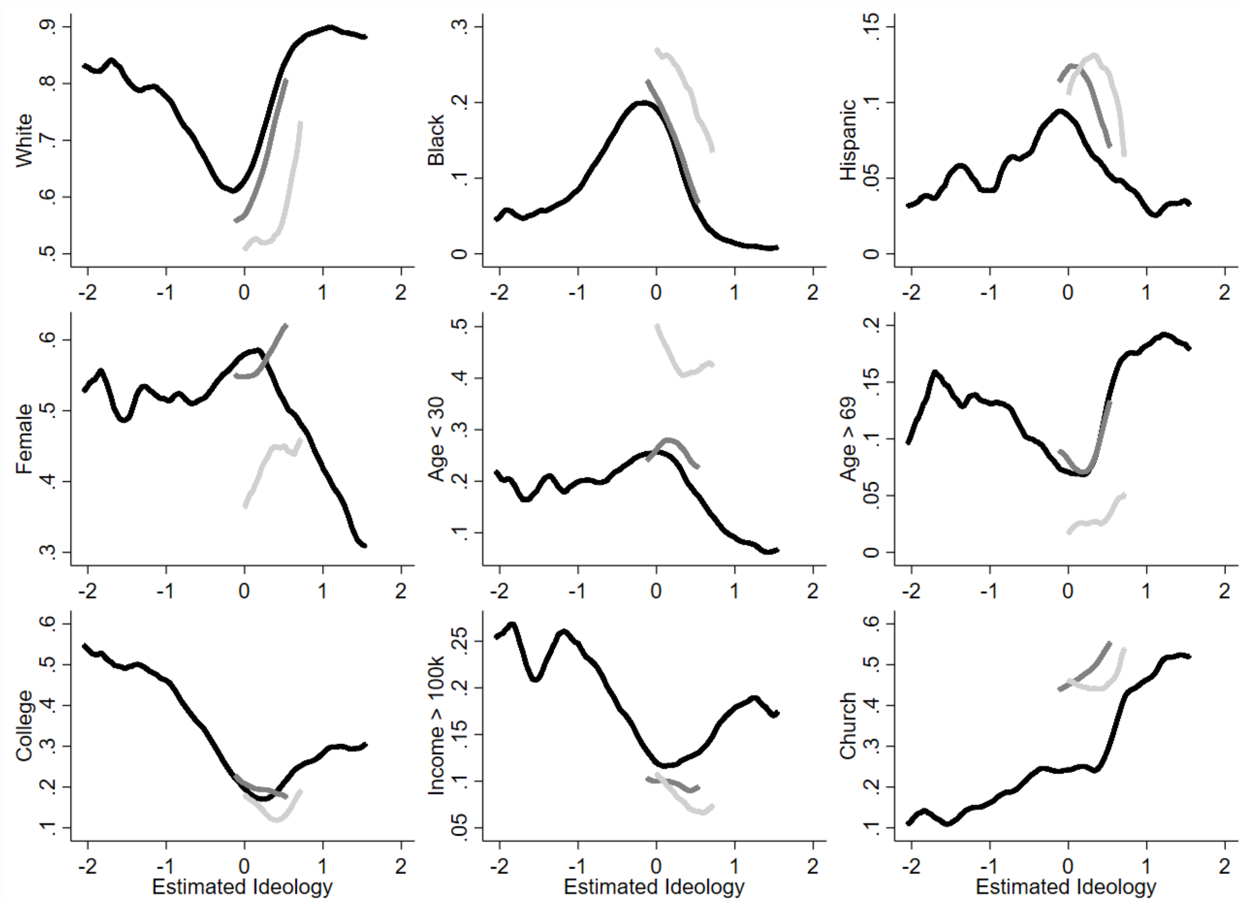
	DV = House Vote (Dem = 1, Rep = 0, Abstain/Other = .5)								
	X = Ideological Midpoint			X = Incumbency			X = Experience		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
X*Liberal Independent	.013	.012	.014	-.004	-.002	-.000	-.001	.001	.002
	(.013)	(.013)	(.013)	(.009)	(.009)	(.009)	(.009)	(.009)	(.009)
X*Liberal Republican	.030	.030	.021	.084	.090	.082	.105	.108	.096
	(.046)	(.045)	(.048)	(.036)	(.036)	(.036)	(.037)	(.037)	(.037)
X*Moderate Democrat	.048	.051	.055	.052	.051	.052	.055	.056	.057
	(.015)	(.015)	(.015)	(.010)	(.010)	(.009)	(.009)	(.009)	(.009)
X*Moderate Independent	.029	.028	.029	.024	.028	.026	.020	.023	.021
	(.013)	(.013)	(.013)	(.009)	(.009)	(.010)	(.010)	(.010)	(.010)
X*Moderate Republican	.051	.051	.051	.059	.066	.065	.058	.065	.064
	(.020)	(.020)	(.020)	(.014)	(.014)	(.014)	(.014)	(.014)	(.014)
X*Conservative Democrat	.062	.067	.069	.043	.046	.040	.066	.070	.067
	(.070)	(.065)	(.066)	(.035)	(.034)	(.034)	(.035)	(.034)	(.033)
X*Conservative Independent	.046	.045	.045	.027	.029	.027	.025	.026	.023
	(.018)	(.018)	(.019)	(.014)	(.014)	(.014)	(.014)	(.014)	(.014)
X*Conservative Republican	.017	.016	.020	.008	.014	.015	-.000	.006	.007
	(.015)	(.015)	(.016)	(.012)	(.013)	(.013)	(.013)	(.013)	(.013)
X*Conversian Democrat	.020	.021	.020	.038	.038	.034	.040	.039	.035
	(.016)	(.015)	(.015)	(.010)	(.009)	(.009)	(.010)	(.010)	(.010)
X*Conversian Independent	.063	.062	.065	.040	.040	.037	.035	.035	.033
	(.018)	(.017)	(.017)	(.010)	(.010)	(.010)	(.010)	(.010)	(.010)
X*Conversian Republican	.071	.075	.084	.070	.076	.075	.064	.072	.071
	(.020)	(.020)	(.020)	(.015)	(.015)	(.016)	(.015)	(.016)	(.016)
X*Inattentive Democrat	.007	.014	.023	.017	.016	.008	.013	.010	.001
	(.031)	(.030)	(.030)	(.019)	(.019)	(.019)	(.020)	(.019)	(.019)
X*Inattentive Independent	.061	.056	.050	.019	.019	.010	.007	.007	-.004
	(.022)	(.022)	(.021)	(.015)	(.015)	(.015)	(.015)	(.015)	(.015)
X*Inattentive Conservative	.003	.000	.007	.052	.050	.046	.054	.053	.048
	(.038)	(.037)	(.037)	(.025)	(.025)	(.025)	(.026)	(.026)	(.026)
X	.013	-.011		.060	.013		.061	.003	
	(.009)	(.010)		(.007)	(.011)		(.007)	(.011)	
