

# Estimating ideal points in the British House of Commons using Early Day Motions\*

Michael Kellermann<sup>†</sup>

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## Abstract

This paper develops a new method for estimating the ideological preferences of members of the British House of Commons. Existing methods produce implausible results due to high levels of party cohesion and strategic voting on the part of opposition parties. To circumvent these problems, this paper estimates MP preferences using Early Day Motions (EDMs) as an alternative to roll call votes. The Bayesian ideal point model for the decision to sign an EDM takes into account both policy preferences and signing costs. The estimates obtained have greater face validity than previous attempts to measure preferences in the House of Commons, recovering the expected order of parties and of members within parties. The estimates successfully predict voting behavior in the House of Commons. As with other Bayesian ideal point methods, this approach produces natural uncertainty estimates and allows for easy calculation of quantities of interest such as member ranks.

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<sup>†</sup>Assistant Professor, Political Science Department, United States Naval Academy

Spatial voting models constitute a central building block of theories of electoral and legislative politics. Spatial models assume that political preferences can be represented as points in one or more policy dimensions that characterize each actor's most preferred policy outcome, or ideal point. In the legislative setting, these models imply that actors support proposals that move policy outcomes closer to their ideal points, given the institutional constraints that they face. Evaluating theories of legislative behavior depends crucially on the availability of ideal point estimates, and several methods have been developed to obtain such estimates based on roll call votes in the United States Congress and other legislative bodies (Clinton, Jackman and Rivers 2004*a*; Heckman and Snyder 1997; Poole and Rosenthal 1985). These methods employ historical data that is publicly available, produce estimates that have high face validity, and are closely linked to theoretical constructs incorporated in the spatial model. In recent years, these preference estimates have provided the opportunity to go beyond description of preferences to evaluate competing theories of legislative behavior.

In British politics, estimating the political preferences of members of the House of Commons and the relationship of those preferences to legislative behavior has proved difficult. Measuring the attitudes of legislators remains challenging in Britain thirty years after Franklin and Tappin (1977) identified this problem as a central impediment to studies of behavior in Parliament. The high degree of party influence on recorded votes (divisions) in the House of Commons prevents the direct application of ideal point models developed in other contexts to the British case. Existing methods do not produce reasonable estimates when voting is characterized by high levels of party cohesion and opposition parties vote insincerely in order to embarrass the government (Spirling and McLean 2007).

High levels of party cohesion contribute to the longstanding view of rank and file MPs as lobby fodder for their leaders and hence relatively uninteresting as political agents, making the development of alternative methods of preference estimation less critical. Yet many of the most interesting features of British politics in the past two decades can only be understood with reference to the distribution of preferences within the major political parties: the longstanding feud within the Conservative Party over Britain's relationship to

Europe (Berrington and Hague 1998), the strong (and increasingly public) opposition among Labour backbenchers to the Blair government's policies post 2001 (Cowley and Stuart 2004), and ongoing questions as to the position of the Liberal Democrats *vis a vis* Labour (Russell and Fieldhouse 2005). Systematic estimates of backbench preferences would enable critical examination of these and other developments in the light of theories of legislative behavior.

Given the nature of voting in the House of Commons, preference estimates must be obtained from other data sources. Each of these alternative data sources presents certain problems. Surveys or interviews can provide information on preferences, but they require the participation of MPs. Moreover, researchers cannot obtain survey-based estimates from earlier parliaments unless those surveys happened to have asked questions about member preferences. Early Day Motions provide another source of information about MP preferences, and have been used frequently to estimate preferences on particular issues (Berrington 1973; Finer, Berrington and Bartholomew 1961; Franklin and Tappin 1977; Leece and Berrington 1977). Unique features of Early Day Motions, however, have inhibited the development of methods using EDMs to estimate legislator positions along the conventional left-right dimension of British politics.

This paper develops a new method to derive preference estimates for British parliamentarians using Early Day Motions. The statistical model builds upon standard ideal point models in two ways, one substantive and the other technical. First, the model makes more realistic behavioral assumptions about the process that generates signatures on EDMs. It allows for variation in the rate at which MPs sign Early Day Motions and uses the identity of each EDM's sponsor to link member preferences with the policy positions implied by motions. Second, the model is estimated within a Bayesian framework using computer simulation techniques (Jackman 2001; Bafumi et al. 2005). This approach generates un-

certainty estimates for member ideal points, allowing for assessments of the precision with which preferences are estimated.<sup>1</sup>

The EDM model produces preference estimates that are far more plausible than existing methods. The approach is demonstrated using Early Day Motions from the 1998–99 session of Parliament. Parties appear in the expected order and self-identified extreme members within each party are estimated to have extreme preferences. Moreover, the resulting ideal point estimates improve predictions of support for the Labour Party position on divisions in the House within each party. With both face validity and predictive skill, this method can be extended to generate preference estimates over time and to build more appropriate statistical models for other forms of legislative behavior in Britain.

## Existing approaches to ideal point estimation

The idea that political actors can be ordered along a continuum of policy preferences goes back over 100 years. While the spatial metaphor for politics first arose in Revolutionary France, political competition in Britain has long been described in terms of left and right. These ideas extend to differences of opinion within the major political parties. The Labour Party has been divided between the center, left, and far left. Likewise, Conservatives under Margaret Thatcher could be categorized into “wets” in the center and “drys” on the right, with varying degrees of dampness in between (Norton 1990). Political observers and commentators typically have strong beliefs about the appropriate ordering of politicians, but quantifying this intuition presents non-trivial statistical problems.

Ideal point models provide a method to estimate the preferences of individual legislators. These models assume that political preferences can be summarized by points in one or more dimensions representing each actor’s most preferred policy outcomes. Statistical

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<sup>1</sup>Optimal classification and classical parametric approaches to ideal point estimation do not produce uncertainty estimates without additional assumptions (Clinton, Jackman and Rivers 2004*a*; Poole 2005).

models for ideal points that use roll call data assume that legislators will support a proposal that moves policy closer to their ideal point than the status quo that the proposal seeks to overturn, allowing for some stochastic error. Each vote, therefore, divides legislators into two groups at a cutpoint located on the policy dimension. Legislators on one side are expected to support the proposal and those on the other are expected to oppose it. These cutpoints in turn enable the estimation of legislator ideal points.

Since political preferences cannot be observed directly, ideal point estimates provide useful descriptive information about legislators. In the United States, where these techniques have been used most extensively, ideal points have been used to measure polarization in Congress, estimate the dimensionality of policy space, and identify the median voter in legislative or judicial bodies (Clinton, Jackman and Rivers 2004*a*; Martin, Quinn and Epstein 2005; McCarty, Poole and Rosenthal 2006; Poole and Rosenthal 1997). Ideal point estimates have even entered the discourse of political competition, with candidates accusing each other of being the “most liberal” or “most conservative” (in the American sense) member of the House or Senate based on simple ideal-point-like measures (Clinton, Jackman and Rivers 2004*b*).

Ideal point models can be extended to characterize the evolution of political preferences. Such methods may consider the aggregate distribution of preferences, examining changes in the dimensions structuring political competition and the ideological cohesiveness of political parties (Poole and Rosenthal 1997). At the individual level, models can be used to estimate the degree to which legislator preferences shift (Martin and Quinn 2002). These estimates, in turn, can determine whether changing preference distributions at the party level are a function of evolving preferences on the part of existing party members or of replacement by new cohorts with distinct preferences. Estimating the evolution of preferences over time requires additional assumptions to link across sessions, but to the extent that those assumptions are plausible, the questions that can be addressed increase significantly.

While ideal point estimates have many uses for descriptive purposes, they also enable the comparison of theoretical models of legislative behavior that would otherwise be difficult

to evaluate empirically. Starting with the basic spatial voting models of Black (1958) and Downs (1957), a large theoretical literature has developed assuming that political preferences can be represented by ideal points. Politicians attempt to move policy toward their most preferred outcomes given the constraints imposed by the institutions within which they act. These theories have implications for the kinds of proposals that come to the floor, the roles of committees in the legislative process, the responsiveness of policy to election results, and a variety of other outcomes. Adjudicating between competing theories would be simple if the locations of preferences and policy outcomes could be observed.

Since policy space cannot be observed, estimates must be recovered from observed behavior such as votes on bills or signatures on petitions. The appropriate way to evaluate these theories requires that implications from the theoretical model be incorporated into the statistical model used to estimate preferences (Clinton and Meirowitz 2003). Since most ideal point models build on simple spatial voting ideas, it is typically straightforward to elaborate them with more complicated theoretical models of legislative behavior.

While the use of ideal point estimation is most developed in the context of American politics, those methods have been used in other settings with varying degrees of success. Ideal point estimates have been produced for the UN General Assembly (Voeten 2000), European Parliament (Hix, Noury and Roland 2006), and national legislatures in Europe (Poole 2005; Rosenthal and Voeten 2004) and Latin America (Londregan 2000; Morgenstern 2004). In general, the usefulness of the resulting estimates depends strongly on the degree to which party affiliation structures voting behavior. In legislatures with highly cohesive parties, Poole (2005) and Rosenthal and Voeten (2004) suggest non-parametric methods such as optimal classification for ideal point estimation. These authors argue that the high degree of party discipline makes the assumption of independence between votes (conditional on preferences) implausible. While non-parametric models eliminate the need for distributional assumptions, they simultaneously weaken the link to theoretical models of legislative behavior. In cases such as the British House of Commons, even these non-parametric models do not produce plausible preference estimates (Spirling and McLean 2007).

## Ideal points in the House of Commons

Recovering ideal points from divisions in the House of Commons has proved to be difficult. Both parametric random-utility models and optimal classification approaches produce estimates that are implausible on their face.<sup>2</sup> These models make assumptions about the behavior of legislators that are simply untenable in the House of Commons. The two most problematic features of divisions are the high levels of party cohesion and a tradition of oppositional voting (Spirling and McLean 2007).

Parties in the House of Commons are remarkably cohesive in parliamentary divisions. In the 1997–2001 Parliament, more than 98% of Labour Party MPs voted together on 90% of divisions (including free votes). Cohesion is a function of several factors. Party discipline is strong: the vast majority of divisions are subject to party whips, and party leaders possess an array of tools to induce compliance, including the promise of advancement for those loyal to the party and the threat that the whip will be withdrawn from those who rebel. Cohesion is reinforced by the government’s control of the agenda, which enables it to keep proposals that would divide the governing party from coming to the floor. High party cohesion implies that little information can be retrieved from the data about preferences within parties. There are few questions that differentiate among members of a party and those questions are likely to be highly unrepresentative.

Oppositional voting presents a more serious problem for conventional ideal point estimates. Both parametric and non-parametric approaches assume that, with some stochastic noise, legislators who vote together have similar preferences. In a system where the duty of the opposition is to oppose, this assumption is violated. When the opposition sincerely prefers the status quo to a government proposal, this presents no fundamental problem for preference estimation. Problems arise when the opposition votes against a proposal that it

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<sup>2</sup>Spirling and McLean (2007) report estimates using an optimal classification approach; estimates generated from a one-dimensional parametric item response model using MCMC-pack (Martin and Quinn 2006) are qualitatively similar.

would otherwise endorse (that is, a proposal that moves policy outcomes closer to the ideal points of opposition members) in order to embarrass the government. This can produce a situation in which opposition party members join with government party rebels in voting against the government.

In the presence of this nonmonotonicity in voting, ideal point models produce government support scores rather than preference estimates (Spirling and McLean 2007). Typically, government members and core supporters anchor one extreme, followed by government rebels, genuine independents, opposition rebels, and finally the leaders of the opposition. In this situation, the tendency for the ends of the political spectrum to unite against the middle makes it appear that extremists from both parties have similar preferences. The resulting estimates “cannot be interpreted as ideological continua” (Spirling and McLean 2007, 86).

