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Uncertainty in Issue Placements and Spatial Voting

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Abstract

Empirical applications of spatial voting approaches frequently rely on ordinal policy scales to measure the policy preferences of voters and their perceptions about party or candidate platforms. Even though it is well known that these placements are affected by uncertainty, only a few empirical voter choice models incorporate uncertainty into the choice rule. In this manuscript, we develop a two-stage approach to further the understanding of how uncertainty impacts on spatial issue voting. First, we model survey responses to ordinal policy scales where specific response styles capture the uncertainty structure in issue placements. At the second stage, we model voter choice and use the placements adjusted for the detected uncertainty as predictors in calculating spatial proximity. We apply the approach to the 2016 US presidential election and study voter preferences and perceptions of the two major candidate platforms on the traditional liberal-conservative scale and three specific issues. Our approach gives insights into how voters attribute issue positions and spatial voting behavior, and performs better than a voter choice model without accounting for uncertainty measured by AIC.

Keywords: Ordinal Policy Scales, Issue Placements, Uncertainty, Spatial Voting, Mixture Models

1 Introduction

Spatial voting approaches assume that citizens elect parties or candidates that offer policy platforms that coincide with their preferences. Empirical applications frequently rely on ordinal policy scales to determine the citizens' policy preferences and their perceptions about party platforms. This practice presupposes that (1) voters have well-defined individual preferences about public policy issues, and (2) parties take certain policy positions and voters perceive these platforms. It is well recognized that uncertainty influences these placements. Within spatial voting approaches, uncertainty is mainly considered as one that stems from candidate or party platforms (Shepsle 1972; Enelow and Hinich 1981). The literature argues that ambiguous or vague position taking (or campaigning) and limitation in voter information cause uncertainty in the positions a candidate or party represents and therefore in the decision of voters. Recently, it has been reasoned that voters might not be equipped with consistent and well-structured policy preferences as well (Stoetzer 2017). As a consequence, uncertainty seems to play a central role in both perceptions of party platforms and voters' policy preferences. However, there are only a few neo-Downsian empirical models that incorporate voter uncertainty into the choice rule (Bartels 1986; Gill 2005; Berinsky and Lewis 2007).

The purpose of this paper is twofold. First, we aim to understand what drives survey response variability in political perceptions and policy preferences: how are the perceptions of party platforms and policy preferences of voters structured and what role does uncertainty play in these perceptions and placements? Second, we want to further the understanding of how uncertainty impacts on spatial issue voting behavior. We develop an approach that allows studying the behavioral implications of uncertainty in political perceptions and policy preferences and its consequences for political representation. The approach consists of two analysis steps. First, we model survey responses to ordinal policy scales where specific response styles capture the uncertainty structure in issue placements. We use the so-called BetaBin model (Tutz and Schneider 2019; Mauerer and Schneider 2019), which belongs to the class of mixture models for ordinal responses. The model permits accounting for both the placement and uncertainty structure of survey responses, which can be modeled by covariates. In addition, it allows modeling specific response patterns, such as the tendency to select the middle category (see, e.g., Aldrich et al. 1982; Alvarez and Franklin 1994) or the tendency to choose extreme categories (Baumgartner and Steenkamp 2001; Vaerenbergh and Thomas 2013). At this first stage, we determine the positions on the policy scales accounting for uncertainty. At the second stage, we model voter choices and use the adjusted placement values estimated by the mixture model. This procedure allows us to improve the vote choice model by accounting for individual uncertainty in issue placements.

The empirical application uses survey data from the 2016 US presidential election and examines how voters' perceptions of candidate platforms are structured on the traditional liberal-conservative dimension and specific policy issues. The results indicate that voter show much less uncertainty in placing themselves than in attributing positions to the candidates. Our findings also suggest, for instance, that voter who identify themselves with the Democratic or Republican party, respectively, tend to push their self-placements toward the perceived candidate platforms. Furthermore, our approach improves model performance measures at all stages.

2 Uncertainty in Policy Preferences and Platforms

Survey responses to ordinal policy scales are frequently used to measure the policy preferences of the electorate and perceptions of party or candidate policy platforms. In public opinion research, several studies assess variability in policy preferences and examine competing explanations based on uncertainty, ambivalence or equivocation. Some studies explore specific attitudes towards, for instance, abortion, racial policies or European integration (Alvarez and Brehm 1995, 1997, 1998, 2002; De Vries and Steenbergen 2013), others explore variability in Left-Right placements (Harbers, De Vries and Steenbergen 2013).

However, there is also work that argues that relying on individual placements and perceptions of party locations might cause difficulties due to interpersonal incomparability of survey responses or rationalization processes. The first difficulty arises when respondents have a subjective understanding of issue scales, the so-called differential-item functioning (Brady 1985), which distorts the placements. Starting with the Aldrich-McKelvey scaling method (Aldrich and McKelvey 1977), a considerable amount of research proposes statistical procedures to correct for the interpersonal incomparability of survey responses to issue scales (see, e.g., Hare et al. 2015; Poole et al. 2016; Poole 1998). Based on issue scale data, these approaches provide estimates for self-placements and party locations to construct common underlying latent policy dimensions.

The second difficulty stems from rationalization processes that induce distortions in attributing issue positions to parties or candidates. Markus and Converse (1979) already introduced the concepts of persuasion and projection. Persuasion means that voters are persuaded by the parties or candidates so that they change their positions to bring them closer to the position of favored parties. Projection means that voters project their own positions onto parties they favor, i.e., a tendency to adjust the policy location of parties they prefer. Drawing from balance theory (Heider 1946, 1958) and the social judgment-involvement approach (Sherif and Hovland 1961), two types of projection effects can be distinguished: assimilation and contrast (see, e.g., Merrill III, Grofman and Adams 2001; Merrill III and Grofman 1999; Conover and Feldman 1982, 1981; Granberg and Brown 1992; Granberg and Brent 1980; Granberg and Jenks 1977; Granberg 1987; Feldman and Conover 1983). The first effect is based on the argument that respondents assimilate the stances of parties they prefer by reducing the perceived distance between their policy preferences and the party they favor to move them closer to their own preferences. The latter refers to the effect that respondents tend to contrast the positions of parties they dislike, i.e., respondents project parties they dislike away by exaggerating the ideological distance to those. To evaluate these effects, Merrill III, Grofman and Adams (2001), for instance, divide the respondents into two groups, supporters and non-supporters of a particular party. Then, they relate the self-placement to the median candidate placement, separately for the two groups at the population level. Their results indicate that in many cases, the group of supporters behaves differently than non-supporters in placing the candidates. For instance, the more conservative the supporters place themselves on average, the higher the median placement of the supported candidate.

The existing literature offers a few approaches to measure and model variability and uncertainty in issue placements. One approach is to directly measure uncertainty by asking respondents to report how certain they are about party or candidate platforms (e.g., Alvarez and Franklin 1994), or to adjust the 7-point or 11-point policy scales by range formats (see, e.g., Tomz and Van Houweling 2009; Aldrich et al. 1982; Alvarez 1999).

