Testing spatial voting models using simulated data

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Abstract

The debate on how voters use party positions to determine their vote choice has remained inconclusive. This is partly because it is difficult to distinguish empirically between rival spatial models of voting. We argue that simulations can provide important new insights. Specifically, we use simulations to see what results we estimate for each spatial model with the advantage of knowing which specific model our simulated 'voters' based their vote choice on. We therefore proceed by first simulating sets of voters who choose parties based on one specific spatial model. Then, we run rival models on these data and examine the resulting model parameters. We find that we usually *underestimate* the 'true' effect of spatial voting effects on vote choices. Moreover, it is impossible to distinguish empirically between directional and compensational voters. Our findings encourage researchers to test these models in experiments or to consider the theories' observable implications.

Keywords

compensational voting; directional voting; discounting; proximity voting; spatial models

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Introduction

One of the biggest debates in the literature on voting behaviour has been on how voters use the policy positions of political parties to determine their electoral choice. Downs (1957) originally argued that it was the simple distance that mattered, with voters favouring the party closest to them. The most prominent rival model is that of Rabinowitz and Macdonald (1989), who argue that voters will instead favour the party that is one the same side of the issue as them and that defends that position with the greatest intensity. Some models have combined both approaches into mixed models (Iversen, 1994; Rabinowitz and Macdonald, 1989), while recently Kedar (2005, 2009) has suggested that voters are interested more in how parties affect the post-election policy outcome.

Much empirical work has gone into distinguishing between these rival models of voting (see e.g. Adams et al., 2004; Blais et al., 2001; Herrmann, 2008; Kramer and Rattinger, 1997; Macdonald et al., 1998; Merrill and Grofman, 1997, 1999; Morris and Rabinowitz, 1997; Pardos-Prado and Dinas, 2010; Westholm, 1997). Yet so far the debate remains frustratingly inconclusive. Lewis and King (2000) show that this is because evaluations of the models hinge on (untestable) assumptions made in the statistical models. As some assumptions favour one model and others another, it is not possible to determine which model is in fact correct.

A further difficulty is that the predictions made by each model are seldom distinct, despite the distinct theoretical assumptions that underlie them. It is thus often difficult to attribute correct empirical predictions to one model or another (Fazekas and Méder, 2012). One reason for this is that the models often have identical consequences for voting behaviour even though they differ in their theoretical approach. For example, it may be that voters sometimes prefer parties that have relatively extreme positions rather than parties that are closest to them in terms of policy preferences. Two explanations for this are equally plausible: such voters may take into account post-election bargaining and compensate for the 'watering down' of policy compromises (Grofman, 1985; Kedar, 2005, 2009), or they may prefer those parties that share their (binary) policy preference and defend it with the greatest intensity (Rabinowitz and Macdonald, 1989).

In this paper, we aim to move this debate forward by using simulations to understand the empirical behaviour of the various models. Simulations are often used to assess the performance of statistical models when the underlying assumptions are violated (see e.g. King et al., 2004; Macdonald et al., 2007; Manning and Mullahy, 2001; Proksch and Slapin, 2009; Shor et al., 2007; Tomz et al., 2002). For spatial voting models, Macdonald et al. (2007) recently used the same technique to study the effects of projection bias on the evaluation of proximity and directional voting models.

In this paper, we simulate artificial data where we *know* how voters arrive at their vote choice. In other words, we create a world where voters by definition follow a specific model of vote choice, for example the proximity model. Then, we examine how other proposed models of spatial voting capture and represent this simulated world. For instance, we may ask what kind of results we would get if we use the directional model to analyse the voting behaviour of proximity voters. Our approach, where we examine the model parameters in a situation where the true parameters are known, enables us to answer this and similar questions. In doing so, we can see whether the estimated model parameters over- or underestimate the true parameters and thus lead us to wrong conclusions about the reasoning underlying vote choices. We do this for four models: a pure proximity model, a pure directional model, a mixed proximity-directional model and Kedar's compensational-proximity model.