Given the difficulties of estimating legislator preferences from division data, there are two approaches available to scholars interested in legislative behavior in the House of Commons. One option is to abandon the spatial voting framework entirely, focusing instead on non-spatial models that identify clusters of MPs who have similar voting histories (Spirling and Quinn 2010). The other option, pursued in this project, is to use alternative sources of data to estimate the spatial preferences of legislators.

## **Early Day Motions**

Early Day Motions are formal, non-binding expressions of opinion by members of the House of Commons; they are essentially petitions signed by MPs. Any member can sponsor an EDM on any topic, from criticizing the government to congratulating local sports teams. Once introduced, other MPs can indicate their support for the policy proposed in the motion by “signing” the EDM; their name is then associated with the motion and can be seen by other legislators and the public. By convention, cabinet members, opposition front-benchers, and party whips rarely introduce EDMs or sign those introduced by others. Unlike bills,

which survive for the duration of a Parliament, EDMs are closed to new signatures at the end of each session.

The current use of Early Day Motions arose from a nineteenth century practice in which members of Parliament would introduce motions for consideration “at an early day”: an unspecified date in the future (House of Commons Information Office 2000). As governments consolidated their control of the legislative agenda during the late 1900s (Cox 1987), such motions were rarely debated. By the 1940s, the clerks of the House had developed a system to number the motions and record the names of supporters. Since then, the number of EDMs has grown dramatically over time, from fewer than 100 per session in the 1940s to over 1,000 per session since the mid-80s.

Early Day Motions can be classified into several categories based on the nature of the proposition being advanced. Many EDMs are policy-related, in that they support or oppose some action that the sitting government could take. For example, Gordon Prentice introduced an EDM early in the 1998-99 session calling on the government to implement “legally enforceable environmental rights including a right of access to common land, open country, mountain and moorland” (EDM 98/15). The “Freedom to Roam” was a totemic issue for certain parts of the Labour Party, and the EDM attracted more than 200 Labour signatures. At the same time, several Liberal Democrat MPs also signed the motion. Motions such as this one can be quite informative about the preferences of legislators. In legislatures where leaders exercise weaker control of the agenda, similar proposals would be subject to votes on the floor.

On the other hand, many EDMs are proposed for primarily parochial reasons. Early Day Motions provide MPs with a way to gain attention in their constituencies by recognizing the activities of local individuals or organizations. Typical of this category were motions congratulating the Swansea City Football Club for an upset victory (EDM 98/186), recognizing the 50th anniversary of the Cheltenham Festival of Literature (EDM 98/919), or applauding the Essex County Council Library Service for its summer reading programs (EDM 98/952).

While these EDMs may provide information about local concerns, they do not help to locate members along the major ideological dimensions structuring political competition.

A third group of motions aim to score party political points without necessarily advocating particular policies. Examples include EDMs suggesting that the Chancellor of the Exchequer had misled Parliament (EDM 98/1007) or mocking members of the opposition for their apparent lack of knowledge about the member states of the European Union (EDM 98/935). While signatures on these motions may be more a function of partisanship than of preferences per se, to the extent that these two characteristics vary together such motions provide some information about member preferences.

Finally, a small subset of Early Day Motions are used by opposition party leaders to prompt debate on secondary legislation (regulations promulgated by the government). These EDMs, known as prayers, can be identified by their language and the pattern of signatures, which are typically limited to members of the opposition front bench. Since backbenchers rarely sign prayers, they do not help to identify member preferences.

Early Day Motions have been widely used in studies of the political preferences of members of the House of Commons. Their popularity stems from the challenges presented by division data along with the relative dearth of alternatives that Franklin and Tappin (1977) describe as “unobtrusive measures of backbench opinion”: data sources that are easy to collect and do not require the participation of members themselves. Several approaches to the use of EDMs appear in the literature. Some studies use small subsets of EDMs focused on common themes as indicators of member preferences on issues such as European integration or women’s issues (Berrington and Hague 1998; Childs and Withey 2004). Other studies survey a larger set of motions in an attempt to identify blocks of MPs with common interests (Berrington 1973; Finer, Berrington and Bartholomew 1961; Franklin and Tappin 1977). Bailey and Nason (2008) use Early Day Motions to explore changes in cohesion within each major party over shorter periods of time. Finally, a few studies attempt to construct scales of MP preferences on one or more dimensions using EDM data (Leece and Berrington 1977; Nason 2001). This paper extends the final approach by developing a more appropriate

statistical model of EDM signing behavior and using it to estimate the ideal points of British parliamentarians.

Using Early Day Motions provides several advantages relative to divisions as a basis for estimating member preferences in the House of Commons. First and foremost, parties exert far less influence over signatures on EDMs than they do over divisions in the House. While the party whip organizations monitor signatures on motions, they typically do not attempt to influence their members.<sup>3</sup> Without the influence of the whips, there is greater scope for differentiation in revealed preferences among party members. Second, since EDMs are non-binding, there is little incentive for opposition party members to join government rebels in an “ends against the middle” attempt to embarrass or defeat the government. This type of voting is one of the principal reasons that existing methods using division data fail to recover plausible preference estimates (Spirling and McLean 2007). Instead, two motions would typically be introduced: one consistent with the policy preferences of the rebels and another consistent with the preference of the opposition.<sup>4</sup>

Other characteristics of Early Day Motions, while not as important as the relative weakness of party influence, are still useful for preference estimation. Since any MP can sponsor an EDM, agenda control is weak to non-existent and a wide range of policy proposals will be observed. Agenda control is potentially problematic when estimating ideal points, since it may restrict the distribution of proposals in ways that produce misleading estimates

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<sup>3</sup>Labour members are required to give the whips’ office one day’s notice before tabling an EDM, while members of the other parties face no restrictions (House of Commons Information Office 2000).

<sup>4</sup>An example of this occurred in the debate over top-up fees for universities during the 2002–03 session. Members on the left of the Labour Party who opposed the introduction of top-up fees primarily because of fears of a two-tier system of higher education signed EDM 02/2, introduced by Labour MP Paul Farrelly. On the other hand, Conservative MPs opposed top-up fees because they would affect core upper-middle class constituents, and instead signed EDM 02/264 introduced by Conservative MP Damian Green.

(Clinton and Meirowitz 2001). Finally, there are simply many more Early Day Motions — on the order of ten times as many — than divisions in a given Parliament.

While Early Day Motions have several advantages over divisions, using EDMs to estimate legislator preferences is not unproblematic. Since party leaders typically do not sign EDMs, they cannot be used to estimate frontbench preferences. While this is unfortunate, it does not present any fundamental challenge to the validity of the estimates for backbench MPs presented here. More serious challenges arise from the differences between EDMs and roll call votes. First, unlike roll call votes, EDMs do not provide legislators with any way to record opposition to the policy change proposed in the motion. Failing to sign a particular EDM could indicate either abstention or opposition. Second, unlike roll call votes, EDMs do not have formal implications for the policy enacted by the government. As a result, they can be viewed as a form of cheap talk or expressive gesture rather than as an expression of political preferences (McLean 1995, 126). While these problems have been addressed at length by previous authors (Berrington 1973; Finer, Berrington and Bartholomew 1961; Franklin and Tappin 1977), they are reviewed here given their importance to the statistical model developed in the next section.

There is little doubt that members vary in their propensity to sign Early Day Motions. Most EDMs are signed by a small number of parliamentarians, making it inappropriate to assume that all non-signatures indicate opposition to the policy advocated in the motion. On the other hand, a few MPs are quite promiscuous in their signing behavior, lending credence to the claim that some members “will sign anything they are asked to sign” (Franklin and Tappin 1977, 54). Differences in the rate at which members sign are a function of several factors: the amount of time spent at Westminster, the density of connections to other MPs, and the personal importance that each parliamentarian assigns to EDMs. Both the distribution of signatures and the qualitative evidence on signing behavior suggest that differences in the propensity to sign must be modelled explicitly.

Determining whether signatures on EDMs reflect underlying preferences presents a more difficult problem. A strongly consequentialist view of legislative behavior would suggest

skepticism since EDMs do not directly affect policy outcomes. At the same time, there are several reasons to believe that EDM signatures (after taking differences in signing propensity into account) do reflect the revealed preferences of members. Signing or failing to sign an EDM does impose some costs. The press reports on EDMs dealing with salient political issues, and advocacy groups often organize letter-writing campaigns urging members to sign. Moreover, Early Day Motions are one of the few ways by which MPs can differentiate themselves from their party leadership, giving them an incentive to consider carefully their decision to sign. In the end, this issue is best addressed by evaluating the validity of the resulting estimates, in terms of the degree to which the estimates both correspond to qualitative beliefs about member preferences and predict other forms of legislative behavior. The results in the following sections suggest that the ideal point estimates perform well on both of these aspects of validity.

## **A model for EDM signatures**

This section develops a statistical model for Early Day Motion signatures based on the behavioral assumptions discussed above. While a formal behavioral model is not necessary to generate preference estimates<sup>5</sup>, such a model does link the results more closely to theoretical models of legislative behavior. The EDM model assumes that the decision to sign an EDM is driven by three factors: the policy utility derived from the proposed EDM relative to the status quo, the cost to the MP of signing any EDM, and a stochastic component representing idiosyncratic characteristics influencing the decision to sign. This model takes a standard

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<sup>5</sup>For example, Poole (2000, 2005) proposes a non-parametric optimal classification approach to estimate ideal points in several parliamentary systems. Rosenthal and Voeten (2004) argue that the OC approach is more appropriate for legislatures with strong party discipline, although Spirling and McLean (2007) show that it does not guarantee plausible results.

ideal point model based on spatial voting and elaborates it by including a cost term unique to each legislator.

## Sampling distribution

Operationalizing the model requires assumptions about the form of legislator utility functions and the distribution of the stochastic utility term. I follow Clinton, Jackman and Rivers (2004a) and Martin and Quinn (2002) in assuming quadratic policy utility functions and normal errors. In particular, let  $i = 1, \dots, I$  index legislators and  $j = 1, \dots, J$  index Early Day Motions. Each legislator is assumed to have an ideal point  $\theta_i$  along the single policy dimension.<sup>6</sup> Each early day motion has a policy position implied by the motion  $m_j$  and an associated status quo  $s_j$  that the motion seeks to overturn. The utility of supporting motion  $j$  for legislator  $i$  is thus

$$u(m_j) = -(\theta_i - m_j)^2 + v_{ij}$$

while the utility of supporting the status quo is

$$u(s_j) = -(\theta_i - s_j)^2 + w_{ij}$$

where  $w_{ij}$  and  $v_{ij}$  are i.i.d. normal. The utility  $z_{ij}$  of signing motion  $j$  is thus

$$z_{ij} = u(m_j) - u(s_j) = (s_j^2 - m_j^2) + 2\theta_i(m_j - s_j) + (v_{ij} - w_{ij})$$

The utility  $z_{ij}$  is unobserved; instead,  $y_{ij} = 1$  (the motion is signed) if  $z_{ij} > 0$  and  $y_{ij} = 0$  otherwise. The  $i \times j$  matrix of observed signatures and non-signatures is the only observed data in the standard model. If  $Var(v_{ij} - w_{ij}) = 1$ , which can be achieved through a simple

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<sup>6</sup>The model generalizes immediately to multiple dimensions, but for ease of exposition I assume a one-dimensional policy space.

standardization, this produces a basic probit likelihood with unobserved predictors. Since  $m_j$  and  $s_j$  are not separately identified, the model is often collapsed to

$$z_{ij} = \alpha_j + \theta_i \beta_j + \epsilon_{ij}$$

where  $\alpha_j = s_j^2 - m_j^2$ ,  $\beta_j = 2(m_j - s_j)$ , and  $\epsilon_{ij} = v_{ij} - w_{ij}$ . This is equivalent to a standard two-parameter item response model from the psychometric literature (Baker 1992), and has been successfully applied and elaborated in political science contexts (Bafumi et al. 2005; Clinton, Jackman and Rivers 2004a; Martin and Quinn 2002).