Another way to measure uncertainty is to rely on indirect methods. Harvey (1976) introduced the heteroscedastic regression framework, which models the variance of the disturbance by predictors and is applied, for instance, in Harbers, De Vries and Steenbergen (2013); De Vries and Steenbergen (2013). Alvarez and Brehm (1995), for example, use a heteroscedastic binary probit model. Bartels (1986) infers uncertainty from patterns in missing data, based on the idea that respondents who are uncertain are not able to provide placements at all. In a two-stage procedure, he first relies on a model of survey responses where non-responses indicate uncertainty and are a function of attributes of the candidate, the voter, and the political setting. In the second stage, the estimated probabilities of non-response are used to examine the impact of uncertainty on voting behavior, applying a linear probability model in both analysis steps. Aldrich et al. (2018) follow a similar approach. First, they estimate the probability of not placing themselves or at least two parties on ordinal scales. Then, they use these probabilities as well as other covariates to evaluate the variability in the difference between the individual-specific party placement and the sample mean party placement.

Campbell (1983*b*,*a*) also uses an indirect measure by using sample standard deviations of placements. Gill (2005) connects uncertainty with the entropy concept. He develops an approach that provides an aggregate measure of uncertainty by relying on aggregated responses and information on candidate characteristics, the issue to be assessed, and the respective survey questions. His uncertainty term is more flexible than the one by Bartels (1986)'s by allowing it to vary across candidates and issues, but it still assumes homogenous uncertainty across voters. Rozenas (2013) offers an approach that integrates variance heterogeneity (Harvey 1976) and non-response (Bartels 1986), resulting in a quite difficult model with hyper parameters for whom appropriate prior distributions need to be selected.

The handling of missing values also plays a central role in the study of uncertainty.

Current approaches treat missing values in diverse ways. Some studies use observed values only and do not rely on any missing data, such as applications of the pure heteroscedastic models (e.g., Harvey 1976; Alvarez and Brehm 1995). Others reason that uncertainty induces missing data in the survey responses (e.g., Bartels 1986; Rozenas 2013). We believe that the crucial issue here is whether a particular underlying mechanism generates missing data. Missing values in the response structure might reflect uncertainty, but also other processes might cause missing data. For instance, respondents might show clear preferences and political perceptions but refuse to report them due to social desirability. A lack of motivation or time might also cause that respondents do not provide placements. In such cases, missing values would embody both certain and uncertain placements. Our survey response model does not include any missing data (including 'don't know' replies). Usually, we do not know the true missing-data generating process. Therefore, we assume that missing data in survey responses to policy scales is not directly linked to uncertainty.

The model of survey responses we develop in this paper, which then forms the basis for the voter choice model, differs from existing approaches in the following aspects. First, our approach does not require additional survey questions in which respondents state how uncertain they are about policy platforms (Alvarez and Franklin 1994) nor does it adjust the original 7-point or 11-point policy scales (e.g., Tomz and Van Houweling 2009; Aldrich et al. 1982; Alvarez 1999). Second, the model explicitly takes into account the ordinal nature of policy scales, which is in contrast to previous studies that use the linear regression model (e.g., Harbers, De Vries and Steenbergen 2013; De Vries and Steenbergen 2013) or binary outcome-models based on logit/probit link functions (e.g., Alvarez and Brehm 1995). Especially when dealing with limited ordinal policy scales, it is not clear whether the distance between each category is equal, which is assumed in the linear regression framework. In addition, the error terms might be not normally distributed, and the linear regression might predict values lower, in between or above the limited ordinal response scale. Third, the model can handle three specific response styles: a random choice, a tendency to moderate, and a tendency to extreme placements on the policy scales. This allows detecting particular uncertainty structures that can be modeled by explanatory variables, in contrast to models such as the heteroscedastic regression model (e.g., Harvey 1976; Alvarez and Brehm 1995) where additional scale parameters are used to model only low or high variance, and therefore rather unstructured variability.

3 Modeling Issue Placements and Spatial Voting under Uncertainty

Our approach proceeds in two steps. In the first stage, we develop a model of survey responses for ordinal policy scales. Here, we estimate the positions on the policy scales corrected by uncertainty. In the second stage, we specify a voter choice model that is based on these adjusted values as the key predictors.

3.1 Stage 1: Survey Response Model

The model of survey responses belongs to the class of mixture models (McLachlan and Peel 2000; Iannario and Piccolo 2016; Piccolo and Simone 2019) which can be used to model variability in ordinal response data. As human choices or political perceptions can be understood as a combination of placement and uncertainty, we rely on a mixture model with two components

$$f = \sum_{g=1}^{2} \pi_g f_g, \tag{1}$$

where the mixture proportion or weight π_g can take values between 0 and 1, and $\sum_{g=1}^{2} \pi_g = 1$. The density f can be described by the combination of f_1 and f_2. We only consider density functions that are in accord with the nature of ordinal data. Examples for the placement component are the cumulative logit model or the adjacent categories model (Tutz et al. 2017). The uncertainty component allows taking into account specific response styles. D'Elia and Piccolo (2005) or Tutz et al. (2017), for instance, rely on the uniform distribution, which reflects a random choice of the response category. We use the BetaBin model (Tutz and Schneider 2019) that enables us to model both the response styles and the placement structure in a flexible way. In contrast to other possible approaches, this model can handle response styles to the middle as well as to extreme categories to model uncertainty in policy placements.

The mixture model BetaBin assumes that we observe the response of an individual i to an ordinal policy scale, denoted by R_i. Let Y_i be the unobserved random variable that gives the placement on the ordinal policy scale. U_i is the unobserved uncertainty component which models the type of response style. All these variables take the ordered values $\{1, \ldots, k\}$. The mixture model BetaBin has the form

$$P(R_i = r|\boldsymbol{x}_i, \boldsymbol{w}_i) = \pi_i P_M(Y_i = r|\boldsymbol{x}_i) + (1 - \pi_i) P_U(U_i = r|\boldsymbol{w}_i), \tag{2}$$

where $\boldsymbol{x}_i$ and $\boldsymbol{w}_i$ are vectors of explanatory variables. Both the placement and the uncertainty part can be modeled by the same, overlapping or entirely distinct covariates. π_i is the mixture probability that indicates the weight of the structural component in the mixture. Consequently, $1 - \pi_i$ represents the strength of the uncertainty component. As a result, the observed response R_i stems from a discrete mixture of the uncertainty and the placement part.

Any ordinal model can be used for the placement part $P_M(Y_i = r|\boldsymbol{x}_i)$ of the model. We rely on the cumulative logit model (aka ordered/ordinal logit model, proportional odds model) (see Tutz 2012):

$$\begin{aligned} \log\left(\frac{P(Y_i \leq r|\boldsymbol{x}_i)}{P(Y_i > r|\boldsymbol{x}_i)}\right) &= \gamma_{0r} + \boldsymbol{x}_i^T\boldsymbol{\gamma}, \quad \text{or} \\ P(Y_i \leq r) &= \frac{\exp(\gamma_{0r} + \boldsymbol{x}_i^T\boldsymbol{\gamma})}{1 + \exp(\gamma_{0r} + \boldsymbol{x}_i^T\boldsymbol{\gamma})}, \quad r = 1, \ldots, k-1. \end{aligned}$$

γ_{0r} denote the thresholds or intercepts and $\boldsymbol{\gamma}$ the estimated effects that do not depend on r. In our notation, positive values increase the ratio $\log\left(\frac{P(Y_i \leq r|\boldsymbol{x}_i)}{P(Y_i > r|\boldsymbol{x}_i)}\right)$ and connote that lower categories are more likely than higher ones. Regarding the uncertainty part $P_U(U_i = r|\boldsymbol{w}_i)$, the model assumes that the random variable U follows a Beta-Binomial distribution: $U \sim \textit{Beta-Binomial}(k|\alpha, \beta)$

$$f(u) = \begin{cases} \binom{k-1}{u-1} \frac{B(\alpha+u-1, \beta+k-u+1)}{B(\alpha, \beta)} & u \in \{1, \ldots, k\} \\ 0 & \text{otherwise.} \end{cases}$$