Using this method, we uncover two new findings. First, the overall importance of spatial voting is underestimated if the model that we use fails to reflect how voters in fact determine their choices. Second, it is empirically very difficult to distinguish a world where voters are part directional/part proximity from one where voters are part compensational/part proximity. The overall implications of our findings are straightforward: there is little to gain from further cross-sectional analyses of survey data if we want to distinguish between the rival models of spatial voting. Rather, we believe that researchers should take advantage of alternative methodological approaches or consider potential observable implications of the various spatial voting models.

We proceed as follows. First, we present the four spatial models of voting that form the focus of this paper. We then describe how we carried out the simulations and present key results. We conclude by stating the implications of this research for the debate on spatial voting and suggest two ways forward.

Four spatial models of voting

The two basic spatial models are the *proximity model* by Downs (1957) and the *directional model* by Rabinowitz and Macdonald (1989). To these we can add the *mixed model* by Rabinowitz and Macdonald (1989), which combines directional and proximity components. Finally, the most recent approach is the *compensational model* (Kedar, 2005, 2009), which combines a proximity with a compensatory component.

Each model has a different understanding of how voters use policy positions to determine their vote choice. In the *proximity model*, voters choose that party whose policy position is most similar to their own.[1] Specifically, a voter's utility is expressed as:

$$U_{ij} = -\alpha \cdot (v_i - p_{ij})^2,$$

with v the voter i's policy position, p the position of party j (as perceived by voter i) and α the overall weight of policy distance in determining utility. We choose the squared Euclidean distance because it is most widely used way to measure distance and is also used in the more

[1] Throughout this paper, we speak of voters comparing different *parties*, though all models (except for the compensational model) can also be applied to choices between *candidates*, e.g. for the presidency.

complex 'mixed' spatial models.[2] In this paper, we see α as the parameter measuring the overall *policy importance*, that is, the extent to which voting decisions are determined by spatial considerations.

The *directional model* of vote choice assumes that voters are either for or against a policy, and that this support or opposition is held with a certain amount of intensity. In other words, individuals do not hold positions and compare them to those of parties. Instead, they are for or against a policy and evaluate (1) whether each party shares that overall binary position on an issue (i.e., for/against) and (2) how intensely the party holds that view. The directional model predicts that voters will support the party that most intensely defends their view.[3] The distinction between 'for' and 'against' positions is made referring to a neutral point (usually the midpoint of a policy scale). In the following, we assume (without loss of generalizability) that this neutral point equals zero. A voter's utility in this model is as follows:

$$U_{ij} = \alpha \cdot v_i p_{ij}.$$

So, a voter's utility is the product of the policy positions of the voter v and the party p, weighted by the policy importance parameter α.

The *mixed model* combines proximity model and the directional theory of voting in a joint model of voting. In this model of vote choice individuals' electoral decisions have a proximity component and a directional component. This model therefore allows voters to mix both types of approaches in how they determine their vote choice. In this model, voter utility can be expressed as

$$U_{ij} = \alpha \cdot \left[-\beta_m \left(v_i - p_{ij}\right)^2 + (1 - \beta_m) \cdot \left(v_i p_{ij}\right)\right],$$

[2] Moreover, differences between metrics are less severe in the one-dimensional space analysed here (Grynaviski and Corrigan, 2006: 397).

[3] Only parties outside a 'region of acceptability' are not rewarded for the intensity of preferences.

with β_m the weight of the proximity component and 1- β_m that of the directional component. In other words, β_m determines the extent to which voters are either motivated by directional or by proximity considerations. In this paper, we term β_m the *mixing parameter*, so the weight each model has in determining voting decisions. It is worth noting that the mixed model is closely related to two additional spatial models, Iversen's (1994) representational policy leadership model and Grofman's (1985) discounting voting model. Their theoretical rationales differ but under some conditions all three models are mathematically equivalent and make identical model predictions.[4] Thus, we will not discuss these models in greater detail below. However, we acknowledge that the results reported below may also resemble the theoretical underpinning of these two models rather than those of the mixed model.