As discussed above, this simple two-parameter model is inappropriate for Early Day Motions because it ignores the fact that while a legislator can express support by signing the EDM, there is no way to express opposition to the proposal. Applying the standard model to EDM data produces implausible preference estimates; instead, the results are strongly correlated to the number of EDMs signed. Most members of Parliament sign few Early Day Motions, but some are quite prolific. The variability in the rate at which members sign Early Day Motions is too great to be plausibly explained by the content of the motions themselves; therefore, I assume that there is a legislator-specific cost  $c_i$  associated with signing any EDM. This changes the expression for the latent utility to

$$z_{ij} = (s_j^2 - m_j^2) + 2\theta_i(m_j - s_j) + c_i + \epsilon_{ij}$$

Under the assumption of independent error terms, the likelihood is thus:

$$L(\mathbf{m}, \mathbf{s}, \mathbf{c}, \boldsymbol{\theta} | \mathbf{y}) \propto \prod_{i=1}^I \prod_{j=1}^J \{ \Phi(s_j^2 - m_j^2 + 2\theta_i(m_j - s_j) + c_i)^{y_{ij}} \times [1 - \Phi(s_j^2 - m_j^2 + 2\theta_i(m_j - s_j) + c_i)]^{(1-y_{ij})} \}$$

As is typically the case with ideal point models, the likelihood is not identified without further restrictions on the parameters (Bafumi et al. 2005; Jackman 2001).<sup>7</sup> A frequentist approach requires that the restrictions be sufficiently strong to ensure identification of the likelihood. In the Bayesian context, likelihood identification is not strictly necessary; instead, the selection of appropriate prior distributions for each block of parameters ensures that the posterior distribution is well-behaved.

## Prior distributions

Restricting the posterior distribution in substantively interesting ways is key to obtaining useful estimates of legislator ideal points from this model. For the prior distributions on the legislator parameters  $\theta$  and  $c$ , I assume standard normal distributions (with one exception), such that  $\theta_i \sim N(0, 1)$  and  $c_i \sim N(0, 1)$ . This implies that prior beliefs about the ideal points and signing costs for each legislator are the same. This is a conservative assumption, as it does not take advantage of our knowledge of MP policy preferences. The one exception is that the prior for the ideal point of one member of Parliament known to be extreme is restricted to one side of zero; in the case of a Labour member, the restricted prior is  $\theta_{i'} \sim N(0, 1)\mathbb{I}(\theta_{i'} < 0)$ . This orients the policy space by placing Labour on the left.

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<sup>7</sup>The best-known of these problems is reflection invariance; since  $\theta_i(m_j - s_j) = -\theta_i(s_j - m_j)$ , the likelihood does not distinguish right from left. Likewise, the model as written does not produce unique location estimates, since adding  $k$  to  $\theta_i$ ,  $m_j$  and  $s_j$  leaves the likelihood unchanged. Including the cost term  $c_i$  introduces a further identification issue; by subtracting a constant  $b$  from each  $c_i$  and adding  $\frac{b}{2(s_j - m_j)}$  to  $s_j$  and  $m_j$  for all  $j$ , the likelihood is again unchanged. Finally, there is the typical identification issue for  $s_j$  and  $m_j$  if the motion does not discriminate amongst MPs, which occurs when  $m_j - s_j = 0$ . Another identification issue relevant to the two-parameter model, scale invariance, does not arise in this model because retaining the motion and status quo parameters in the model preserves a link between the discrimination and difficulty aspects of each bill.

The prior distributions for the motion parameters  $m_j$  are more informative. The nature of Early Day Motions reduces the incentive to make proposals that can gain the support of a majority of legislators. As a result, it is plausible to assume that MPs sponsor Early Day Motions that support policy outcomes close to their most-preferred outcomes. Since the sponsor of each EDM is known, I assume a hierarchical normal prior on each motion parameter centered around the ideal point  $\theta_{m_j}$  of the member making the proposal  $m_i$ :

$$m_j | \theta_{m_j} \sim N(\theta_{m_j}, \sigma_m^2)$$

The variance of the normal prior is assumed known and constant across motions, with smaller values of  $\sigma_m^2$  implying prior beliefs that proposal locations are more closely linked to the preferences of their sponsors. This prior introduces a significant amount of additional information to the model, since the estimated ideal point of a legislator depends not just on the motions signed by that legislator, but also on the ideal points of those who signed an EDM sponsored by the legislator, and vice versa.

Finally, the model is closed out by assuming prior distributions on the status quo points  $s_i$ . These are assumed to have normal priors centered at zero with variance  $\sigma_s^2$ , such that  $s_j \sim N(0, \sigma_s^2)$ . In this case, a smaller prior variance gives more weight to centrist status quo positions.

## Posterior distribution

Given the assumptions of the EDM model, the posterior distribution is proportional to the likelihood multiplied by the prior distributions for each block of parameters. The posterior distribution  $f(\theta, \mathbf{c}, \mathbf{m}, \mathbf{s} | \mathbf{Y})$  provides the joint probability distribution for all of the parameters of interest conditional on the observed data. This distribution does not have a standard functional form, so estimates of posterior quantities must be obtained through simulation (Gelman et al. 2004).

To sample from the posterior distribution, I construct a Markov Chain Monte Carlo (MCMC) algorithm that over time converges to the desired distribution. The algorithm used to estimate the model samples alternately from the conditional distributions of the legislator and bill parameters, using the slice sampling approach suggested by Neal (2003). Details of the algorithm and diagnostics for the resulting samples from the posterior are presented in the Supporting Information.

## Data

Since the primary goal of this paper is to demonstrate that the model presented in the previous section can recover plausible estimates of the preferences of Members of Parliament, the choice of data for analysis is driven by practical considerations. Nason (2001) makes available EDM signature matrices for the first three sessions of the 1997 Parliament. Since the computational difficulty of estimating the EDM model is not trivial, I use data from the 1998–99 session as it has the fewest motions (and as a consequence the fewest parameters) of the available data. This session, which lasted from 24 November 1998 to 11 November 1999, had only 149 sitting days, a small number for a session not ending in a general election. This dataset provides evidence of member preferences in the early years of the Blair government. Major issues considered in the 1998–99 session included constitutional changes (creation of the Greater London Authority and reforms to the House of Lords) and welfare and pension reform.

Before estimating the model, some motions and legislators must be removed from the data. Prayers for the reconsideration of secondary legislation are excluded; since signatures on these motions are typically limited to party leaders (who rarely sign other motions), it is inappropriate to include these EDMs in the data. In addition, motions withdrawn by their sponsors are deleted because members may not have had equal opportunities to sign before the motion was withdrawn. Finally, motions signed only by their sponsor are eliminated, since the data provides essentially no information to nail down the locations of

such proposals. After deleting these motions, any MP who did not sign any of the remaining EDMs is likewise removed from the dataset. All of these members would have the same posterior estimates for ideal points and signing costs, since the data provides no information with which to differentiate them.<sup>8</sup>

The final dataset includes 546 out of the 659 members who sat in the 1998–99 session of the House of Commons. As explained above, notable members not appearing in the dataset include Prime Minister Tony Blair, Chancellor Gordon Brown, and Conservative Party leader William Hague. The final dataset contains 991 motions, which received an average of 50 signatures. Among the MPs in the data, 109 members signed fewer than 10 motions. At the other extreme, Labour MP John McDonnell signed 668 EDMs, the most of any member. Liberal Democrat MPs are the most active sponsors and signers of EDMs, followed by Labour and Conservative members. Liberal Democrat members sponsored and signed EDMs at more than six times the rates of their Conservative colleagues. These behavioral differences in turn affect the precision with which preferences can be estimated.

## Legislative ideal points

The model produces estimates from the joint posterior distribution of ideal points, signing costs, and motion characteristics.<sup>9</sup> With two parameters for each MP and each EDM, there are over 3000 parameters in the model fit to the 1998-99 data. The large number of parameters makes graphical summarization useful in characterizing the results of the model. This section presents a number of graphical summaries to highlight different aspects of the distribution of ideal points in the 1998-99 session.

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<sup>8</sup>This does not imply, however, that the posterior distributions for these members would be identical to the prior distributions assumed, since failing to sign any motions provides a great deal of information about member signing costs as they are conceived of in this paper.

<sup>9</sup>The results for motion characteristics are discussed in the Supporting Information.

To build intuition about the results of the model, it is useful to consider estimates for a few prominent Members of Parliament. Figure 1 shows the posterior distributions for the ideal points of six MPs: Ken Livingstone, Diane Abbott, Giles Radice (Labour); Martin Bell (Independent); and Virginia Bottomley and Christopher Chope (Conservative). The optimal classification estimates presented by Spirling and McLean (2007) identify Radice as the most extreme member of the Labour Party. The EDM estimates, in contrast, place Radice at the center of the political spectrum as one would suspect from a former chair of the Manifesto Group in the early 80s who later described the revision of Clause Four ending Labour’s commitment to public ownership as “a great moment in my political life” (Radice 2004, 333). His estimated ideal point is slightly to the left of Martin Bell, a former BBC war correspondent and the first MP elected to the House of Commons as an independent in over 40 years. The ideal point estimate for Radice is less precise than the estimate for Bell; Radice signed only six EDMs while Bell signed fifty-eight.

[Figure 1 about here.]

Ideal point estimates generated from voting data locate Labour rebels close to independents such as Bell. In the Spirling and McLean (2007) estimates, which rank MPs in order from left to right, Abbott is the 415th most left-wing MP, while Livingstone and Bell occupy positions 422, and 432, respectively. The EDM estimates are far more plausible, showing Livingstone at the far left and Abbott slightly, but distinctly, to his right. Ken Livingstone, affectionately known as “Red Ken”, was expelled from the Labour Party for running against Blair’s chosen candidate for Mayor of London. Abbott, while less prominent than Livingstone, was the first black woman to serve in Parliament and is well known as a member of the Labour left. By correctly placing these MPs to the left of the bulk of the Labour Party, the EDM model eliminates one of the key problems with preference estimates generated by other approaches.

The increased face validity of the estimates generated by the EDM model extend to members of the opposition. The two Conservative MPs shown in Figure 1, Bottomley and

Chope, come from opposite wings of the party. Bottomley is a life member of the Tory Reform Group; Chope, in contrast, is active in Conservative Way Forward.<sup>10</sup> As expected given these affiliations, Bottomley is located closer to Labour members. Chope’s estimated ideal point is among the furthest right of all Conservative MPs. Taken together, these results suggest that the preferences of government and opposition members are being estimated on a common scale that accords with conventional understandings of the left-right dimension in British politics.

Having examined the ideal points for a few notable MPs, Figure 2 summarizes the preferences for all legislators in the dataset.<sup>11</sup> Posterior mean estimates for ideal points are plotted on the horizontal axis and signing costs are on the vertical dimension. In this figure, members from the three major parties resolve into three distinct clusters. Labour members fall predominantly on the left of the plot, Conservatives on the right, and Liberal Democrats in the center. There is considerable overlap, however, between Liberal Democrat MPs and the more moderate members of the Labour party. The Liberal Democrats had abandoned their policy of “equidistance” a few years earlier, and Blair and Ashdown had collaborated on efforts to promote cooperation between the two parties (Russell and Fieldhouse 2005, 39–42), so this overlap is not surprising. Figure 2 also reveals considerable heterogeneity in the implied signing costs faced by MPs within each party. As expected, Liberal Democrats have the lowest average signing costs, although the differences across parties are smaller than would be expected from the observed difference in the average number of EDMs signed.