$\alpha, \beta > 0$ are the parameters of the distribution, and $B(\alpha, \beta)$ gives the beta function:

$$B(\alpha, \beta) = \Gamma(\alpha)\Gamma(\beta)/\Gamma(\alpha+\beta) = \int_0^1 t^{\alpha-1}(1-t)^{\beta-1} dt.$$

By assuming that $\mu = \alpha/(\alpha+\beta)$ and $\delta = 1/(\alpha+\beta+1)$[1], the expected value $E(U)$ and the variance $var(U)$ are

$$E(U) = (k-1)\mu + 1, \quad \text{var}(U) = (k-1)\mu(1-\mu)[1+(k-2)\delta].$$

The beta-binomial distribution converges to the (shifted) binomial distribution $B(k, \mu)$ with mean μ and categories $\{1, \ldots, k\}$ when δ approaches 0. We aim to model two response styles: a tendency to middle or extreme categories. This is achieved by setting $\alpha = \beta$ so that $\mu = 0.5$ and $\delta = 1/(2\alpha+1)$. As a result, μ, which gives the location of the distribution, is set at the middle of the policy scale. α and δ are not fixed: smaller α values result in larger δ values, and therefore greater variance. Figure 1 depicts the restricted beta-binomial distribution for different α values. For $\alpha = 1$, one obtains the discrete

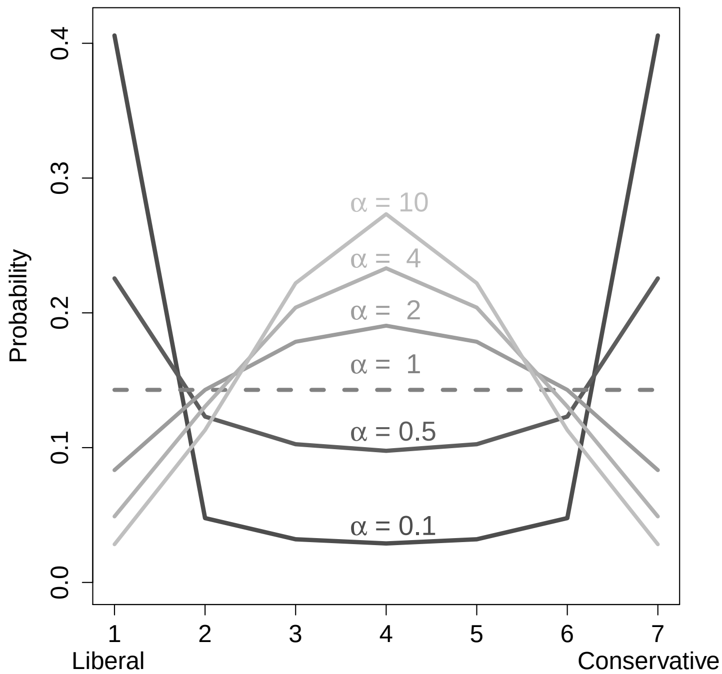


Figure 1: Probability mass on 7-point liberal-conservative scale for different α values.

uniform distribution. $\alpha > 1$ indicates a tendency to the middle categories and $\alpha < 1$ a

[1]Note that this reformulation is required because α and β do not correspond with the location and scale of the distribution.

tendency to extreme categories. Given different α values, the distribution encompasses a (shifted) binomial distribution with the mode in the middle of the scale, which reflects a strong tendency to middle categories, and one with almost equal point mass at the endpoints of the scale, which corresponds with a strong tendency to extreme categories (i.e., minimum and maximum of k). Between these two extremes, any gradations are feasible.

The coefficient α, the parameter of the restricted beta-binomial distribution, ascertains the shape of the distribution in the uncertainty component and is connected to the explanatory variables $\boldsymbol{w}_i$ by

$$\alpha = \exp(\boldsymbol{w}_i^T \boldsymbol{\alpha}) = \exp(\alpha_0) \exp(\alpha_1)^{w_{i1}} \ldots\ldots \exp(\alpha_m)^{w_{im}}.$$

The parameter α_j contains the effect of the explanatory variable w_{ij}. Since the exponential function links the explanatory variables to α, the coefficient α changes by the factor $\exp(\alpha_j)$ for every one-unit change in w_{ij}, holding all other variables constant. The parameters indicate how a variable impacts on the tendency to middle or extreme placements: $\alpha_j > 0$ results in $\alpha > 1$ and imply a tendency to middle categories; $\alpha_j < 0$ results in $\alpha < 1$ and imply a tendency to extreme placements.

3.2 Stage 2: Voter Choice Model

Following the classical proximity model (Downs 1957; Davis, Hinich and Ordeshook 1970; Enelow and Hinich 1984), the voter choice model is decision theoretical and focuses on the impact of spatial considerations on voting. To identify each candidate's amount of utility, voters are assumed to compare candidates' policy proposals on several issues and choose the one that offers issue positions that are closest to the voters' most preferred issue positions. The model also accounts for nonpolicy factors (e.g., Adams, Merrill III and Grofman 2005; Adams and Merrill III 1999; Thurner 2000), such as voters' socioeconomic characteristics.

For voter $i \in \{1, \ldots, n\}$ and candidate or party $j \in \{1, \ldots, J\}$, define V_{ij} as a linear predictor for each candidate j that accumulates the systematic determinants of the vote choice in a scalar quantity. V_{ij} consists of voter-party proximity measures

$z_{ijk}, k \in \{1, \ldots, K\}$, that represent the proximity between voter i and party j on each issue k. The model is based on respondent-specific perceptions of party positions and applies linear utility losses in the calculation of issue distances. Let $s_{il},\ l \in \{1, , \ldots, p\}$ refer to voter characteristics. The deterministic part of utility takes the form:

$$V_{ij} = \beta_{j0} + \sum_{k=1}^{K} z_{ijk}\alpha_k + \sum_{l=1}^{p} s_{il}\beta_{jl} = \beta_{j0} + \boldsymbol{z}_{ij}^T\boldsymbol{\alpha} + \boldsymbol{s}_i^T\boldsymbol{\beta}_j. \quad (3)$$

The parameters $\beta_{10}, \ldots, \beta_{J0}$ represent alternative-specific constants (ASCs). These coefficients contain the unmeasured utility components. $\boldsymbol{\alpha}_1, \ldots, \boldsymbol{\alpha}_K$ is a k-dimensional vector related to the voter-party proximity measures $\boldsymbol{z}_{ij}$. $\boldsymbol{\beta}_1, \ldots, \boldsymbol{\beta}_J$ is a p-dimensional coefficient vector related to voter attributes contained in the covariate vector $\boldsymbol{s}_i$. The corresponding coefficients indicate segment-specific evaluations of parties. The utility expression V_{ij} is linked to voter choice by a logit link function:

$$P(Y = j|\boldsymbol{z}_{ij}, \boldsymbol{s}_i) = \frac{\exp(\beta_{j0} + \boldsymbol{z}_{ij}^T\boldsymbol{\alpha} + \boldsymbol{s}_i^T\boldsymbol{\beta}_j)}{\sum_{r=1}^{J}\exp(\beta_{r0} + \boldsymbol{z}_{ij}^T\boldsymbol{\alpha} + \boldsymbol{s}_i^T\boldsymbol{\beta}_r)}, \quad (4)$$

where $Y \in \{1, ..., J\}$ denotes the j-categorical, probabilistic response variable.