Liberal Independent	-.096	-.094	-.095	-.081	-.084	-.084	-.083	-.085	-.085
	(.008)	(.008)	(.008)	(.007)	(.006)	(.006)	(.007)	(.007)	(.007)
Liberal Republican	-.340	-.334	-.328	-.355	-.353	-.350	-.366	-.363	-.358
	(.028)	(.028)	(.029)	(.023)	(.023)	(.023)	(.025)	(.024)	(.025)
Moderate Democrat	-.185	-.183	-.185	-.182	-.179	-.178	-.185	-.182	-.182
	(.009)	(.009)	(.009)	(.007)	(.007)	(.006)	(.007)	(.007)	(.006)
Moderate Independent	-.384	-.378	-.378	-.354	-.353	-.352	-.352	-.351	-.350
	(.008)	(.008)	(.008)	(.007)	(.007)	(.007)	(.007)	(.007)	(.007)
Moderate Republican	-.640	-.632	-.630	-.599	-.598	-.596	-.601	-.599	-.596
	(.011)	(.011)	(.011)	(.009)	(.009)	(.008)	(.009)	(.009)	(.009)
Conservative Democrat	-.455	-.448	-.450	-.420	-.417	-.411	-.431	-.428	-.424
	(.032)	(.031)	(.031)	(.023)	(.022)	(.021)	(.023)	(.022)	(.022)
Conservative Independent	-.724	-.717	-.716	-.666	-.665	-.664	-.667	-.664	-.663
	(.010)	(.010)	(.010)	(.008)	(.008)	(.008)	(.009)	(.009)	(.009)
Conservative Republican	-.771	-.762	-.763	-.720	-.718	-.717	-.717	-.715	-.714
	(.009)	(.009)	(.009)	(.008)	(.008)	(.008)	(.008)	(.009)	(.009)
Conversian Democrat	-.160	-.158	-.159	-.159	-.157	-.157	-.161	-.158	-.158
	(.010)	(.010)	(.010)	(.007)	(.007)	(.007)	(.007)	(.007)	(.007)
Conversian Independent	-.375	-.369	-.371	-.339	-.337	-.336	-.338	-.335	-.335
	(.009)	(.009)	(.009)	(.007)	(.007)	(.007)	(.007)	(.007)	(.007)
Conversian Republican	-.630	-.623	-.627	-.580	-.578	-.578	-.580	-.579	-.578
	(.011)	(.011)	(.011)	(.009)	(.009)	(.009)	(.009)	(.010)	(.010)
Inattentive Democrat	-.201	-.201	-.205	-.201	-.200	-.200	-.200	-.197	-.196
	(.020)	(.019)	(.019)	(.014)	(.014)	(.014)	(.015)	(.015)	(.014)
Inattentive Independent	-.402	-.393	-.391	-.361	-.358	-.356	-.356	-.353	-.349
	(.012)	(.012)	(.012)	(.010)	(.010)	(.010)	(.010)	(.010)	(.010)
Inattentive Conservative	-.584	-.574	-.579	-.557	-.551	-.551	-.559	-.553	-.553
	(.019)	(.019)	(.019)	(.014)	(.014)	(.014)	(.014)	(.015)	(.015)
Year FEs	✓	✓		✓	✓		✓	✓	
District FEs		✓			✓			✓	
District-Year FEs			✓			✓			✓
Observations	159,006	159,006	159,006	233,445	233,445	233,445	233,445	233,445	233,445