[Figure 2 about here.]

As Figure 1 illustrates, point estimates of ideal points provide only a partial picture of legislator preferences. They provide no information about the uncertainty inherent in the

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<sup>10</sup>Going back to the Thatcher government, Norton (1990, 53–54) identifies Bottomley as a ‘Damp’ and Chope as a neo-Liberal ‘Dry’.

<sup>11</sup>Posterior means and 95% central credible intervals are provided in the Supporting Information for each member in the dataset.

estimates.<sup>12</sup> Interval estimates provide an alternative summary of MP preferences, at the cost of some interpretive complexity. Figure 3 presents two alternative interval estimates for MP ideal points. The left-hand panels display 95% central credible intervals<sup>13</sup> for the location of each member in the dataset, ordered by their posterior means. Each party’s MPs are shown in a different panel to reveal differences across the major parties. As the figure shows, there is considerable variation in the precision with which member ideal points are estimated. Focusing on the posterior intervals for the Labour Party reveals that the interval estimates for far-left MPs such as Livingstone or Abbott are far narrower than those for Labour moderates.

This pattern of precise estimates for extremists and vague estimates for moderates runs contrary to the usual pattern in ideal point estimation. Typically, it is difficult to estimate precisely the preferences of politicians at one end of a political dimension because few issues arise that can distinguish between them. In the case of Early Day Motions, however, the lack of agenda control makes it possible to differentiate between the conventional left and the far left in the Labour Party.<sup>14</sup> In contrast, while there are many EDMs that could differentiate between moderate members, EDM data provides little information for members who choose not to sign many motions. This characteristic is best illustrated by

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<sup>12</sup>This accounts for the debates in American politics mentioned above over which legislator is the “most liberal” or “most conservative” in the House or Senate. Since presidential candidates sitting in Congress typically return to vote only on the most politically polarized issues, it is common for them to have extreme but imprecisely estimated ideal points (Clinton, Jackman and Rivers 2004*b*).

<sup>13</sup>In Bayesian inference, a 95% credible interval provides an interval estimate such that 2.5% of the posterior probability is above the interval and 2.5% is below the interval.

<sup>14</sup>For example, Tony Benn’s motion applauding the acquittal of three women in Scotland who “had disarmed an integral part of the UK Trident nuclear weapon system” (EDM 98/959) received only 21 signatures, most of which came from members of the Socialist Campaign Group.

comparing the estimates for moderate Labour MPs with those of Liberal Democrats. While there is considerable overlap between the two, Liberal Democrat intervals are much narrower, less than half the width of Labour members with similar preference estimates.

[Figure 3 about here.]

Posterior ranks, in which members are placed in order from left to right based on their estimated ideal points, provide an alternative means to summarize the preferences of Members of the House of Commons. These ranks are obtained by taking each set of ideal points generated by the MCMC sampler, ordering them from left to right, and assigning each the appropriate rank number. Measuring the rank order of MP preferences rather than their location can be useful for two reasons. First, the scale on which ideal points are measured has no inherent meaning, and it is not clear that the resulting estimates contain interval-level information. Second, many theories of legislative behavior, from the median voter theorem forward, make predictions in terms of quantiles of the distribution of preferences. While the identity of the median voter in the House of Commons cannot be estimated using Early Day Motions since not all members appear in the dataset, posterior ranks do provide some insight into the distribution of preferences. The right-hand panels of Figure 3 show 95% central credible intervals for the in-sample ranks of each major-party MP in the dataset. Aside from the intervals for members estimated to have extreme ideal points, the rank interval estimates are quite broad, particularly within the Labour Party. The combination of relatively noisy ideal point estimates and the high density of MPs with relatively similar preferences makes it difficult to recover the ordering of the bulk of Labour members.

## Validity

A problem with all ideal point methods is the difficulty in determining whether the resulting estimates are measuring underlying preferences or some other quantity. As with any method used to estimate latent characteristics, the model proposed in this paper would

produce results given any signature matrix. Moreover, purely statistical criteria cannot resolve this problem. Indeed, models applied to division data within the House of Commons tend to fit the data quite well; Spirling and McLean (2007) report correct classification proportions exceeding .99 for divisions in the 1997–2001 Parliament. Instead, the resulting estimates are so inconsistent with prior beliefs about the preferences of MPs that they are rejected as lacking face validity.

In the absence of clear statistical criteria, one must rely on other factors to assess the utility of ideal point estimates. These criteria include the plausibility of the behavioral assumptions underpinning the statistical model, the consistency of the results with qualitative knowledge about legislator preferences, and the ability of the resulting estimates to predict other forms of legislative behavior. The first two criteria have been described above. Augmenting a standard ideal point model with an individual-specific signing cost addresses one of the key differences between voting and EDM data. The resulting estimates place the parties in the expected order and recover more plausible orderings within parties, reversing the standard outcomes in which party rebels are estimated to have moderate preferences.

The remainder of this section attempts to validate the ideal point estimates generated by the EDM model, using them to predict behavior on divisions in the House of Commons. Since standard models of voting in legislatures are based on the same spatial representation of preferences used in this paper, the ideal point estimates should provide more information about the way MPs vote than their party affiliation alone. To summarize voting behavior, I construct a simple measure of support for Labour in parliamentary divisions. Using data from the 1997–2001 Parliament (Firth and Spirling 2005), I first identify the outcome supported by the majority of Labour MPs voting on each division. Defining this outcome as the Labour position, I calculate the proportion of votes in which each parliamentarian supported the Labour position.

The ideal point estimates improve predictions of Labour support scores, although this relationship is mediated by party. Figure 4 plots Labour support scores as a function of the estimated ideal points for the three major parties. The dominant role of party affiliation

in structuring behavior during divisions is obvious from the figure. Labour members have extremely high Labour support scores (greater than 90%), Conservatives have low scores, and Liberal Democrats fall in the middle. Differences within each party allow for a better evaluation of the ideal point estimates generated by the EDM model. A simple model of legislative behavior would predict that support for Labour majority positions should be highest near the center of the Labour Party. This implies that the relationship between Labour support and estimated ideal points should be positive on the Labour left and negative for parties to the right of Labour. The lines in Figure 4 represent local weighted regressions estimated within each party. As expected, the members of the Labour Party least likely to support the majority are those located at the extreme left, including Livingstone, Abbott, Tony Benn, and Jeremy Corbyn, among others. On the other hand, Liberal Democrats closest to the Conservatives are the least likely to support Labour. Tory support for Labour positions is weakest at the right of the party, although the relationship is not as strong as for Liberal Democrats.

[Figure 4 about here.]

The qualitative results in Figure 4 are confirmed by robust linear regressions within each party caucus of Labour support on estimated ideal points.<sup>15</sup> As in the figure, ideal points are defined as the posterior mean for each MP. The results in Table 1 show that the relationship is positive and significant for Labour MPs and negative and significant for Liberal Democrats. Among Conservative MPs, the relationship is negative as expected but not statistically significant. This is likely a function of the lower precision with which Conservative preferences are measured. Overall, however, the results suggest that the ideal point estimates are in fact measuring preference rather than government support or some other latent characteristic of parliamentarians.

[Table 1 about here.]

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<sup>15</sup>The robust linear regressions use the MM-estimator in the MASS library (Venables and Ripley 2010) for the R statistical computing environment.

## Discussion

Estimating the preferences of British MPs has presented a longstanding challenge. The intractability of standard methods using roll call votes argues for the use of alternative sources of information about legislator preferences. The approach presented in this article builds on earlier efforts to use Early Day Motions by constructing a more realistic model of the process by which members sign EDMs. Following similar efforts in other contexts, the EDM model uses a Bayesian approach to produce estimates that would be difficult to obtain using classical methods. While estimates from the EDM model come at the expense of some computational complexity, they offer the prospect of “unobtrusive measures of backbench opinion” that are far more plausible than existing alternatives.

The ideal point estimated generated from EDMs signed in the 1998–99 session indicate the utility of these estimates for understanding British politics. They reveal a significant degree of heterogeneity in MP preferences within each party. The estimates also reveal the common ground between the Liberal Democrats and the moderate wing of the Labour Party during this period, a congruence often remarked upon but difficult to measure. While the main purpose of this article is to develop and validate a method of preference estimation, these observations suggest questions that could be addressed using estimates generated by the model.

The model developed in this paper and the results that it produces can be extended in a number of ways. First, the model can be elaborated to generate estimates of preferences over time. The distribution of preferences within the House of Commons or within a party caucus can change in two ways: either through the replacement of legislators with new cohorts of MPs or through the evolution of the preferences of existing members. The major parties have seen significant turnover in the past 30 years; estimating preferences over time could reveal, for example, the degree to which Labour’s move to the center in the 1990s was a function of a new generation of Labour MPs. Estimating individual-level preference change requires additional assumptions, but this could resolve the question of whether the

increased rebelliousness of Labour backbenchers in the closing years of the Blair government was a function of radicalization in preferences or simple a weakening of discipline within the party.

Estimates generated using this approach also offer the prospect of evaluating theories of legislative behavior in the context of the British Parliament. Attempts to measure the strength of party discipline on particular votes in the House of Commons have been hampered by the inability to separate out the effects of discipline from the effects of preferences. The best way to approach this problem is not to use the point estimates generated from this model to explain voting behavior. Instead, one should estimate vote choice and EDM signatures simultaneously, assuming a common preference structure but allowing for discipline on divisions.

More broadly, the model developed in this paper could be applied to obtain ideal point estimates in other cases where petition-like data is available. As such, it adds to the growing array of models and data sources that have been used to estimate preferences. While all of these approaches have merit, there are several advantages to the use of petition based data. In legislatures where party discipline is strong, petitions provide more information about the preferences of individual legislators. At the same time, the choice to sign or not sign a petition is a behavior more similar to voting than, for example, the decision to cite certain experts or to use particular words in debate. As such, petition data is more analogous to the decision-making contexts in which ideal points have been a useful way to think about the preferences of politicians.

## References

- Bafumi, Joseph, Andrew Gelman, David K. Park and Noah Kaplan. 2005. "Understanding Bayesian Ideal Point Estimation." *Political Analysis* 13:171–187.
- Bailey, Daniel and Guy P. Nason. 2008. "Cohesion of Major Political Parties." *British Politics* 3:390–417.
- Baker, Frank B. 1992. *Item Response Theory*. New York: Marcel Dekker.
- Berrington, Hugh B. 1973. *Backbench Opinion in the House of Commons, 1945–55*. Oxford: Pergamon Press.
- Berrington, Hugh and Rod Hague. 1998. "Europe, Thatcherism and Traditionalism: Opinion, Rebellion and the Maastricht Treaty in the Backbench Conservative Party, 1992–1994." *Western European Politics* 21:44–71.
- Black, Duncan. 1958. *The Theory of Committees and Elections*. Cambridge: Cambridge University Press.
- Childs, Sarah and Julie Withey. 2004. "Women Representatives Acting for Women: Sex and the Signing of Early Day Motions in the 1997 British Parliament." *Political Studies* 52:552–564.
- Clinton, Joshua D. and Adam Meirowitz. 2001. "Agenda Constrained Legislator Ideal Points and the Spatial Voting Model." *Political Analysis* 9:242–259.
- Clinton, Joshua D. and Adam Meirowitz. 2003. "Integrating Voting Theory and Roll Call Analysis: A Framework." *Political Analysis* 11(4):381–396.
- Clinton, Joshua, Simon Jackman and Douglas Rivers. 2004a. "The Statistical Analysis of Roll Call Data." *American Political Science Review* 98:355–370.