4 Empirical Application

We apply our approach to the 2016 US presidential election and focus on the two major party candidates, the Democratic nominee Hillary Clinton and the Republican opponent Donald Trump. The empirical application examines how self-placements and political perceptions are structured on both the traditional liberal-conservative scale and three specific policy issues (Spending and Services, Defense Spending, Health Insurance).[2] The respondents were asked to state where they place themselves and perceive each of the candidates on seven-point scales. The liberal-conservative scale runs from (1) “extremely liberal” to (7) “extremely conservative”. The first specific issue measures attitudes and political perceptions on public spending and services, with (1) representing “Government should provide many fewer services” and (7) “Government should provide many more

[2]Note that the 2016 American National Election Study (ANES) includes additional position issues that we do not consider. Our analysis is based on the cross-sectional pre-election survey.

services". The second scale captures attitudes on the amount of the budget spent on defense, running from (1) "Government should decrease defense spending" to (7) "Government should increase defense spending". The third taps positions on public versus private medical support (1 "Government insurance plan", 7 "Private insurance plan"). We restrict our analysis to those respondents that provided self-placements and party placements for both the Democrat and the Republican, and reported voting for one of the two major candidates.

4.1 Survey Responses to Placements

The stated positions give the observed response R_i in Equation 2. Figure 2 depicts the distribution of issue placements on the liberal-conservative scale and the three specific issue scales. All bar plots show the percentages for each category on the ordinal scales. While the distributions of the self-placements are in most cases rather unstructured, with a small tendency to middle categories (except for the issue of health insurance), the densities of the perceived candidate positions are mostly skewed. The modal value of the candidate positions is in all cases at the opposite sides, except for the issue of defense spending. Inspecting, for instance, the liberal-conservative scale reveals that the majority of the probability mass for the Republican candidate is located at high categories (5,6,7), while the majority of the probability mass for Democratic candidate is located at the opposite side (1,2,3). The tendency to the left or right side of the scales depends on the policy and the scale coding. Thus, voters perceive the Republican candidate as offering more conservative positions, favoring the increase of defense spending and private health insurance. By contrast, voters ascribe the Democratic candidate more liberal positions and perceive the candidate as favoring government health insurance. The only exception to this pattern is observed for the issue of defense spending, where the voters perceive the Democratic candidate as taking a more moderate position. The same opposite tendency is noticeable for the issue of spending and services, but in reversed corners of the scale because of the different coding. Here, the distribution of Democratic candidate placements is left-skewed corresponding with more services and higher categories, whereas the distribution of perceived stances for the Republican candidate is right-skewed corresponding with fewer services at smaller categories.

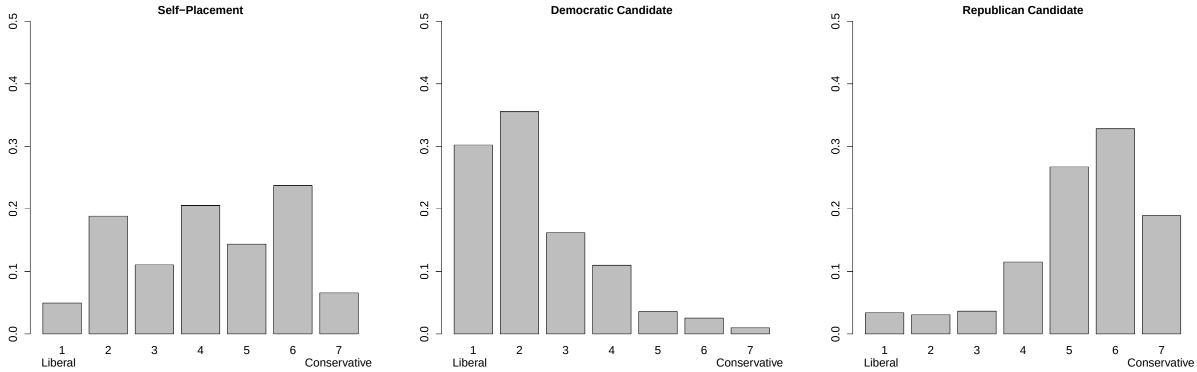
4.2 Stage 1: Predictors for Uncertainty and Placements

The model of survey responses can link both the placement and uncertainty structure of self-placements and candidate placements to explanatory variables. Note that we model the shape of the uncertainty structure by covariates but not the uncertainty weights. We examine two sets of covariates which enter both components. The first three variables relate to cognitive processes or information costs. Voters vary in political sophistication or awareness (e.g., Luskin 1987, 1990; Delli Carpini and Keeter 1993; Rapeli 2013). It is frequently reasoned in the literature that voters with lower information costs are more informed about the stances parties or candidates take on public policies. We hypothesize, therefore that voters who are equipped with higher levels of political information are more certain about their own placements and party platforms. We rely on three measures to explore whether different levels of political sophistication yield special response patterns due to uncertainty or placements in a particular direction. The first is the level of education, measured in 8 categories from 1 (high school degree or less) to 8 (doctorate). The second variable captures the strength of political interest and employs self-reports on how much attention the respondent pays to politics and elections. The original five-point scale was reversed so that 1 represents the response "never" and 5 "always". To distinguish segments with different political knowledge, we use factual knowledge questions with correct and incorrect responses. The respondents were asked to recognize the job or political office the following persons hold: Vice-President Joe Biden, Speaker of the House Paul Ryan, Chancellor of Germany Angela Merkel, President of Russia Vladimir Putin, US Supreme Ct Chief Justice John Roberts. We computed an additive knowledge score where each incorrect reply gives a value of 0 and correct answers a value of 1. We counted the number of times each respondent reported right answers yielding a six-categorical variable (0 none correct, 5 all answers correct).

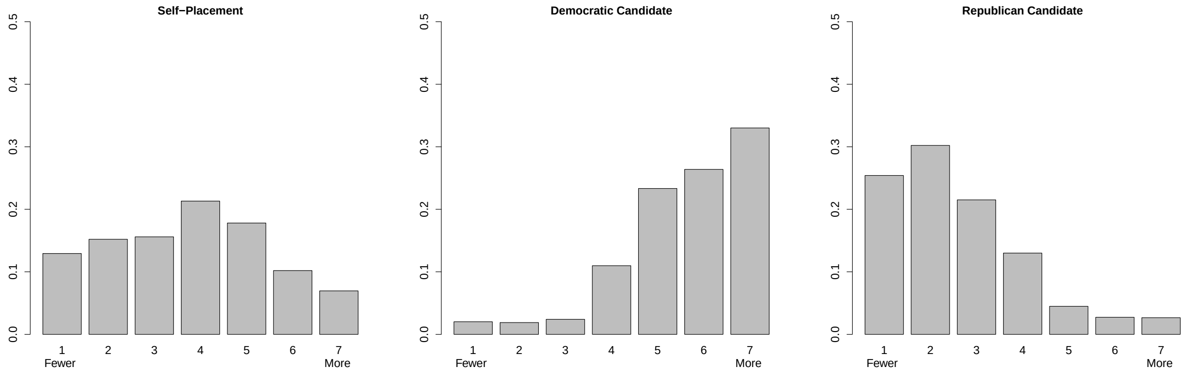
The second set of predictors are partisan variables and assessments of personal or character qualities of the candidates. We hypothesize that voters are more certain where to locate the candidates on the policy scales when they have a long-standing leaning