District-clustered standard errors in parentheses. Liberal Democrats are the omitted category.

F Demographics of Ideological Types

In this section, we assess the descriptive characteristics of the different types of respondents we identify. Figure A6 shows the same kinds of analyses utilized in Figure 6 in the text but for various demographic and social characteristics of interest.

Figure A6: Demographics across Types



The figure shows kernel regressions (bandwidth = .1) of demographic characteristics across estimated ideologies for Downsians (black), Conversians (dark gray), and inattentive (light gray) respondents in the 2016 CCES.

Generally speaking, liberals and conservatives are more likely to be white, male, older, college educated and high income than Downsian moderates, Conversians, and inattentive respondents are. Also as expected, conservatives are more likely to attend church, while liberals are especially more likely to be young or have a college degree.

Focusing on non-ideologues with moderate estimated ideologies, Downsian moderates are more likely to be white, more likely to be high income, and less likely to attend church. Inattentive respondents are more likely than other groups to be Black or young.

Although demographics are correlated with our classifications, demographics would not necessarily allow one to accurately predict a respondent's type. For example, among our 2016 respondents, approximately 2.8 percent of those who are 30 years of age or older are classified as inattentive, while approximately 8.1 percent of those under 30 are classified as inattentive. So young people are much more likely to be inattentive, but only a small minority of young voters are inattentive. For these reasons, we would caution against researchers utilizing demographics as a proxy for whether survey respondents are Downsian, Conversian, or inattentive, as this would likely result in many misclassifications.