Similar to the mixed model, the *compensational model* also features two components, a proximity component and a compensational component. The compensational component captures the outcome orientation of voters. Outcome-oriented voters compare two potential policy outcomes: (1) the expected policy outcome if all parties are elected to the legislature and (2) a counterfactual policy outcome where one party is excluded from the policy process. They will choose that party where the distance between the two scenarios is greatest, providing the party shifts the expected policy outcome in the desired direction (Kedar, 2005: 186). Thus, the compensational component reflects the extent to which individuals use their vote to achieve policy outcomes. In this model, utility can be expressed as:

$$U_{ij} = \alpha \cdot \left[-\beta_c\left(v_i - p_{ij}\right)^2 - (1 - \beta_c) \cdot \left((v_i - O)^2 - \left(v_i - O_{-j}\right)^2\right)\right],$$

[4] Iversen's (1994) representational policy leadership model also merges directional and proximity voting but provides a different theoretical rationale than the mixed model (see also Merrill and Grofman, 1999; Adams and Merrill, 2000; for a critical review Warwick, 2004). Grofman's (1985) discounting voting model argues that voters discount the parties' ability to shift the policy outcome away from the status quo. It is usually assumed that the status quo is located at the centre of the policy space, which also makes Grofman's discounting model equivalent to the mixed model (cf. Merrill and Grofman, 1999: 170-172).

with O denoting the policy outcome (weighted by party size) and O_{-j} denotes the (hypothetical) policy outcome if party j were not elected. β_c is the mixing parameter for the compensational model, similar to β_m in the mixed model. The remaining parameters are as above.

Table 1: Overview over spatial models of voting

Spatial model	Formula	Model parameters
Proximity model	$U_{ij} = \alpha \cdot -\left(v_i - p_{ij}\right)^2$	α
Directional model	$U_{ij} = \alpha \cdot v_i p_{ij}$	α
Mixed model	$U_{ij} = \alpha \cdot \left[-\beta_m\left(v_i - p_{ij}\right)^2 + (1-\beta_m) \cdot \left(v_i p_{ij}\right)\right]$	α, β_m
Compensational model	$U_{ij} = \alpha \cdot \left[-\beta_c\left(v_i - p_{ij}\right)^2 - (1-\beta_c) \cdot \left((v_i - O)^2 - \left(v_i - O_{-j}\right)^2\right)\right]$	α, β_c

These four models are summarised in Table 1. Finally, it is important to note that in this paper we only consider unidimensional spatial voting models, so ones where there is one dimension of policy competition. All models can also be extended to multidimensional competition.

Testing the models using simulations: the rationale

Many researchers have tried to determine which of these models fits actual voter decision-making best. Yet, we argue that using survey data is of limited use in this endeavour for various reasons. First, in order to test voting models researchers need to make assumptions, and these choices favour one model or the other (Lewis and King, 2000). Second, the models' predictions are seldom distinct. Instead, they often overlap and predict the same vote choices, making it difficult to clearly identify 'predictive successes' for the different theories. This is particularly relevant because the consequences of the various models overlap. While proximity voting predicts voting for the closest party, both directional and compensational voting predict that voters often will choose more extreme parties. Yet, it is difficult to say whether voters prefer the more extreme platform because they anticipate post-election bargaining or because they perceive the policy scale directionally.

In this paper, we turn the standard approach on its head: instead of assessing how well models explain how real voters choose between parties, we assume a decision-making process and consider the results that the models give us. Thus, we use simulations to generate sets of artificial data with 'voters' following each of the four spatial models presented above. We then analyse the model parameters of rival spatial models. Our aim is to see what kinds of estimates are calculated for each model given that we know what model actually generated the data. This will provide us with definite conclusions as to how other models represent – and misrepresent – a world where we know that the voters choose according to a rival model.

Simulations are a powerful means of testing whether statistical models lead to biased estimates (see e.g. King et al., 2004; Macdonald et al., 2007; Manning and Mullahy, 2001; Proksch and Slapin, 2009; Shor et al., 2007; Tomz et al., 2002). Statistical models are based on various assumptions, especially about the distribution of variables and the error structure in the variance-covariance matrix. In empirical data, these assumptions are often violated, and researchers are interested in how these violations affect their results. Simulations offer a way of doing so: we first simulate data using some assumed 'true' underlying data-generating process. Then, we run a regression model on that data in order to test whether the estimated coefficients match the (known) true parameters. If they do not, then the model estimates also tell us the size and direction of the bias.