Figure 2: Distribution of Issue Placements

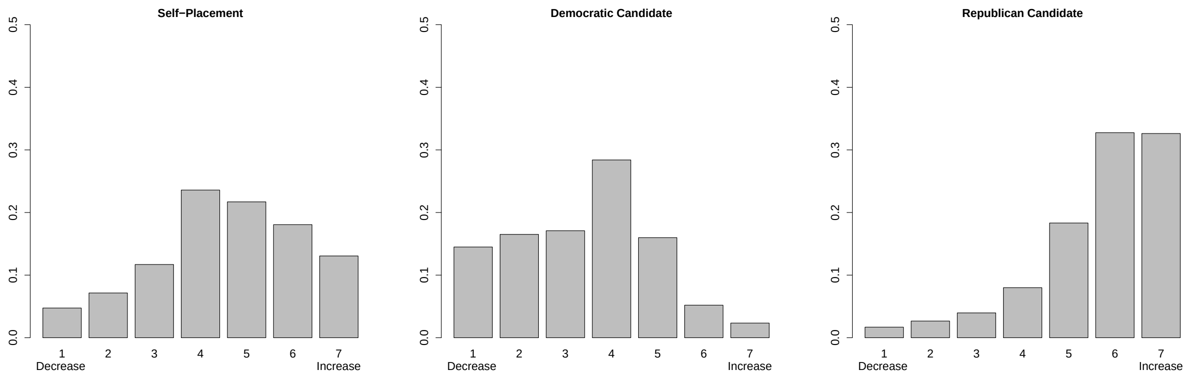
(a) Liberal-Conservative



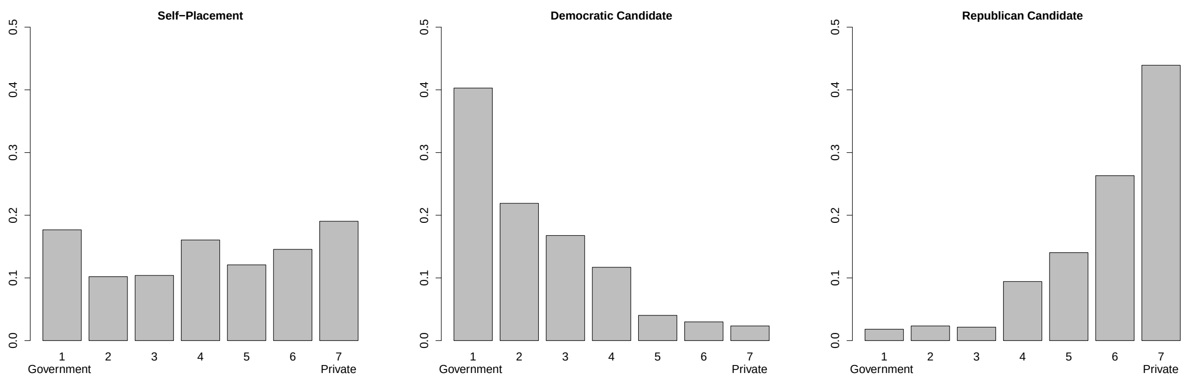
(b) Spending and Services



(c) Defense Spending



(d) Health Insurance



Source: 2016 ANES, N=1539.

toward the party whose candidate they place. By contrast, specific response styles due to uncertainty might be likely to observe when the voter does not identify with the respective party. The same expectation could also be formulated for candidate images. To capture the relationship between the voter and the candidate to be located, we consider party identification, which enters the models by two dummy-coded variables. For each of the two major parties, we generated a variable that takes the value of 1 when the respondent identifies as Democrat or Republican, respectively, and 0 otherwise (i.e., no preference, any other party identification or Independents). We also explore candidate images measured by character traits. The respondents were asked to assess the candidates on six traits (strong leadership, really cares, knowledgeable, honest, speaks mind, and even-tempered), each measured on a five-point scale running from "not well at all" to "extremely well". For each of the two candidates, an index of the overall evaluation was generated by adding all trait evaluations and dividing it by the number of traits.

4.3 Stage 2: Predictors for Vote Choice

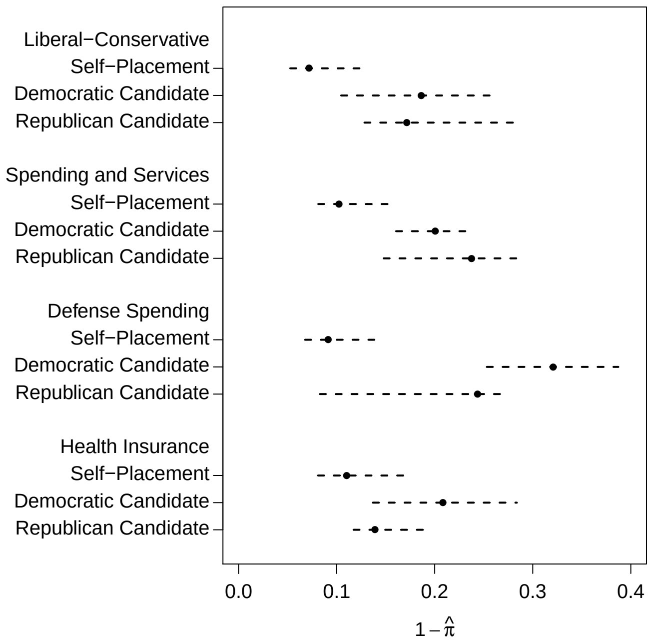
The voter choice model is based on the placement and uncertainty estimates of the underlying survey response models. In addition to these spatial considerations, we also account for standard voter characteristics such as age (centered around the sample mean, measured in decades), gender (1 female, 0 male), regional differences (North Central, Southern and Western part of the US, with Northeast as reference), economic considerations (evaluation of the country-level economy in the past year, ranging from 1 "much worse" to 5 "much better"), two race variables (self-identifications as being Black or Latino), and the level of education. Also here we exclude all missing values.

5 Results

The result presentation proceeds as follows: First, we discuss the findings of the survey response models. Here, we begin by assessing how uncertainty impacts on voters' self-placements and the perceived party platforms. Then, we present the estimates for the placement and the uncertainty part of the models, followed by a comparison of the BetaBin models with the ordinal models without uncertainty component based on performance measures. In the second part of the analysis, we use the estimated placements to predict voter choice between the two major candidates.

5.1 Issue Placements and Issue Uncertainty

We specify for each of the placements separate BetaBin models.[3] Figure 3 illustrates the role of uncertainty in the placements. The mixture probability $\hat{\pi}$ indicates the importance of the structural component in the mixture models. Therefore, $1 - \hat{\pi}$ measures the weight of the uncertainty component and can be understood as an indicator of how certain voters are about their own placements and how clear or unambiguous they perceive the candidate platforms. The closer the weight $\hat{\pi}$ is to 1, the weaker the uncertainty so that $1 - \hat{\pi} = 0$ yields the pure cumulative model without any response styles. The closer the weight $\hat{\pi}$ is to 0, the stronger the uncertainty and the weaker the placement structure. The shape of the uncertainty structure is modeled by covariates, which may lead to a tendency to the middle categories, extreme categories or any graduation between these two extremes. The dotted lines in Figure 3 represent the 2.5% and 97.5% bootstrap quantiles.[4]



Note: Dotted lines correspond to the 2.5% and 97.5% bootstrap quantiles.