- Clinton, Joshua, Simon Jackman and Douglas Rivers. 2004b. ““The Most Liberal Senator”? Analyzing and Interpreting Congressional Roll Calls.” *PS: Political Science and Politics* 37:805–811.
- Cowley, Philip and Mark Stuart. 2004. “When Sheep Bark: the Parliamentary Labour Party since 2001.” *Journal of Elections, Public Opinion and Parties* 14:211–229.
- Cox, Gary W. 1987. *The Efficient Secret: The Cabinet and the Development of Political Parties in Victorian England*. Cambridge: Cambridge University Press.
- Downs, Anthony. 1957. *An Economic Theory of Democracy*. New York: Harper and Row.
- Finer, Samuel E., Hugh B. Berrington and D. J. Bartholomew. 1961. *Backbench Opinion in the House of Commons, 1955–59*. Oxford: Pergamon Press.
- Firth, David and Arthur Spirling. 2005. “tapiR: Tools for Accessing UK Parliamentary Information in R.”. R package version 0.7-2.
- Franklin, Mark N. and Michael Tappin. 1977. “Early Day Motions as Unobtrusive Measures of Backbench Opinion in Britain.” *British Journal of Political Science* 7:49–69.
- Gelman, Andrew, John B. Carlin, Hal S. Stern and Donald B. Rubin. 2004. *Bayesian Data Analysis*. 2nd. ed. Boca Raton, Florida: Chapman and Hall/CRC.
- Heckman, James J. and James M. Snyder. 1997. “Linear Probability Models of the Demand for Attributes with an Empirical Application to Estimating the Preference of Legislators.” *RAND Journal of Economics* 28:S142–S189.
- Hix, Simon, Abdul Noury and Grard Roland. 2006. “Dimensions of Politics in the European Parliament.” *American Journal of Political Science* 50(2):494–520.
- House of Commons Information Office. 2000. “Factsheet 30: Early Day Motions.” Series P No. 3 ISSN 0144-4689.

- Jackman, Simon. 2001. "Multidimensional Analysis of Roll Call Data via Bayesian Simulation: Identification, Estimation, Inference, and Model Checking." *Political Analysis* 9:227–241.
- Leece, John and Hugh Berrington. 1977. "Measurements of Backbench Attitudes by Guttman Scaling of Early Day Motions: A Pilot Study, Labour, 1968–69." *British Journal of Political Science* 7:529–541.
- Londregan, John. 2000. *Legislative Institutions and Ideology in Chile's Democratic Transition*. Cambridge: Cambridge University Press.
- Martin, Andrew D. and Kevin M. Quinn. 2002. "Dynamic Ideal Point Estimation via Markov Chain Monte Carlo for the U.S. Supreme Court, 1953–1999." *Political Analysis* 10:134–153.
- Martin, Andrew D. and Kevin M. Quinn. 2006. "MCMCpack: Markov Chain Monte Carlo package for R."
- Martin, Andrew, Kevin Quinn and Lee Epstein. 2005. "The Median Justice on the United States Supreme Court." *North Carolina Law Review* 83:1275–1320.
- McCarty, Nolan, Keith T. Poole and Howard Rosenthal. 2006. *Polarized America: The Dance of Ideology and Unequal Riches*. Cambridge, Mass.: MIT Press.
- McLean, Iain. 1995. Backbench Opinion Revisited. In *Party, Parliament and Personality: Essays presented to Hugh Berrington*, ed. Peter Jones. London: Routledge pp. 121–140.
- Morgenstern, Scott. 2004. *Patterns of Legislative Politics: Roll-Call Voting in Latin America and the United States*. Cambridge: Cambridge University Press.
- Nason, Guy P. 2001. "Early Day Motions: Exploring backbench opinion during 1997-2000." Working paper, University of Bristol.
- Neal, Radford M. 2003. "Slice Sampling." *Annals of Statistics* 31:705–767.

- Norton, Philip. 1990. “‘The Lady’s Not for Turning’ But What About the Rest? Margaret Thatcher and the Conservative Party 1979–89.” *Parliamentary Affairs* 43:41–58.
- Poole, Keith T. 2000. “Non-parametric Unfolding of Binary Choice Data.” *Political Analysis* 8:211–232.
- Poole, Keith T. 2005. *Spatial Models of Parliamentary Voting*. New York: Cambridge University Press.
- Poole, Keith T. and Howard Rosenthal. 1985. “A Spatial Model of Legislative Roll Call Analysis.” *American Journal of Political Science* 29:357–384.
- Poole, Keith T. and Howard Rosenthal. 1997. *Congress: A Political-Economic History of Roll Call Voting*. Oxford: Oxford University Press.
- Radice, Giles. 2004. *Diaries 1980–2001: From Political Disaster to Election Triumph*. London: Weidenfeld and Nicolson.
- Rosenthal, Howard and Erik Voeten. 2004. “Analyzing Roll Calls with Perfect Spatial Voting: France 1946–1958.” *American Journal of Political Science* 48:620–632.
- Russell, Andrew and Edward Fieldhouse. 2005. *Neither Left nor Right? The Liberal Democrats and the Electorate*. Manchester: Manchester University Press.
- Spirling, Arthur and Iain McLean. 2007. “UK OC OK? Interpreting Optimal Classification Scores for the U.K. House of Commons.” *Political Analysis* 15:85–96.
- Spirling, Arthur and Kevin Quinn. 2010. “Identifying Intraparty Voting Blocks in the UK House of Commons.” *Journal of the American Statistical Association* p. Forthcoming.
- Venables, William and Brian Ripley. 2010. “MASS: Modern Applied Statistics with S.”. R package version 7.3-5.
- Voeten, Eric. 2000. “Clashes in the Assembly.” *International Organization* 54:185–215.

	Labour	Lib Dem	Conservative
Intercept	0.998 (0.001)	0.444 (0.012)	0.057 (0.002)
Estimated ideal points	0.006 (0.001)	-0.084 (0.035)	-0.003 (0.006)
N	318	45	154

Note: Dependent variable is proportion of votes in which MP voted with majority of Labour members. Estimates generated using MM estimator; standard errors in parenthesis.

Table 1: Robust linear regression of Labour support on estimated ideal points

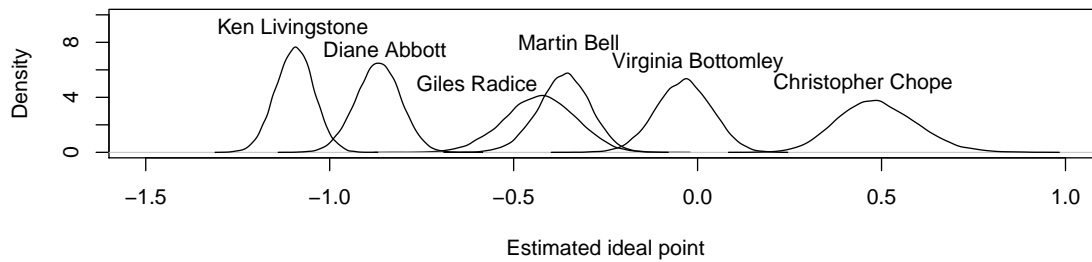


Figure 1: Posterior distributions of ideal points for selected MPs

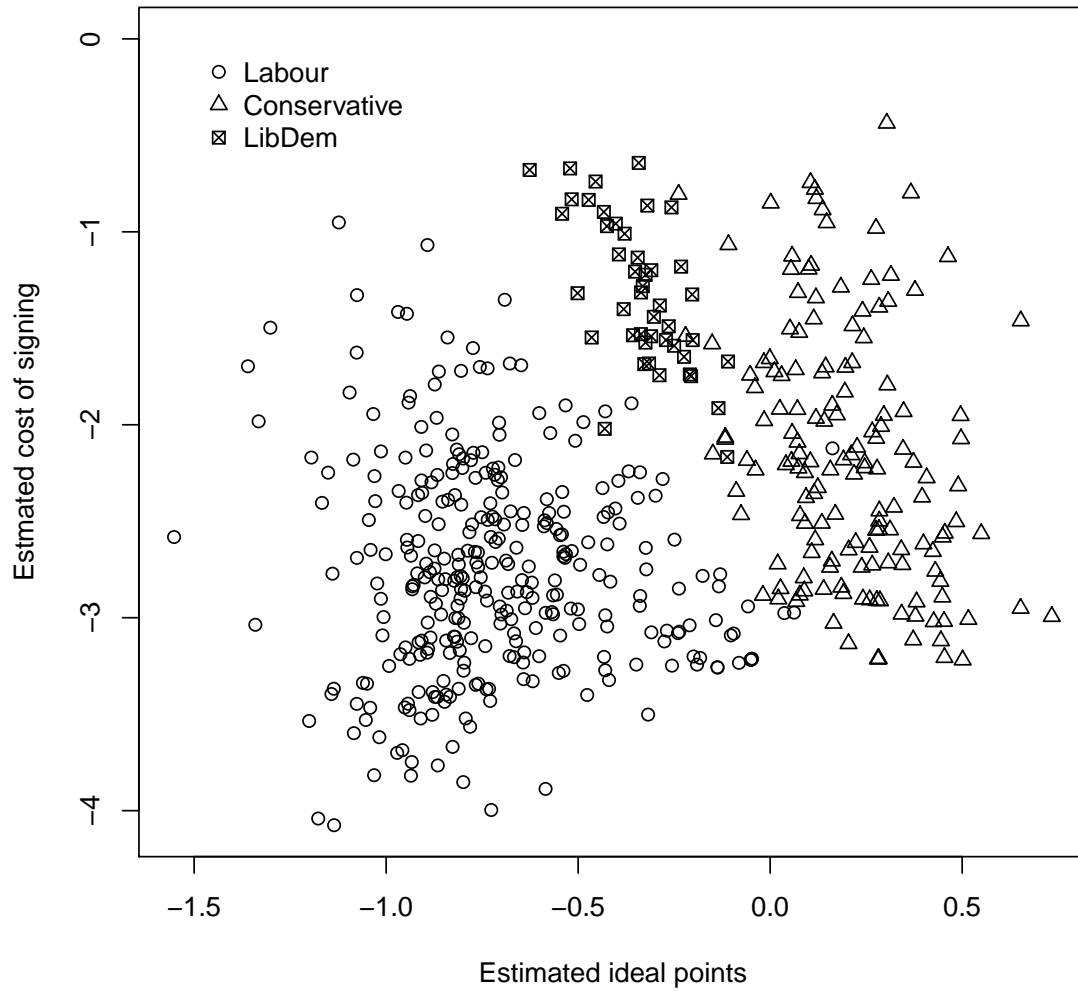


Figure 2: Estimated ideal points and signing costs (posterior means) for major party MPs