Generating our own data using simulations allows us to overcome many problems present in all real-world empirical data. Most importantly, we know the voters' 'true' decision-making processes. This allows us to clearly establish where model estimates are biased. Moreover, using simulations avoids some of the difficult choices we need to take with empirical data. One problem with using survey data is how we measure party positions. Voter evaluations of these positions are plagued by projection bias and other unobserved party- and voter-specific factors (Drummond, 2011; Granberg and Holmberg, 1988; Macdonald et al., 2007; Merrill et al., 2001; Page and Jones, 1979). In empirical applications, researchers use different model setups to deal with these difficulties (see e.g. Blais et al., 2001; Macdonald et al., 1998; Rabinowitz and Macdonald, 1989; Westholm, 1997) but these decisions favour one model or another (Lewis and King, 2000). Using simulations, we can assume that neither projection bias nor any other unknown factors are influencing vote choice.

Simulating the four models

To simulate the four spatial models outlined above, we only need two data-generating processes, the mixed model and the compensational model. This is because the proximity and the directional models are special cases of the mixed model when the mixing parameter β_m approaches 0 (directional model) or 1 (proximity model). For each process we generate a population of 1,000 voters whose preferences are formed based on that model and who vote accordingly. To generate the data for both models, we set the 'true' value of the policy importance parameter α to one and let the 'true' values of the mixing parameters β_m and β_c vary from 0 to 1. We also add an error term to the respective formulas in Table 1; this is drawn from a Type I extreme value distribution following the assumptions of the multinomial regression model.

For the analyses that follow, we also need to set additional model parameters. The voters' policy preferences and party policy positions are located on a 0-10 left-right scale. Voter policy preferences v_i are drawn from a normal distribution with mean 5 (the midpoint of the 0-10 policy scale) and a standard deviation of 2.5. The latter value is a reasonable proxy for the distribution of voter preferences in empirical data.[5] The results presented below are based on a 5-party system policy positions located at 3,4,5,6, and 7 on the 0-10 left-right scale.[6] Voter perceptions of these party policy positions are unbiased (i.e. the mean equals the true party policy positions) and modelled as draws from normal distributions with a standard deviation of 2. Again, the latter parameter choice seems reasonable in light of empirical data.[7]

In the next section, we examine how the *estimated* parameters of rival spatial models, the policy importance parameter α and the mixing parameter β, behave given our specification of the 'true' model. Deviations from these 'true' parameters will indicate misfit in the estimated models.

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[5] These estimates are from the 2009 European Election Survey (EES, 2009) that also employs a 0-10 left-right scale. On average, voters have policy preferences on the midpoint of the policy scale and the standard deviation is reasonably close to 2.5.

[6] To test the robustness of the findings provided below, we also ran additional simulations with varying number of competing parties (from 3 to 7) and different levels of party polarization on the left-right scale. These results (not reported here) are very similar to the ones presented below.

[7] It is worth noting that variation in voters' perception of party policy platforms varies somewhat with the number of parties in the system. On average, however, our chosen parameter is fairly close to the average standard deviation in the European Election Survey.