Figure 3: Importance of the uncertainty component $(1 - \hat{\pi})$

[3]Details on the EM-Algorithm to estimate the models can be found in Tutz and Schneider (2019). We also used the R packages MRSP (Pößnecker 2019) and VGAM (Yee 2016).

[4]Note that it is not unusual when the intervals are non-symmetric around the estimate because no distribution assumption is made.

We obtain the weakest uncertainty weights for the self-placements, ranging from 0.07 to 0.11. This result indicates that respondents exhibit clear positions on the ideological and policy scales. Much higher uncertainty levels are detected for the placements of the two presidential candidates. Voters are the most certain where to place both candidates on the liberal-conservative scale. We also observe comparatively moderate uncertainty weights for the Republican candidate on the issue of health insurance. A little higher uncertainty weights are estimated for the issue of spending and services. Regarding the issue of defense spending, the quite large weight for the Democratic candidate (0.32) suggests that voters exhibit much more difficulties in placing Hillary Clinton as compared to Donald Trump (0.24).

Tables 1 - 3 display the results of the mixture models. In each of the tables, the upper part gives the estimates for the placement component ($\boldsymbol{\gamma}$), the lower part the estimates for uncertainty response style effects ($\boldsymbol{\alpha}$). We also report the 2.5% and 97.5% quantiles of 300 non-parametric bootstrap samples for each effect. We consider an estimate as significant at the 5%-level when the bootstrap confidence intervals cover the estimate but not zero. The interpretation is as follows: Positive coefficients in the preference part suggest that lower categories are more likely, negative coefficients that higher categories are more likely. Regarding the uncertainty part, which contains the estimates for the shape of the uncertainty distribution, positive values suggest a tendency to locations at middle categories, that is, moderate positions. Negative values indicate a tendency to the extremes of the scales.

Let us first focus on the results for the self-placements, displayed in Table 1. Regarding the placement effects, we observe positive effects for education on self-placements on the liberal-conservative scale and the defense spending scale. The higher the level of education, the more the voters position themselves toward liberal stances or favor the decrease of defense spending. Political interest exhibits an effect on the liberal-conservative scale and political knowledge on spending and services. The negative coefficient for political interest suggests that the more attention the voters pay to politics and elections, the more they tend to have conservative views. The positive effect for political knowledge indicates that the higher the level of political knowledge, the more they favor fewer services.

Regarding the partisan variables, we obtain very plausible results. Here, one should keep in mind that the placements perceived as 'democratic' correspond with lower categories on the liberal-conservative scale and health insurance, and with higher categories on the issue of spending and services (see Figure 2). The perceived Republican positions are associated with higher categories on the liberal-conservative scale, defense spending and health insurance, and with lower categories on spending and services. Thus, the effects of party identification and candidate traits correspond with these tendencies. In particular, we observe in three out of the four cases a negative effect for Republican identifiers, with a particularly large one on the liberal-conservative scale, which is consistent with the perceived candidate position that is located at higher categories. Nevertheless, the positive effect on spending and services is also in line with this interpretation since it is the only scale where the perceived Republican position corresponds with lower categories. Accordingly, Democrats have more liberal stances and favor more services.

Concerning the Democratic candidate traits, we obtain significant effects on all scales: the higher the assessment of the Democratic candidate, the more liberal is the self-placement, the more they favor the increase of services, the decrease of defense spending and government health insurance. The Republican candidate traits also significantly impact on all self-placements, with reversed effects: the higher voters assess the qualities of the Republican candidate, the more conservative the attitudes, the more they favor fewer services, the increase in defense spending and private insurance.

As can be seen at the bottom of Table 1, we obtain only four significant response style effects for uncertainty and small uncertainty weights. When the voters' political interest increases, they tend to favor extreme positions, which is only statistically significant on the liberal-conservative and the spending and services scales. The positive effects for political knowledge indicate a tendency to favor a moderate position, which is only statistically significant for spending and services. Since the uncertainty weights are small, the estimated effects of the uncertainty part should be interpreted with caution.

Table 2 contains the placement and uncertainty estimates for the perceived Democratic candidate platforms. Voters with a higher level of political interest tend to ascribe the Democratic candidate more liberal positions and in favor of increasing spending and services. Those with higher political knowledge scores locate the candidate towards offering a stance in favor of government health insurance. The more liberal the voters, the more liberal positions they ascribe to the candidate. The positive coefficient for the candidate traits suggest that the higher the voters assess the qualities of the candidate, the more they perceive the Democratic candidate as taking a fewer-services stance.

The estimates for the uncertainty response styles suggest that the own positions have a strong impact on the shape of the uncertainty component. The strongest impact is found on the liberal-conservative scale. The more conservative the voters, the more they tend to locate the Democratic candidate towards extreme stances on the liberal-conservative, defense spending and health insurance scales. One may interpret this behavior as ‘contrast’. However, extreme stances include both sides of the scale. The positive effect indicates that voters with more conservative views tend to ascribe the candidate a moderate position on spending and services. The same tendency is estimated for Democratic party identifiers and the assessment of candidate traits for the issue of services and spending and the issue of health insurance.

Table 3 reports the results for the Republican candidate placements. Here, most of the estimated coefficients are not in line with the tendencies detected for the candidate positions in Figure 2. For instance, voters who identify with the Republican party and assign the Republican candidate higher quality traits, tend to place the candidate toward positions that correspond with more spending and services. Thus, the estimates differ from the perceived candidate tendency. Regarding the uncertainty estimates, only one significant effect is obtained: The higher the voters assess the candidate traits, the more they tend to perceive the candidate as taking moderate positions on the liberal-conservative scale.