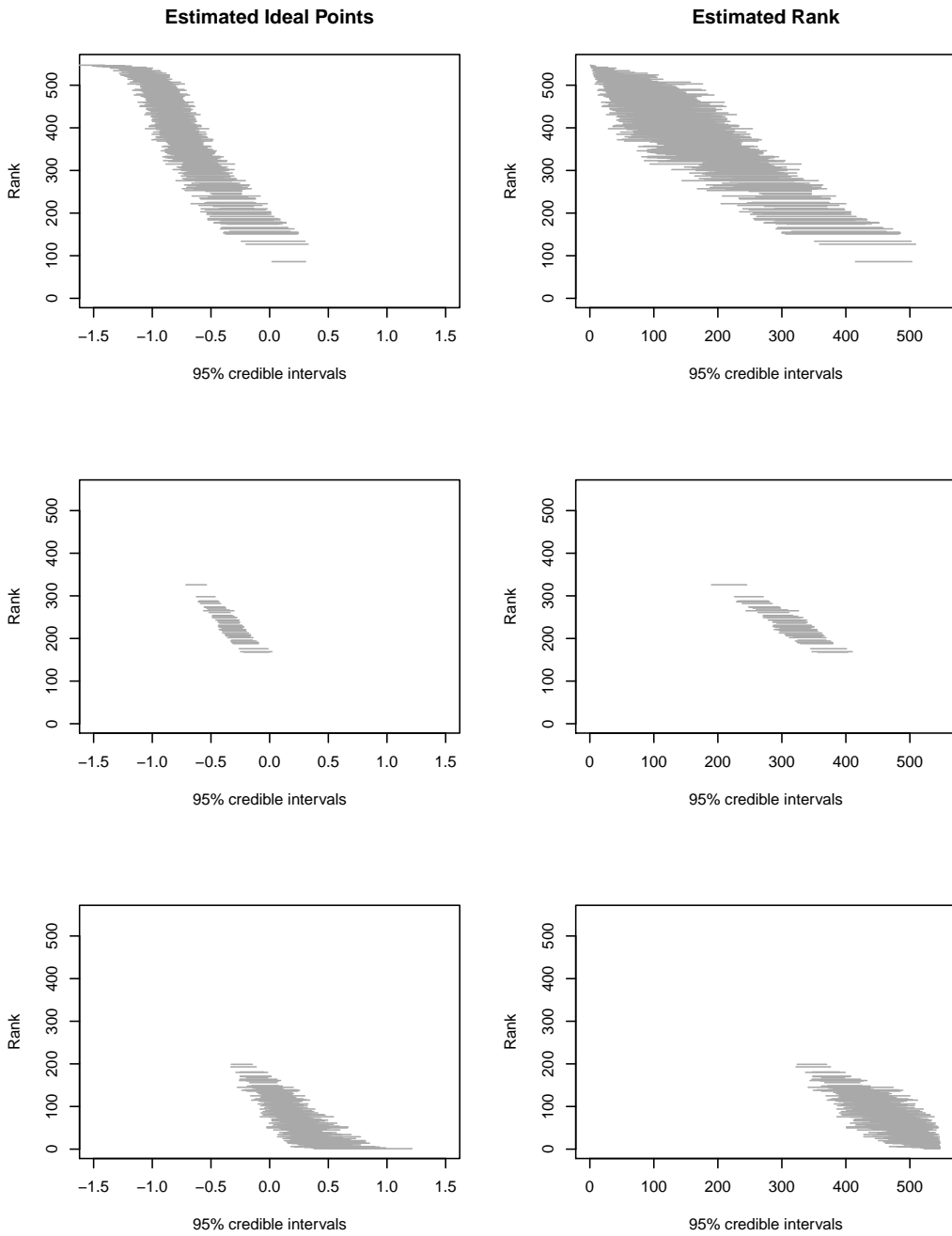


Figure 3: Interval estimates for member ideal points and ranks (95% central credible intervals), by major party

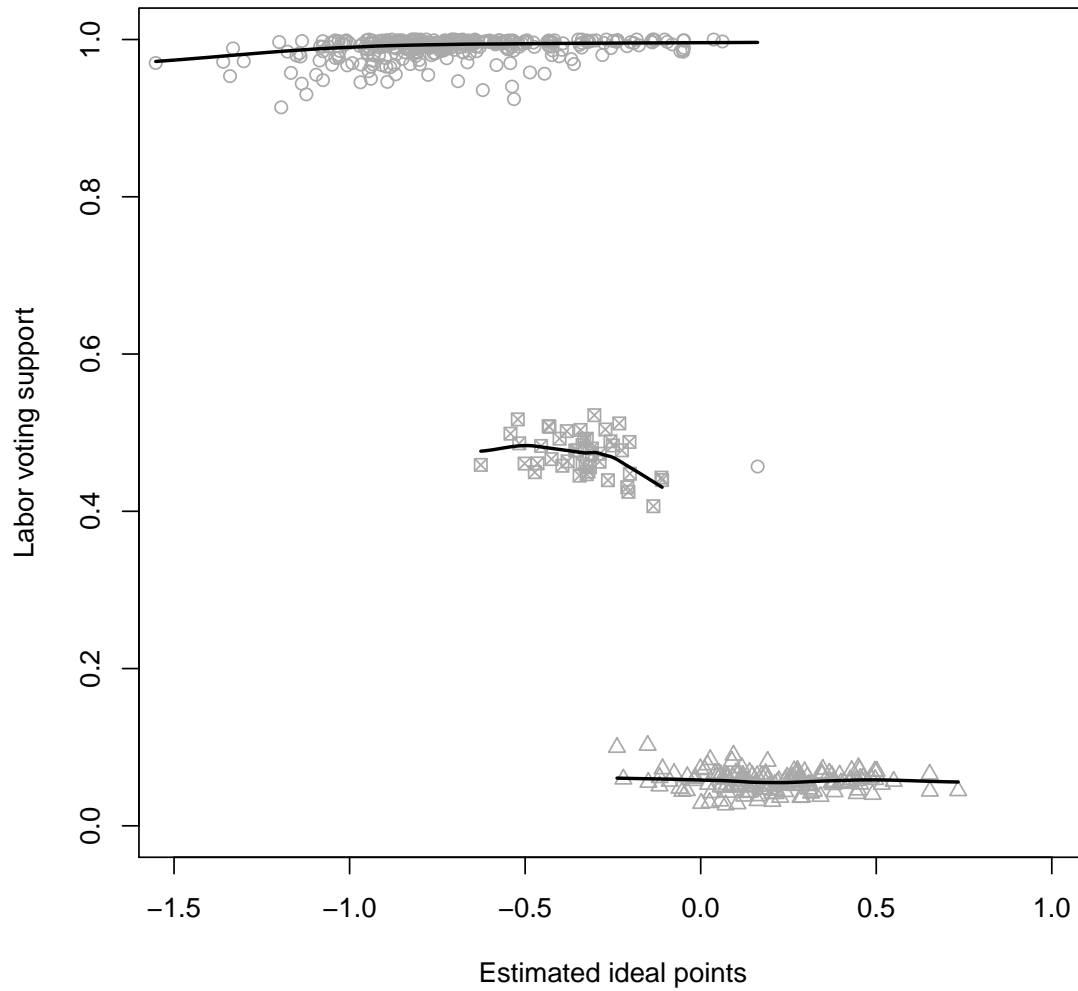


Figure 4: Support for Labour majority position on divisions as a function of estimated ideal points

# Supporting Information for “Estimating ideal points in the British House of Commons using Early Day Motions”

This supporting information provides additional information about the computational algorithm used to estimate the EDM model outlined in the paper, discusses estimates of the status quo and proposal locations for Early Day Motions, and presents posterior mean and 95% central credible interval estimates from MP ideal points.

## Sampling algorithm

For all but the simplest problems, Bayesian inference requires that samples be drawn from the joint posterior distribution of the parameters of interest (Gelman et al. 2004). The joint posterior generated by the EDM model does not have a known distributional form; as a result, it is not feasible to sample directly from the posterior. Instead, I use the standard method of constructing a Markov Chain Monte Carlo (MCMC) algorithm, which generates a series of dependent draws from the posterior. Under certain regularity conditions, which are satisfied in this model, the chain generated by the MCMC algorithm will eventually converge to the desired distribution. This approach is widely used in complex Bayesian models in general and ideal point models in particular (Clinton, Jackman and Rivers 2004; Martin and Quinn 2002).

Even using the MCMC approach, it is not practical to sample all of the parameters simultaneously; the amount of time required to find an appropriate jump would be excessive in a model with thousands of parameters. Instead, it is possible to break the problem of sampling from the posterior down further, sampling from the distribution of a smaller subset of parameters conditional on the current values of the remaining parameters. In the EDM model, the most straight-forward way to proceed is as follows:

1. Sample from the distribution of the parameters for bill  $j$  conditional on the current values of the legislator parameters:

$$\begin{aligned}
f(m_j, s_j | m_{-j}, s_{-j}, \theta, \mathbf{c}, \mathbf{Y}) &\propto \prod_{i=1}^I [\Phi(s_j^2 - m_j^2 + 2\theta_i(m_j - s_j) + c_i)^{y_{i,j}} \\
&\quad \times (1 - \Phi(s_j^2 - m_j^2 + 2\theta_i(m_j - s_j) + c_i))^{(1-y_{i,j})}] \\
&\quad \times p(m_j | \theta_{w_j}) p(s_j)
\end{aligned}$$

2. Sample from the distribution of the parameters for legislator  $i$  conditional on the current values of the bill parameters.

$$\begin{aligned}
f(\theta_i, c_i | \theta_{-i}, c_{-i}, \mathbf{m}, \mathbf{s}, \mathbf{Y}) &\propto \prod_{j=1}^J [\Phi(s_j^2 - m_j^2 + 2\theta_i(m_j - s_j) + c_i)^{y_{i,j}} \\
&\quad \times (1 - \Phi(s_j^2 - m_j^2 + 2\theta_i(m_j - s_j) + c_i))^{(1-y_{i,j})}] \\
&\quad \times p(\theta_i) p(c_i) \prod_{w_j=i} p(m_j | \theta_{w_j})
\end{aligned}$$

The advantage of this approach is that, conditional on the bill (legislator) parameters, each pair of legislator (bill) parameters is independent of the remaining legislator (bill) parameters. This reduces the problem to one of sampling from a series of bivariate densities. A single iteration of the algorithm consists of sampling from each pair of bill parameters, then moving on to sample from each pair of legislator parameters.

The conditional distributions for  $(m_j, s_j)$  would not have a standard form even if the latent utilities  $z_{ij}$  were observed. This makes the data augmentation approach of sampling from the posterior distribution of the latent utilities less attractive than it is in the standard two-parameter ideal point model. Moreover, the presence of squared terms raises the prospect of multimodality in the posterior distribution. To deal with this issue, I sample from each set of bivariate conditional densities using a version of the slice sampling approach proposed by Neal (2003). This method takes advantage of the fact that one can generate draws from a distribution by sampling uniformly from the space underneath the density. To do this

for the legislator parameters, an auxiliary variable  $v_i^{(t)}$  is drawn uniformly from the interval  $(0, f(\theta_i^{(t)}, c_i^{(t)} | \mathbf{m}, \mathbf{s}, \mathbf{Y}))$ . A new draw  $(\theta_i^{(t+1)}, c_i^{(t+1)})$  is then generated by sampling uniformly from the region satisfying  $z_i^{(t)} < f(\theta_i, c_i | \mathbf{m}, \mathbf{s}, \mathbf{Y})$ . A similar approach is used to draw from  $f(m_j, s_j | \theta, \mathbf{c}, \mathbf{Y})$ . Draws of the auxiliary variables have no substantive interpretation and are therefore discarded.

To estimate the model, I began by running a pilot chain of 50,000 iterations to begin to explore the posterior distribution. After discarding the first 10,000 iterations and checking to see that the results were plausible, I initialized four chains using starting values that were overdispersed relative to the posterior means from the pilot chain. These chains were run for 420,000 iterations, discarding the first 20,000 and retaining every 400th draw for a posterior sample of 1000 draws. The model was run using C code written by the author and analyzed using the coda package in the R statistical environment. Replication data and code are available on request.

Convergence of the chains was assessed using a variety of diagnostic techniques. The Gelman-Rubin statistic (Gelman et al. 2004) for the convergence of multiple chains was checked for each parameter; the highest value obtained was 1.05. Convergence was also checked for the mean of each set of parameters. These also appear to have converged to the posterior distribution, although the autocorrelation of the means was somewhat higher than the autocorrelation for any individual parameter.