G Stability of Estimates

In this section we assess the stability of our estimates using data from the 2010-2014 Cooperative Congressional Election Panel Study (Schaffner and Ansolabehere, 2015). This data includes panel re-interviews for 9,500 respondents in the 2010, 2012, and 2014 waves of the Cooperative Congressional Election Studies. These respondents were asked the same questions as the respondents in our main results. We re-estimated our model for each of these three waves separately, and compared the estimates for each of these groups.

We are interested in the degree to which respondents retain the same "type" from wave to wave, particularly the degree to which respondents who are estimated to be Downsians in one wave are also classified as Downsians in other waves. Although we don't have a strong prediction for how often respondents should change types, we take stability as evidence of for the validity of the measurement. We are also interested in the degree to which respondent ideal points are stable. In particular, if our types are meaningful then the ideal points of Downsians should be more stable than the ideal points of non-Downsians.

Table A10 shows the percentage of respondents who are classified as Downsian or non-Downsian in 2010 and 2012. It shows that 82% of respondents are classified as Downsians in both years; and 94% of respondents classified as Downsian in 2010 are still classified as Downsian in 2012. Table A11 shows the same numbers for 2012 and 2014: 84% of respondents are classified as Downsian in both years, and among Downsians in 2012, 93% are still classified as Downsians in 2014. Our estimates across these years appear to be quite consistent when it comes to respondents classified as Downsians.

Table A10: Percent of respondents classified as Downsian in 2010 and 2012

	Downsian in 2012	Not Downsian in 2012
Downsian in 2010	82.2%	8.3%
Not Downsian in 2010	5.2%	4.3%

Table A11: Percent of respondents classified as Downsian in 2012 and 2014

	Downsian in 2014	Not Downsian in 2014
Downsian in 2012	84.4%	6.1%
Not Downsian in 2012	4.2%	5.3%

Figure A7 plots the estimated ideal points of non-Downsians and Downsians in 2012 and 2014. For non-Downsians, the correlation across these two time periods is 0.62. For Downsians, the correlation is 0.86. Doubtless some of this has to with the range of estimated ideal points, which is very compressed for non-Downsians. However the high degree of stability of the estimated ideal points of Downsians across two years is reassuring evidence that Downsians have meaningful policy views.

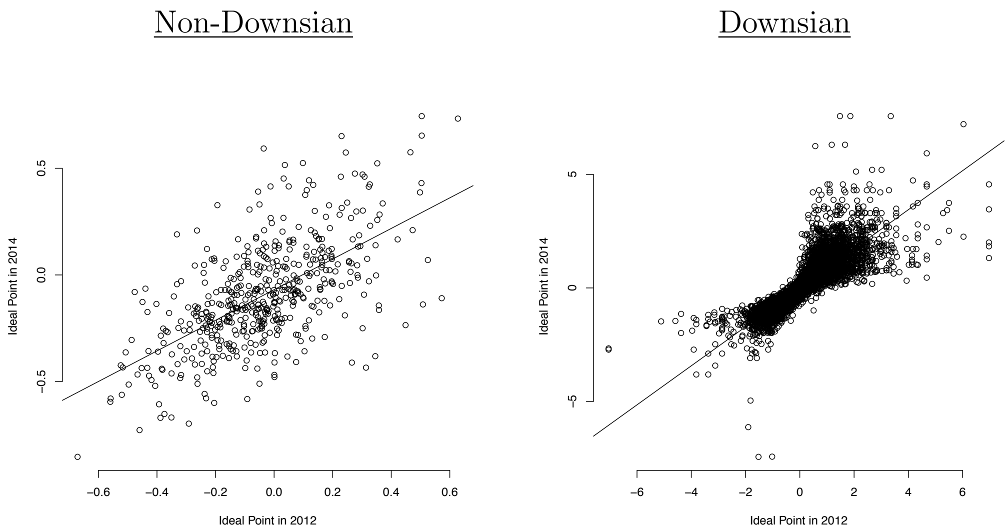


Figure A7: Stability of Estimated Ideal Points

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