Table 1: Parameter estimates of the BetaBin model: Self-Placements

	Liberal-Conservative				Spending and Services				Defense Spending				Health Insurance			
	Estimate	BS.2.5	BS.97.5	sig.	Estimate	BS.2.5	BS.97.5	sig.	Estimate	BS.2.5	BS.97.5	sig.	Estimate	BS.2.5	BS.97.5	sig.
Placement Part																
Education	0.084	0.035	0.144	*	0.009	-0.046	0.055		0.139	0.086	0.195	*	-0.042	-0.111	0.011	
Political Interest	-0.136	-0.266	-0.014	*	-0.001	-0.121	0.122		-0.188	-0.309	-0.080		-0.021	-0.147	0.083	
Political Knowledge	0.003	-0.117	0.116		0.138	0.043	0.244	*	0.016	-0.083	0.151		0.071	-0.023	0.211	
Democratic Party Identification	0.979	0.712	1.404	*	-0.769	-1.143	-0.467	*	0.000	-0.312	0.327		0.048	-0.306	0.409	
Republican Party Identification	-1.789	-2.233	-1.351	*	0.477	0.177	0.848	*	-0.388	-0.700	-0.120	*	-0.861	-1.213	-0.513	
Democratic Candidate Traits	1.073	0.954	1.279	*	-1.043	-1.268	-0.926	*	0.633	0.467	0.805	*	0.929	0.779	1.208	*
Republican Candidate Traits	-0.967	-1.212	-0.794	*	0.665	0.448	0.908	*	-0.938	-1.169	-0.728	*	-0.824	-1.085	-0.637	*
Uncertainty Part																
Education	0.570	-0.400	1.735		0.486	-0.373	1.415		0.239	-0.656	0.933		0.559	-0.627	1.614	
Political Interest	-3.039	-4.501	-0.213	*	-2.494	-5.367	-0.611	*	-0.940	-4.651	0.231		-0.452	-3.998	0.868	
Political Knowledge	1.378	-1.732	2.070		1.836	0.103	3.282	*	1.379	-1.003	3.605		0.486	-1.437	2.763	
Democratic Party Identification	3.855	-1.664	8.513		0.134	-6.631	6.262		1.816	-8.753	6.791		-2.949	-7.899	8.589	
Republican Party Identification	7.371	-0.789	12.064		1.176	-3.898	8.408		2.153	-2.416	6.277		5.815	-2.803	12.543	
Democratic Candidate Traits	1.933	-1.514	3.198		1.834	-0.965	4.676		1.587	0.299	5.924	*	2.112	-2.398	4.252	
Republican Candidate Traits	3.294	-1.046	7.924		2.366	-1.748	5.617		1.717	-3.325	4.646		-2.468	-5.761	2.861	
$1-\hat{\pi}$	0.072	0.053	0.127		0.102	0.081	0.161		0.091	0.068	0.144		0.110	0.081	0.174	

Source: 2016 ANES. Note: Cut points of the placement part and intercept of uncertainty part are not displayed. An estimate is considered as significant at the 5%-level when the bootstrap confidence intervals cover the estimate but not zero, N=1539.

Table 2: Parameter estimates of the BetaBin model: Democratic Candidate Placements

	Liberal-Conservative				Spending and Services				Defense Spending				Health Insurance			
	Estimate	BS.2.5	BS.97.5	sig.	Estimate	BS.2.5	BS.97.5	sig.	Estimate	BS.2.5	BS.97.5	sig.	Estimate	BS.2.5	BS.97.5	sig.
Placement Part																
Education	0.019	-0.080	0.087		0.023	-0.043	0.087		-0.033	-0.128	0.037		-0.009	-0.085	0.071	
Political Interest	0.165	0.011	0.313	*	-0.330	-0.484	-0.215	*	-0.086	-0.256	0.099		0.163	0.000	0.332	
Political Knowledge	0.096	-0.098	0.272		0.017	-0.110	0.166		0.041	-0.182	0.222		0.196	0.026	0.341	*
Self-Placement	0.272	0.060	0.517	*	0.026	-0.120	0.164		-0.111	-0.265	0.060		0.089	-0.039	0.220	
Democratic Party Identification	-0.229	-0.777	0.313		0.321	-0.004	0.696		-0.531	-1.145	-0.052	*	-0.625	-1.076	-0.231	*
Democratic Candidate Traits	-0.850	-1.107	-0.573	*	1.067	0.863	1.328	*	-1.823	-2.190	-1.553	*	-0.693	-0.923	-0.489	*
Uncertainty Part																
Education	0.078	-0.756	0.537		-0.180	-0.577	0.181		0.064	-0.498	0.419		-0.235	-1.083	0.548	
Political Interest	0.199	-2.011	1.147		-0.191	-0.721	0.572		-0.741	-2.432	0.341		-0.593	-2.560	0.112	
Political Knowledge	0.475	-0.731	1.770		0.157	-0.504	0.599		0.854	-0.280	2.165		0.505	-0.506	2.118	
Self-Placement	-2.823	-3.891	-0.504	*	0.524	0.139	1.685	*	-1.263	-3.111	-0.163	*	-0.775	-2.528	-0.037	*
Democratic Party Identification	2.316	-1.966	5.242		2.576	0.060	13.610	*	0.710	-0.916	11.703		1.789	-0.762	5.166	
Democratic Candidate Traits	1.179	-0.077	4.739		2.120	1.140	3.472	*	0.770	-0.439	2.539		1.867	0.519	4.416	*
$1-\hat{\pi}$	0.186	0.105	0.259		0.201	0.161	0.237		0.321	0.253	0.387		0.208	0.137	0.284	

Source: 2016 ANES. Note: Cut points of the placement part and intercept of uncertainty part are not displayed. An estimate is considered as significant at the 5%-level when the bootstrap confidence intervals cover the estimate but not zero, N=1539.

Table 3: Parameter estimates of the BetaBin model: Republican Candidate Placements

	Liberal-Conservative				Spending and Services				Defense Spending				Health Insurance			
	Estimate	BS.2.5	BS.97.5	sig.	Estimate	BS.2.5	BS.97.5	sig.	Estimate	BS.2.5	BS.97.5	sig.	Estimate	BS.2.5	BS.97.5	sig.
Placement Part																
Education	-0.066	-0.135	0.014		-0.010	-0.076	0.082		0.055	-0.030	0.111		-0.032	-0.097	0.051	
Political Interest	-0.077	-0.237	0.144		0.009	-0.115	0.107		-0.254	-0.403	-0.110		-0.096	-0.245	0.053	
Political Knowledge	0.079	-0.079	0.413		0.093	-0.042	0.270		0.037	-0.107	0.138		-0.015	-0.138	0.105	
Self-Placement	0.413	0.239	0.554	*	0.085	-0.111	0.206		-0.152	-0.375	-0.092		0.054	-0.027	0.154	
Republican Party Identification	-0.522	-0.952	0.046		-0.400	-0.810	-0.043	*	0.751	0.184	1.026	*	0.408	0.109	0.805	*
Republican Candidate Traits	-0.388	-0.698	0.029		-0.556	-0.921	-0.287	*	0.335	-0.071	0.562		0.417	0.126	0.677	*
Uncertainty Part																
Education	0.202	-0.362	1.187		0.106	-0.314	1.590		0.123	-0.316	1.720		0.795	-0.663	1.846	
Political Interest	0.616	-0.754	2.442		-0.070	-1.856	1.293		-0.453	-2.595	0.766		-0.317	-2.008	0.957	
Political Knowledge	0.454	-0.188	2.534		0.700	-0.098	3.644		-0.059	-0.865	2.392		-0.423	-1.553	0.932	
Self-Placement	0.489	-0.262	1.393		-0.381	-2.616	1.505		-3.026	-3.434	2.404		0.546	-2.840	2.434	
Republican Party Identification	1.564	-0.356	9.685		1.032	-0.283	11.849		-0.110	-2.246	11.412		3.137	-1.564	15.647	
Republican Candidate Traits	2.783	1.343	6.417	*	0.838	-1.444	4.606		-2.106	-2.811	5.899		3.254	-0.634	5.839	
$1 - \hat{\pi}$	0.172	0.128	0.285		0.238	0.148	0.286		0.244	0.083	0.275		0.139	0.117	0.189	

Source: 2016 ANES. Note: Cut points of the placement part and intercept of uncertainty part are not displayed. An estimate is considered as significant at the 5%-level when the bootstrap confidence intervals cover the estimate but not zero, N=1539.