## EDM locations

The model developed in this paper produces estimates of the proposal and status quo locations for each Early Day Motion on the same scale as legislator ideal points. The behavioral model assumes that, if the policy proposed in an EDM were enacted, it would shift policy outcomes away from the status quo to a new position. Standard ideal point models produce estimates of the cutpoint between the proposal and status quo rather than their locations. The estimates generated by the EDM model depend crucially on the as-

sumption that MPs propose motions close to their own ideal point. Examining the direction and magnitude of the shift in policy implied by each motion and linking those shifts to the substantive areas covered by particular motions provides insight into the structure of preferences in the House of Commons.

The implied policy shifts associated with Early Day Motions are shown in Figure 5. Labour-sponsored motions are shown in the left panel. The vast majority of Labour-sponsored EDMs would shift policy to the left relative to the status quo if their underlying policy proposals were enacted. This overwhelming pattern is unsurprising given that the 1998 session was only the second year of Labour government after an 18-year period of Tory rule; one would not expect that there were many policy areas where Labour MPs sought to move policy to the right. The pattern for Liberal Democrat-sponsored EDMs is similar, although the results suggest that these motions did not seek to move policy as far to the left as those proposed by Labour members.

[Figure 5 about here.]

Among Labour and Liberal Democrat-sponsored Early Day Motions, a few produce rightward policy shifts. These EDMs attracted significant support from Conservative MPs relative to the number of Labour signers. The topics of these EDMs include support for the independence of church wardens in the Church of England (EDM 98/61), easing administrative requirement on small business (EDM 98/406), and weakening the government's control over the House of Commons (EDM 98/986). It is plausible that all of these motions would move policy to the right.

The distribution of policy shifts implied by Early Day Motions sponsored by Conservative MPs, shown in the rightmost panel of Figure 5, differs greatly from the other two parties. Fully 25% of Conservative motions would shift policy to the left. Examples include motions supporting an elected House of Lords (EDM 98/464) and increased funding for long-term nursing care (EDM 98/369), neither of which were priorities of the Thatcher or Major

governments. Again, this pattern of motions is plausible considering the preceding period of Conservative government.

## Legislator ideal point estimates

The following table presents the posterior mean and 95% central credible intervals for each MP in the dataset, ranked in order of their estimated posterior mean.

Table 2: Estimated posterior mean and 95% CCI for legislator ideal points.

Number	Name	Party	Posterior Mean	95% CCI	
1	Gibb/Nick	Con	0.73	0.38	1.20
2	Paterson/Owen	Con	0.65	0.50	0.81
3	Ottaway/Richard	Con	0.65	0.35	0.99
4	Whittingdale/John	Con	0.55	0.29	0.88
5	May/Theresa	Con	0.52	0.21	0.93
6	Fox/Liam	Con	0.50	0.18	0.89
7	Hammond/Philip	Con	0.50	0.33	0.68
8	Clifton-Brown/Geoffrey	Con	0.50	0.34	0.67
9	Chope/Christopher	Con	0.49	0.30	0.71
10	Duncan/Alan	Con	0.48	0.25	0.77
11	Bercow/John	Con	0.46	0.35	0.58
12	Pickles/Eric	Con	0.45	0.24	0.69
13	Maples/John	Con	0.45	0.19	0.75
14	Arbuthnot/James	Con	0.45	0.15	0.85
15	Boswell/Tim	Con	0.45	0.22	0.73
16	Moss/Malcolm	Con	0.45	0.17	0.83
17	Redwood/John	Con	0.44	0.14	0.81
18	Tyrie/Andrew	Con	0.44	0.22	0.70
19	McIntosh/Anne	Con	0.43	0.17	0.75
20	Cran/James	Con	0.43	0.13	0.82
21	Ainsworth/Peter	Con	0.42	0.21	0.67
22	Page/Richard	Con	0.41	0.22	0.61
23	Davies/Quentin	Con	0.40	0.17	0.68
24	Lait/Jacqui	Con	0.40	0.21	0.61
25	Beresford/Paul	Con	0.38	0.11	0.73
26	Fowler/Norman	Con	0.38	0.15	0.62
27	Hawkins/Nick	Con	0.38	0.27	0.49
28	Atkinson/Peter	Con	0.37	0.20	0.56
29	MacGregor/John	Con	0.37	0.07	0.77

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Table 2 – continued from previous page

Number	Name	Party	Posterior Mean	95% CCI	
30	Swayne/Desmond	Con	0.37	0.27	0.46
31	Lansley/Andrew	Con	0.35	0.20	0.50
32	St Aubyn/Nick	Con	0.35	0.18	0.53
33	Heald/Oliver	Con	0.34	0.11	0.62
34	Green/Damian	Con	0.34	0.07	0.70
35	Whitney/Ray	Con	0.34	0.12	0.60
36	Dorrell/Stephen	Con	0.32	0.14	0.53
37	Gill/Christopher	Con	0.31	0.21	0.43
38	Trend/Michael	Con	0.31	0.12	0.53
39	Maclean/David	Con	0.31	0.08	0.57
40	Roe/Marion	Con	0.31	0.19	0.42
41	Bruce/Ian	Con	0.31	0.17	0.44
42	Lewis/Julian	Con	0.31	0.21	0.39
43	Laing/Eleanor	Con	0.31	0.16	0.44
44	Nicholls/Patrick	Con	0.29	0.14	0.44
45	Spring/Richard	Con	0.29	0.03	0.60
46	Jenkin/Bernard	Con	0.28	0.10	0.48
47	Hamilton/Archie	Con	0.28	0.11	0.47
48	Howarth/Gerald	Con	0.28	0.18	0.39
49	Simpson/Keith	Con	0.28	0.08	0.51
50	Heseltine/Michael	Con	0.28	-0.02	0.67
51	Garnier/Edward	Con	0.28	-0.02	0.66
52	Young/George	Con	0.28	-0.03	0.67
53	Taylor/Ian	Con	0.28	0.11	0.46
54	Paice/James	Con	0.28	0.02	0.59
55	Sayeed/Jonathan	Con	0.28	0.13	0.43
56	Key/Robert	Con	0.28	0.08	0.50
57	Evans/Nigel	Con	0.28	0.18	0.37
58	Lilley/Peter	Con	0.27	0.03	0.53
59	Fraser/Christopher	Con	0.27	0.13	0.40
60	Syms/Robert	Con	0.26	0.16	0.37
61	Willetts/David	Con	0.26	0.00	0.57
62	Lidington/David	Con	0.26	0.05	0.49
63	Clappison/James	Con	0.25	0.09	0.41
64	Gillan/Cheryl	Con	0.25	0.09	0.41
65	Wilshire/David	Con	0.24	0.13	0.37
66	Howard/Michael	Con	0.24	0.03	0.47
67	Ruffley/David	Con	0.24	0.13	0.35
68	Davis/David	Con	0.24	0.02	0.50
69	Lloyd/Peter	Con	0.23	0.07	0.38
70	Madel/David	Con	0.22	0.02	0.45
71	Letwin/Oliver	Con	0.22	0.06	0.39

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Table 2 – continued from previous page

Number	Name	Party	Posterior Mean	95% CCI	
72	Hayes/John	Con	0.21	0.10	0.33
73	Malins/Humfrey	Con	0.21	0.09	0.34
74	Soames/Nicholas	Con	0.21	0.06	0.36
75	Tapsell/Peter	Con	0.20	-0.01	0.44
76	Duncan Smith/Iain	Con	0.20	-0.08	0.55
77	Fallon/Michael	Con	0.20	0.07	0.32
78	Townend/John	Con	0.19	0.06	0.33
79	Gummer/John	Con	0.19	0.04	0.34
80	Widdecombe/Ann	Con	0.19	-0.05	0.47
81	McLoughlin/Patrick	Con	0.19	-0.05	0.45
82	Gray/James	Con	0.18	0.08	0.29
83	Greenway/John	Con	0.17	0.04	0.31
84	Mawhinney/Brian	Con	0.17	-0.01	0.35
85	Yeo/Tim	Con	0.17	-0.07	0.41
86	Woodward/Shawn	Lab	0.16	0.02	0.31
87	Cash/William	Con	0.16	0.04	0.29
88	Stanley/John	Con	0.16	-0.06	0.39
89	Butterfill/John	Con	0.16	0.01	0.31
90	Browning/Angela	Con	0.16	-0.03	0.36
91	Brady/Graham	Con	0.15	0.06	0.24
92	Leigh/Edward	Con	0.14	0.03	0.26
93	Viggers/Peter	Con	0.14	0.01	0.28
94	Ancram/Michael	Con	0.14	-0.09	0.39
95	Winterton/Ann	Con	0.14	0.04	0.23
96	Wells/Bowen	Con	0.14	0.02	0.25
97	Emery/Peter	Con	0.13	-0.04	0.32
98	Faber/David	Con	0.12	-0.04	0.29
99	Wilkinson/John	Con	0.12	0.03	0.21
100	Kirkbride/Julie	Con	0.12	0.02	0.22
101	Burns/Simon	Con	0.12	-0.01	0.25
102	MacKay/Andrew	Con	0.12	-0.07	0.32
103	Loughton/Tim	Con	0.12	0.03	0.21
104	Shephard/Gillian	Con	0.11	-0.05	0.28
105	Robertson/Laurence	Con	0.11	0.00	0.22
106	Cormack/Patrick	Con	0.11	-0.10	0.32
107	Blunt/Crispin	Con	0.11	0.01	0.20
108	Winterton/Nicholas	Con	0.11	0.02	0.19
109	Wardle/Charles	Con	0.10	-0.04	0.25
110	Flight/Howard	Con	0.10	0.00	0.20
111	O'Brien/Stephen	Con	0.09	-0.08	0.27
112	Streeter/Gary	Con	0.09	-0.10	0.28
113	Spelman/Caroline	Con	0.09	-0.06	0.24

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Table 2 – continued from previous page

Number	Name	Party	Posterior Mean	95% CCI
114	Major/John	Con	0.09	-0.16 0.34
115	Clarke/Kenneth	Con	0.09	-0.13 0.31
116	Jack/Michael	Con	0.08	-0.10 0.25
117	Heathcoat-Amory/David	Con	0.08	-0.12 0.29
118	Spicer/Michael	Con	0.08	-0.07 0.22
119	Fabricant/Michael	Con	0.08	-0.03 0.18
120	King/Tom	Con	0.07	-0.08 0.22
121	Chapman/Sydney	Con	0.07	-0.03 0.17
122	Shepherd/Richard	Con	0.07	-0.07 0.21
123	Robathan/Andrew	Con	0.07	-0.05 0.20
124	Collins/Tim	Con	0.07	-0.16 0.29
125	Brazier/Julian	Con	0.07	-0.05 0.18
126	Dowd/Jim	Lab	0.06	-0.21 0.33
127	Norman/Archie	Con	0.06	-0.08 0.19
128	Luff/Peter	Con	0.06	-0.04 0.15
129	Steen/Anthony	Con	0.06	-0.09 0.2
130	Taylor/Teddy	Con	0.05	-0.05 0.15
131	Prior/David	Con	0.05	-0.05 0.16
132	Taylor/John M	Con	0.04	-0.11 0.19
133	Battle/John	Lab	0.04	-0.24 0.3
134	Gorman/Teresa	Con	0.03	-0.09 0.15
135	Gale/Roger	Con	0.03	-0.19 0.25
136	Hunter/Andrew	Con	0.03	-0.10 0.15
137	Hogg/Douglas	Con	0.02	-0.24 0.26
138	Day/Stephen	Con	0.02	-0.21 0.24
139	Mates/Michael	Con	0.01	-0.10 0.12
140	Colvin/Michael	Con	0.00	-0.09 0.09
141	Johnson Smith/Geoffrey	Con	0.00	-0.11 0.11
142	Walter/Robert	Con	-0.02	-0.14 0.11
143	Grieve/Dominic	Con	-0.02	-0.13 0.09
144	Lyell/Nicholas	Con	-0.02	-0.27 0.21
145	Ross/William	UU	-0.03	-0.13 0.07
146	Taylor/John D	UU	-0.04	-0.15 0.07
147	Bottomley/Virginia	Con	-0.04	-0.19 0.11
148	Horam/John	Con	-0.04	-0.15 0.07
149	Maginnis/Ken	UU	-0.04	-0.17 0.09
150	Coffey/Ann	Lab	-0.05	-0.37 0.24
151	Tynan/Bill	Lab	-0.05	-0.38 0.24
152	Jackson/Glenda	Lab	-0.05	-0.38 0.23
153	Bell/Stuart	Lab	-0.05	-0.39 0.24
154	Galbraith/Sam	Lab	-0.05	-0.38 0.24
155	Body/Richard	Con	-0.05	-0.17 0.07