Results

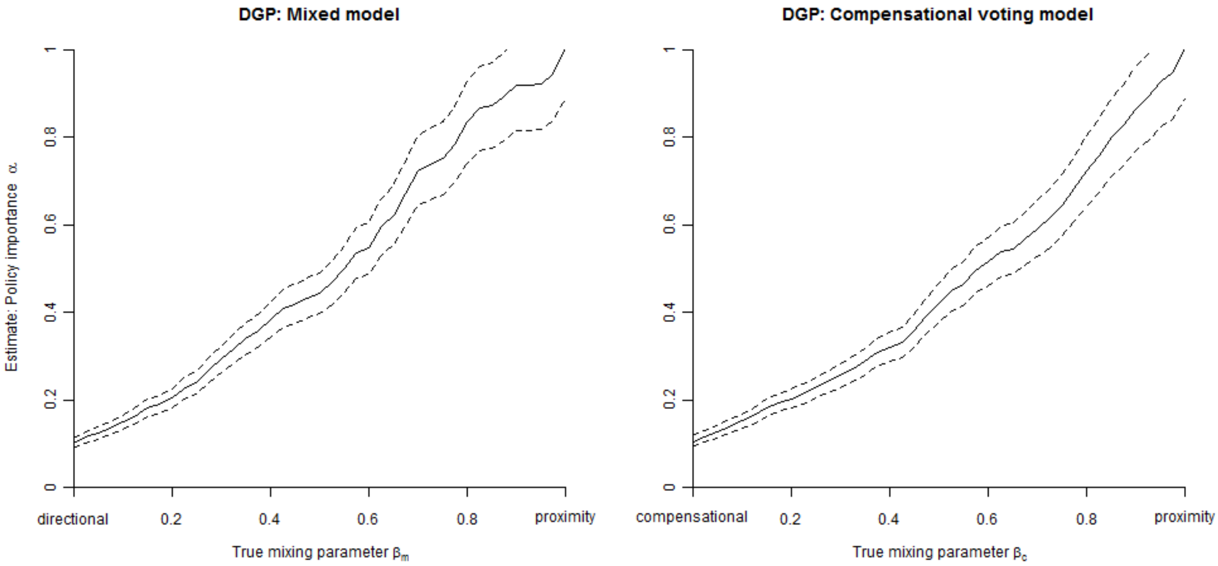
We consider the results for each of the four models in turn, beginning with the proximity model and then moving on to the directional, the mixed and the compensational model.

Proximity model

We begin by presenting the estimated parameters for the proximity model given the two different data-generating processes. Recall that the proximity model requires the estimation of just one parameter, namely the policy importance parameter α, which describes the overall weight of spatial policy considerations in determining vote choice. In our simulations based on the mixed and compensational models, we always set the policy importance parameter to 1, so the overall importance of proximity and directional/compensational components is 1. What varies is the mixing parameter β, which determines the extent to the voter decides based on the proximity or the directional/compensational model, respectively. The closer β is to 1, the more proximity-based the voting decision is.

Figure 1 shows the estimated policy importance α if we run the proximity model on the simulated data generated via the mixed model (left) and the compensational model (right). Unsurprisingly, the estimated α is close to 1 if voters are mainly proximity-oriented (i.e., if β is close to 1). However, we are more interested in what happens when voters mix in directional or compensational considerations, so what α is predicted for lower levels of β. What we see is that the estimated policy importance declines almost linearly as the level of proximity orientation declines. For example, if β is 0.2, then the policy importance parameter is also estimated to be 0.2; this applies to both panels.

Figure 1: Policy importance for the proximity model



Notes: The figures show the estimated regression coefficient α (policy importance) in the proximity voting model for varying levels of proximity voting in the mixed model (left panel) and the compensational voting model (right panel). The dashed lines indicate 95% confidence intervals.

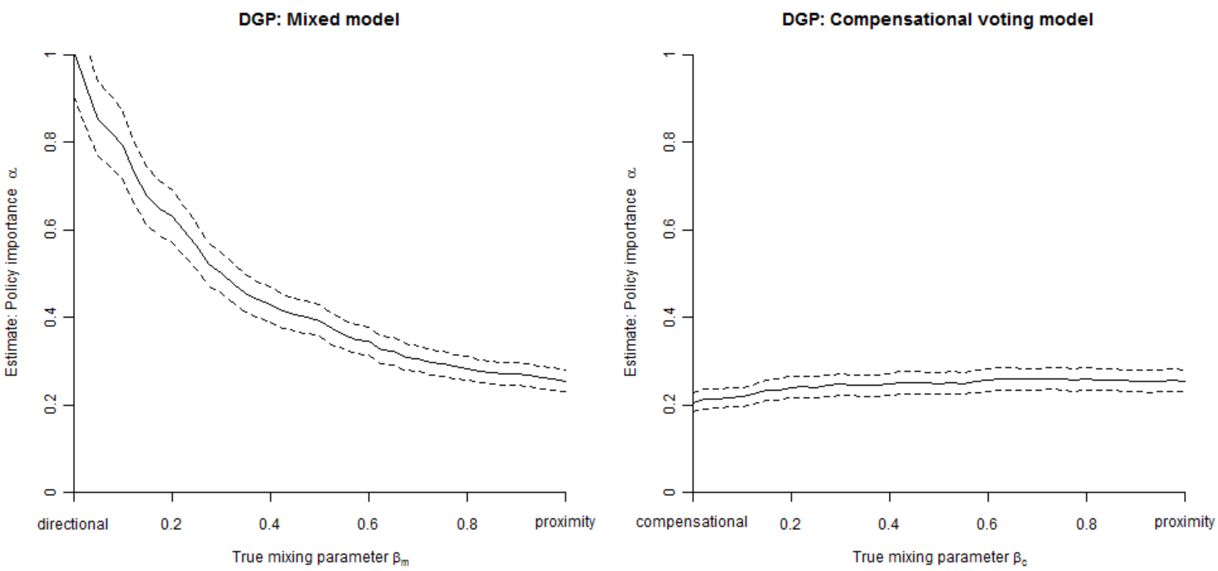
This decline in the policy importance parameter α is important, as this means that this parameter should not be seen as a measure of the overall influence of spatial voting on electoral choices. Instead, it reflects only the extent to which voters proximity-oriented. In other words, voters who choose directionally or compensationally are disregarded and not counted as spatial voters. So, in such situations we could falsely conclude that the true importance of spatial voting is low.