Table 4 contrasts performance measures of the BetaBin models with the cumulative models without uncertainty component. Model performance is measured by the Log-Likelihood (LogL) and the AIC.[5] The values indicate that the mixture models outperform the traditional ordinal models. The model fit described by the Log-Likelihood is better for the mixture model than the pure cumulative model in all settings. Furthermore, almost all AIC values for the pure cumulative models are larger than for the mixture models, except for the self-placement on the issue of health insurance. The performance measures suggest that the mixture models give a better model fit, although the mixture model is much more complex. The pure cumulative models are based on 13 parameters for the self-placements (6 intercepts and 7 covariates) and 12 parameters for the candidate placements (6 intercepts and 6 covariates). The corresponding mixture models are based on a total of 22 and 20, respectively: the identical number of parameters enters the placement part (13 and 12, respectively), parameters to model the shape of the uncertainty distribution (1 intercept, 7 and 6 covariates, respectively), and the parameter for the mixture weight estimate $\hat{\pi}$.

5.2 Spatial Voting under Uncertainty

Next, we compare the voter choice models based on the original placements with the ones we predict based on the mixture models. These survey response models adjust for special response styles due to uncertainty, which leads to somehow biased observed placements. Thus, we correct the observed positions by using the estimates of the structural component to generate positions which are adjusted by the detected uncertainty. The difference of two cumulative probabilities gives the probability π_{ir} for a particular response category r

$$\pi_{ir} = P(Y_i \leq r) - P(Y_i \leq r-1),$$

so that we obtain for each observation i the probability for choosing category $\{1, \ldots, k\}$ based on the estimates of the structural component of the model and the considered predictors. The category with the highest probability is chosen as the most likely position

[5]The AIC is defined by $AIC = -2l(\hat{\boldsymbol{\theta}}) + 2m$, where $l(\hat{\boldsymbol{\theta}})$ is the log-likelihood function computed at the maximum of the estimated parameter vector $\boldsymbol{\theta}$ and m is the number of model parameters, comprising all model parameters.

Table 4: Model comparisons based on performance measures

	LogL		AIC	
	Cumulative	Mixture	Cumulative	Mixture
Liberal-Conservative Scale				
Self-Placements	-2114.413	-2102.812	4254.827	4249.624
Democratic Candidate Placements	-2042.724	-2010.927	4109.449	4061.854
Republican Candidate Placements	-2437.803	-2408.940	4899.607	4857.880
Spending and Services				
Self-Placements	-2477.834	-2461.440	4981.668	4966.880
Democratic Candidate Placements	-2150.124	-2047.078	4324.248	4134.157
Republican Candidate Placements	-2466.211	-2439.574	4956.421	4919.149
Defense Spending				
Self-Placements	-2527.637	-2512.997	5081.274	5069.993
Democratic Candidate Placements	-2412.246	-2325.138	4848.491	4690.276
Republican Candidate Placements	-2341.586	-2305.823	4707.172	4651.647
Health Insurance				
Self-Placements	-2567.289	-2559.251	5160.578	5162.501
Democratic Candidate Placements	-2196.097	-2153.841	4416.193	4347.683
Republican Candidate Placements	-2194.387	-2171.660	4412.774	4383.320

for each observation i. These adjusted values are used as explanatory variables in the vote choice model. At least 50% of the adjusted values are different from the original observed values. With almost 70%, most values are adjusted for self-placement on the issue of spending and services.

Table 5 compares the voter choice models based on the original placements with the ones we predicted based on the mixture models. The estimates for the spatial proximities are displayed at the top, followed by the estimates for the voter attributes. The constant and the parameters related to voter attributes are set to zero for the Republican candidate to ensure model identification. Thus, the interpretation of these coefficients is always relative to Donald Trump. When inspecting the proximities, we observe that the effects are positive in both models so that the larger the proximity between the candidates and the voter, the more likely it is vote for this candidate. However, the effect sizes differ between both models. Based on the original placements, the liberal-conservative scale has the largest impact, followed by attitudes toward defense spending. Spatial proximities on the issue of health insurance show the weakest effect. In the voter choice model based on the adjusted placements, the liberal-conservative scale does not significantly impact on voting anymore, and also the remaining issues differ in effect strength. The effects for both the issues of spending and services and health insurance are more than twice the size of the ones we obtained for the unadjusted placements. We also identify some interesting individual-specific effects, indicating that some segments are more likely to vote for a particular candidate. In the vote choice model based on original placements Blacks and Latinos tend to favor the Democratic candidate Clinton. The same pattern is observed for higher education segments and those that positively evaluate the economy. In the vote choice model with adjusted placements, we observe the same direction of effects, but only the effects for Latinos and economic considerations remain statistically significant. An inspection of some goodness-of-fit measures, reported at the bottom of Table 5, reveals that the vote choice model that accounts for uncertainty in the issue placements performs better according to the Log-Likelihood and AIC than the model that relies on the original, unadjusted placements. In particular, the AIC is reduced by around 27% with the same number of parameters.

6 Discussion and Concluding Remarks

In this manuscript, we developed a vote choice model that accounts for the uncertainty in issue placements, which arises from the difficulty to select a particular category on ordinal policy scales. Our approach consists of two stages. First, the perceived party platforms and policy preferences are adjusted for uncertainty. Then, these values are used to estimate voter choices. Drawing on the 2016 US presidential election and examining voting for one of the two major candidates, we showed that our approach outperforms the traditional models at both stages: the cumulative model without uncertainty at the first stage and the vote choice model without uncertainty correction at the second stage. So far, we focus on goodness-of-fit measures based on the likelihood of the fitted models. However, it might be useful to consider additionally predictive measures to compare the models. One strategy would be to use k-cross-validation, where the data is split into k sets. $k-1$ parts are used for estimation and the kth part to evaluate how good the model

Table 5: Voter Choice Models

	Original Placements			*Adjusted Placements*		
Predictors	coef.	se	p-value	coef.	se	p-value
Liberal-Conservative	0.757	0.093	0.000	0.047	0.149	0.751
Spending and Services	0.419	0.086	0.000	0.949	0.228	0.000
Defense Spending	0.604	0.086	0.000	0.635	0.167	0.000
Health Insurance	0.207	0.055	0.000	0.392	0.132	0.003
Age	0.002	0.087	0.980	-0.200	0.105	0.057
Gender	0.157	0.289	0.586	-0.335	0.350	0.338
Black	2.806	0.768	0.000	0.725	0.678	0.285
Latino	1.736	0.716	0.015	2.047	0.836	0.014
North Central	-0.409	0.386	0.289	-0.727	0.484	0.134
South	-0.648	0.426	0.128	-0.948	0.485	0.051
West	-0.751	0.471	0.111	0.381	0.588	0.517
(Ref: Northeast)						
Economy	0.772	0.167	0.000	0.539	0.206	0.009
Education	0.244	0.074	0.001	0.050	0.089	0.572
Constant	-9.040	1.674	0.000	-4.465	1.877	0.017
LogL		-172.881			-121.825	
AIC		373.762			271.649	
Pseudo R^2		0.838			0.886	
df		14			14	

Source: 2016 ANES. Notes: The response variable is binary and gives the vote intention for either the Democratic or Republican candidate. The interpretation of voter attributes refers to Clinton as compared to Trump. N=1539.

performs. In our application, it may be appropriate to evaluate how many times the predicted choice is identical to the observed choice behavior. There are measures, such as the Brier score, which are appropriate to evaluate discrete responses. Although our empirical application rests on a binary choice model, the approach can be easily extended to a multi-party setting by replacing the binary choice model with a multinomial one. Likewise, the number of issue dimensions can be extended as well.

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