A second observation is also important. When the mixing parameter β approaches zero and proximity voting is almost irrelevant to vote choice, the estimated policy importance parameter α is at around 0.1 and significantly larger than zero. So, when voters choose almost fully based on directional or compensational considerations, we would still assign them a (small) amount of proximity motivation. In other words, we would overestimate the influence of the proximity model in situations where voters primarily choose based on other spatial policy considerations.

Directional model

Figure 2 uses the same approach as for Figure 1, but this time for the directional model. Thus, we run the directional model on data generated using the mixed or compensational model (using a variety of mixing parameters β). Again, the y-axis shows the estimated policy importance parameter α for varying levels of directional voting in the mixed model (left panel) and the compensational voting model (right panel).

Figure 2: Policy importance for the directional model



Notes: The figures present the estimated regression coefficient α (policy importance) in the directional voting model for varying levels of proximity voting in the mixed model (left panel) and the compensational voting model (right panel). The dashed lines indicate 95% confidence intervals.

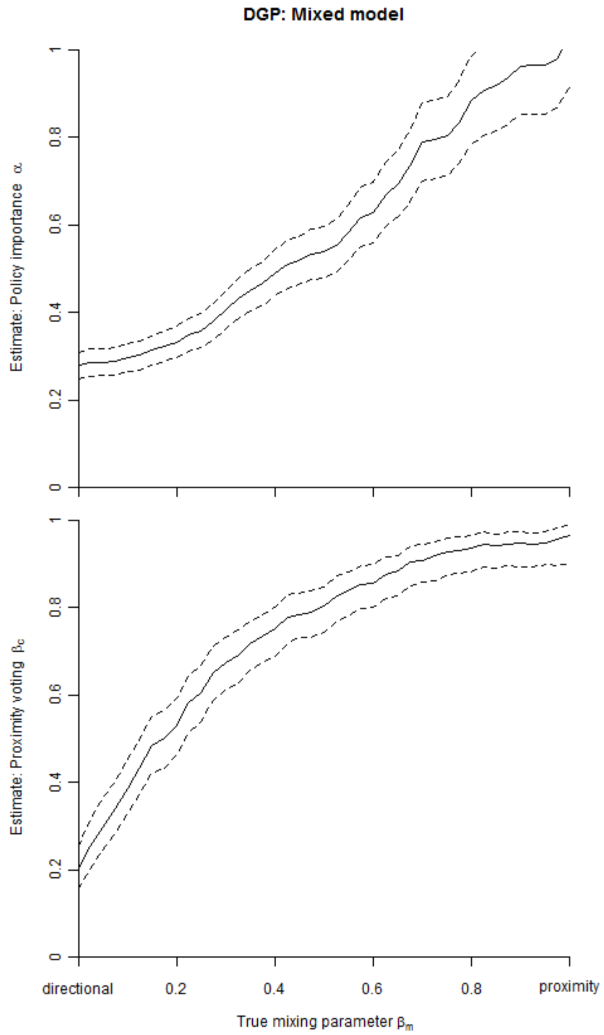
The main conclusion is identical to that for the proximity model: the true importance of spatial voting is underestimated if we predict vote choice using the directional model even though voters arrive at their choices by using other models. The policy importance parameter α is thus best seen as capturing the strength of directional voting only.

Yet, if we do treat α as the importance of directional considerations, then this parameter is often overestimated. In the left panel, this is the case when voters choose based purely on proximity: voters with high values of β, so who are mainly proximity voters, are still seen as having some directional motivation to their voting decision. In the right panel, the choices made by voters who follow the Kedar model and mix proximity and compensational concerns are always identified as being somewhat directional. In sum, if we run proximity or directional models, we will identify some level of proximity or directional voting even if voters make their choices based on a different spatial model.

Compensational model

The next two models, the mixed and compensational models, require the estimation of two parameters: the policy importance parameter α and the mixing parameter β. In Figure 3, we present the model estimates of the compensational voting model if the underlying data were simulated using the mixed model as determining voters' 'true' behaviour. In other words, we now run the compensational model on data generated by mixed-model voters. The top panel reports the estimates for the policy importance parameter α; the bottom panel shows the corresponding estimates for the mixing parameter β_c. In both panels, the x-axis shows the mixing parameter β_m in the mixed model, with 0 signifying purely directional voters and 1 purely proximity voters.

Figure 3: Estimated model parameters for the compensational voting model for a mixed model DGP



Notes: The panels present the estimated regression coefficients for the policy importance α (top panel) and the mixing parameter β_c (bottom panel) in the compensational voting model for varying levels of proximity voting in the mixed model (β_m) on the x-axis. The dashed lines indicate 95% confidence intervals.

The top panel shows that the estimated policy importance parameter for the compensational model increases as the weight of proximity considerations in the mixed model increases. This is similar to the results for the proximity and directional model for the mixed-model data-generating process (see left panels in Figure 1 and 2). As above, this means that the policy importance parameter in the compensational model does not capture the overall importance of spatial considerations if voters also choose directionally. Recall that the policy importance parameter is set to 1 for the simulations, so arguably we underestimate the true policy importance parameter if we apply the 'wrong' model to the data.

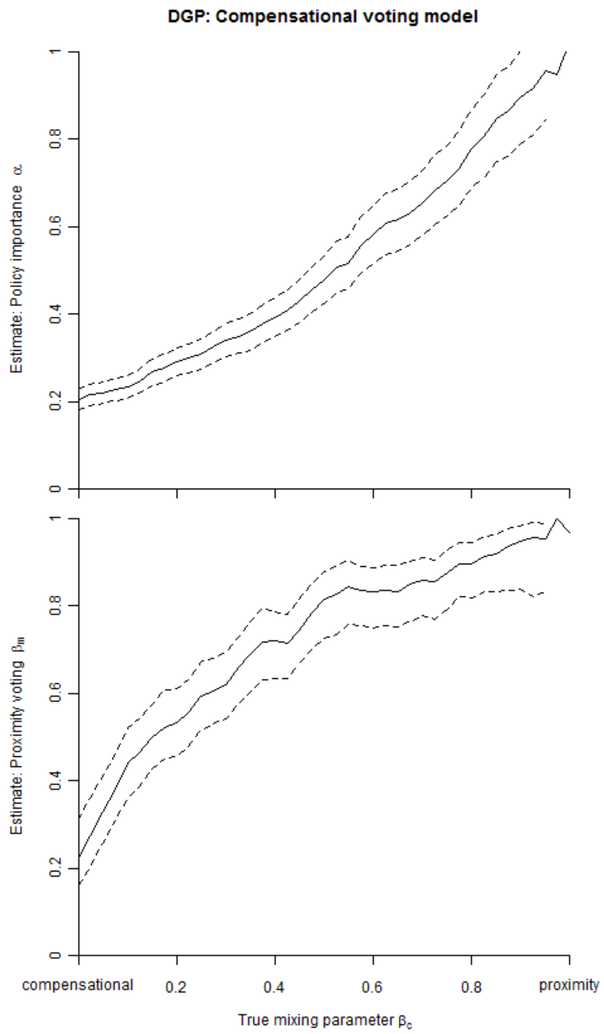
Second, the bottom panel shows that running the compensational model on mixed directional-proximity voters means that we overestimate the weight of compensational considerations. The mixing parameter β_c is larger than the true mixing parameter β_m. For example, if the true mixing parameter β_m is about 0.2, then the estimated mixing parameter β_c is about 0.5. This problem is less pronounced as β_m approaches 1, i.e. when voters are mainly proximity-oriented. The more directional they become, i.e. as β_m gets closer to 0, the more we overestimate the extent of compensational voting.

What we learn from the bottom panel of Figure 3 is that we cannot separate compensational from directional voting, at least if we do not know the voters' decision-making processes. Simply put, it appears that we would treat voters as mainly compensational even if in reality they are mainly directional. So, voters who follow the directional model are wrongly identified as compensational voters who compare policy outcomes.

Mixed model

In Figure 4, we show that the reverse is also true: if voters use compensational voting, the mixed model predicts that voters follow the directional model of voting. As above, the top panel shows the model estimates for the policy importance parameter α, the right panel displays the estimated mixing parameters β_m. The x-axis denotes the varying levels of the mixing parameter β_c in the data-generating process.

Figure 4: Estimated model parameters for the mixed model for a compensational voting DGP



Notes: The panels present the estimated regression coefficients for the policy importance α (top panel) and the mixing parameter β_m (bottom panel) in the mixed model for varying levels of proximity voting in the compensational voting model (β_c) on the x-axis. The dashed lines indicate 95% confidence intervals.

The conclusions to be drawn from Figure 4 are similar to those reported above. First, the top panel shows that the policy importance parameter α mainly reflects the weight of the proximity component, though less so at low levels of proximity voting (i.e. low values of β_c). Second, the bottom panel shows that we would overestimate the presence of directional voting if voters actually mix proximity and compensational concerns. This is very similar to the bottom panel of Figure 3. So, the mixed model attributes the increasing importance of compensational voting (indicated by β_c approaching zero) to the increasing importance of directional voting (indicated by β_m approaching zero). This results in biased model estimates: we overestimate the directional voting component.

Conclusions

Our conclusions from this exercise are simple:

- The policy importance parameter α cannot be taken to signify the overall importance of spatial voting. Instead, it generally measures only the importance of the particular types of models we test for.
- It is very difficult to distinguish between voters who mix directional and proximity concerns and those who mix compensational and proximity concerns. For example, if voters actually mix compensational and proximity considerations in how they use policy positions to choose parties, a mixed model would tell us that voters in fact mix directional and proximity considerations.

These results are similar to the more general omitted variable bias. Yet, we cannot solve this problem simply by ‘controlling’ for rival models. Unlike in the simulations used in this paper, we will never know the ‘true’ underlying data-generating processes, that is, the actual motivations of voters. However, what is problematic is that different models result in similar empirical predictions; this is true especially for the mixed model and the compensational voting model. It is therefore empirically not possible to distinguish between the two models.

Hence, there is no simple statistical way of addressing this problem, for example by simply controlling for rival explanations.

More sophisticated ways forward are therefore needed. Here, we suggest two. First, it may be possible to use alternative methods such as experiments to design situations where it is possible to distinguish between the different models. Tomz and van Houweling (2008) and Lacy and Paolino (2010) have provided first examples of this, and further research in this vein would potentially be useful.

Second, another potential avenue is to study the observable implications of the different spatial theories. For example, Kedar (2005, 2009) argues that how voters mix compensational and proximity concerns will depend on the institutional environment. Similar claims have been made about the weight of directional and proximity concerns (Karp and Banducci, 2002; Pardos-Prado and Dinas, 2010). We could also consider voter heterogeneity in spatial voting (see also Fazekas and Littvay, 2012). Thus, we might expect more knowledgeable voters to be more likely to vote based on policy positions (Andersen et al., 2005; Jessee, 2012; Lachat, 2008). For instance, Kedar (2009: 95) argues that more sophisticated voters may be more likely to vote compensationally than less sophisticated voters. In sum, our findings suggest that future work on spatial models needs to move beyond the simple analysis of cross-sectional surveys.

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