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Table 2 – continued from previous page

Number	Name	Party	Posterior Mean	95% CCI	
156	Sheldon/Robert	Lab	-0.06	-0.33	0.18
157	Trimble/David	UU	-0.06	-0.23	0.10
158	Forsythe/Clifford	UU	-0.06	-0.20	0.07
159	Tredinnick/David	Con	-0.06	-0.20	0.07
160	Curry/David	Con	-0.08	-0.26	0.10
161	Thompson/William	UU	-0.08	-0.18	0.03
162	Caplin/Ivor	Lab	-0.08	-0.42	0.21
163	Baldry/Tony	Con	-0.09	-0.25	0.06
164	Squire/Rachel	Lab	-0.09	-0.39	0.16
165	Ryan/Joan	Lab	-0.10	-0.41	0.15
166	Randall/John	Con	-0.11	-0.20	-0.02
167	Smith/Robert	LDem	-0.11	-0.22	0.00
168	Maclennan/Robert	LDem	-0.11	-0.25	0.02
169	Clark/Michael	Con	-0.12	-0.25	0.01
170	Rowe/Andrew	Con	-0.12	-0.25	0.02
171	Walker/A Cecil	UU	-0.13	-0.27	0.01
172	Paisley/Ian	DU	-0.13	-0.27	0.01
173	Blears/Hazel	Lab	-0.13	-0.37	0.08
174	Doran/Frank	Lab	-0.13	-0.42	0.11
175	Burnett/John	LDem	-0.13	-0.27	-0.01
176	Heal/Sylvia	Lab	-0.14	-0.48	0.15
177	Jenkins/Brian	Lab	-0.14	-0.47	0.14
178	Macdonald/Calum	Lab	-0.14	-0.43	0.10
179	Jackson/Robert	Con	-0.15	-0.29	-0.02
180	Atkinson/David	Con	-0.15	-0.25	-0.05
181	Welsh/Andrew	SNP	-0.18	-0.39	0.01
182	Turner/Neil	Lab	-0.18	-0.42	0.03
183	Corston/Jean	Lab	-0.18	-0.51	0.09
184	Donaldson/Jeffrey	UU	-0.19	-0.28	-0.09
185	Lloyd/Tony	Lab	-0.19	-0.52	0.08
186	Merron/Gillian	Lab	-0.20	-0.52	0.06
187	Moore/Michael	LDem	-0.20	-0.31	-0.10
188	Chidgey/David	LDem	-0.20	-0.30	-0.11
189	Bruce/Malcolm	LDem	-0.21	-0.32	-0.10
190	Kennedy/Charles	LDem	-0.21	-0.33	-0.10
191	Kelly/Ruth	Lab	-0.21	-0.50	0.04
192	Amess/David	Con	-0.22	-0.33	-0.11
193	Webb/Steve	LDem	-0.22	-0.33	-0.12
194	Beggs/Roy	UU	-0.23	-0.31	-0.14
195	Rendel/David	LDem	-0.23	-0.32	-0.14
196	Purchase/Ken	Lab	-0.24	-0.54	0.01
197	Goggins/Paul	Lab	-0.24	-0.49	-0.02

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Number	Name	Party	Posterior Mean	95% CCI
198	Bottomley/Peter	Con	-0.24	-0.33 -0.15
199	Burden/Richard	Lab	-0.24	-0.54 0.01
200	Touhig/Don	Lab	-0.25	-0.46 -0.07
201	Heath/David	LDem	-0.25	-0.36 -0.14
202	Jones/Jon	Lab	-0.26	-0.58 0.02
203	Tyler/Paul	LDem	-0.26	-0.34 -0.17
204	Salmond/Alex	SNP	-0.26	-0.47 -0.08
205	Michie/Ray	LDem	-0.26	-0.37 -0.16
206	Smyth/Martin	UU	-0.27	-0.36 -0.18
207	Leslie/Christopher	Lab	-0.27	-0.55 -0.03
208	Campbell/Menzies	LDem	-0.27	-0.38 -0.16
209	Heppell/John	Lab	-0.28	-0.59 -0.02
210	Anderson/Donald	Lab	-0.28	-0.43 -0.14
211	Opik/Lembit	LDem	-0.29	-0.38 -0.19
212	Kirkwood/Archy	LDem	-0.29	-0.40 -0.18
213	Swinney/John	SNP	-0.29	-0.44 -0.16
214	McCartney/Robert	UKU	-0.29	-0.41 -0.19
215	Meale/Alan	Lab	-0.30	-0.48 -0.14
216	Wallace/James	LDem	-0.30	-0.40 -0.2
217	Henderson/Doug	Lab	-0.31	-0.60 -0.07
218	Sanders/Adrian	LDem	-0.31	-0.40 -0.22
219	Livsey/Richard	LDem	-0.31	-0.42 -0.21
220	Beith/AJ	LDem	-0.32	-0.43 -0.20
221	MacShane/Denis	Lab	-0.32	-0.68 -0.02
222	Keetch/Paul	LDem	-0.32	-0.41 -0.23
223	Mudie/George	Lab	-0.32	-0.56 -0.12
224	McKenna/Rosemary	Lab	-0.32	-0.54 -0.14
225	Davey/Edward	LDem	-0.32	-0.42 -0.23
226	Oaten/Mark	LDem	-0.32	-0.43 -0.22
227	Taylor/Matthew	LDem	-0.33	-0.44 -0.22
228	Cotter/Brian	LDem	-0.33	-0.42 -0.24
229	Hughes/Simon	LDem	-0.34	-0.43 -0.24
230	Foster/Don	LDem	-0.34	-0.44 -0.24
231	Robinson/Peter	DU	-0.34	-0.49 -0.20
232	Harman/Harriet	Lab	-0.34	-0.59 -0.12
233	Adams/Irene	Lab	-0.34	-0.50 -0.19
234	Prentice/Bridget	Lab	-0.34	-0.60 -0.12
235	Fearn/Ronnie	LDem	-0.34	-0.43 -0.26
236	Gapes/Mike	Lab	-0.34	-0.52 -0.18
237	Breed/Colin	LDem	-0.34	-0.44 -0.25
238	Mallon/Seamus	SDLP	-0.35	-0.54 -0.17
239	Alexander/Douglas	Lab	-0.35	-0.67 -0.08

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Table 2 – continued from previous page

Number	Name	Party	Posterior Mean	95% CCI
240	Burstow/Paul	LDem	-0.35	-0.44 -0.27
241	Jones/Ieuan	PC	-0.36	-0.48 -0.24
242	Willis/Phil	LDem	-0.36	-0.46 -0.26
243	Field/Frank	Lab	-0.36	-0.49 -0.24
244	Bell/Martin	Ind	-0.36	-0.51 -0.23
245	Fisher/Mark	Lab	-0.37	-0.50 -0.24
246	Ewing/Margaret	SNP	-0.38	-0.51 -0.25
247	Harris/Evan	LDem	-0.38	-0.47 -0.29
248	Ballard/Jackie	LDem	-0.38	-0.49 -0.28
249	Hume/John	SDLP	-0.39	-0.61 -0.19
250	Church/Judith	Lab	-0.39	-0.55 -0.24
251	Brand/Peter	LDem	-0.39	-0.49 -0.30
252	Hood/Jimmy	Lab	-0.40	-0.71 -0.24
253	Stunell/Andrew	LDem	-0.40	-0.48 -0.32
254	Bennett/Andrew	Lab	-0.40	-0.54 -0.27
255	Browne/Desmond	Lab	-0.42	-0.64 -0.21
256	Home Robertson/John	Lab	-0.42	-0.74 -0.15
257	Hurst/Alan	Lab	-0.42	-0.59 -0.26
258	Rowlands/Ted	Lab	-0.42	-0.62 -0.25
259	Soley/Clive	Lab	-0.42	-0.69 -0.18
260	Brake/Tom	LDem	-0.42	-0.52 -0.34
261	Radice/Giles	Lab	-0.43	-0.62 -0.25
262	Stewart/David	Lab	-0.43	-0.54 -0.32
263	Ainger/Nick	Lab	-0.43	-0.70 -0.18
264	Allan/Richard	LDem	-0.43	-0.57 -0.30
265	Mountford/Kali	Lab	-0.43	-0.73 -0.17
266	Gorrie/Donald	LDem	-0.43	-0.52 -0.34
267	O'Brien/William	Lab	-0.43	-0.60 -0.28
268	Pendry/Tom	Lab	-0.44	-0.58 -0.30
269	Marek/John	Lab	-0.44	-0.66 -0.25
270	Cable/Vincent	LDem	-0.45	-0.54 -0.37
271	Dafis/Cynog	PC	-0.46	-0.58 -0.34
272	Baker/Norman	LDem	-0.46	-0.55 -0.38
273	Harvey/Nick	LDem	-0.47	-0.56 -0.39
274	Maxton/John	Lab	-0.47	-0.63 -0.32
275	Jackson/Helen	Lab	-0.48	-0.79 -0.20
276	Davies/Denzil	Lab	-0.49	-0.62 -0.36
277	Casale/Roger	Lab	-0.49	-0.70 -0.30
278	Rooney/Terry	Lab	-0.50	-0.73 -0.29
279	Cunningham/Roseanna	SNP	-0.50	-0.64 -0.36
280	Twigg/Derek	Lab	-0.50	-0.75 -0.28
281	Tonge/Jenny	LDem	-0.50	-0.59 -0.41

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Table 2 – continued from previous page

Number	Name	Party	Posterior Mean	95% CCI
282	Savidge/Malcolm	Lab	-0.51	-0.62 -0.39
283	Graham/Thomas	Scot Lab	-0.52	-0.73 -0.32
284	Pearson/Ian	Lab	-0.52	-0.71 -0.34
285	George/Andrew	LDem	-0.52	-0.61 -0.43
286	Jones/Fiona	Lab	-0.52	-0.75 -0.31
287	Hancock/Mike	LDem	-0.52	-0.61 -0.44
288	Llwyd/Elfyn	PC	-0.53	-0.63 -0.43
289	Temple-Morris/Peter	Lab	-0.53	-0.72 -0.35
290	Marsden/Paul	Lab	-0.53	-0.64 -0.43
291	Campbell/Alan	Lab	-0.53	-0.73 -0.35
292	Dalyell/Tam	Lab	-0.54	-0.70 -0.38
293	Kaufman/Gerald	Lab	-0.54	-0.77 -0.31
294	Donohoe/Brian	Lab	-0.54	-0.73 -0.36
295	Bradshaw/Ben	Lab	-0.54	-0.68 -0.40
296	Benton/Joe	Lab	-0.54	-0.69 -0.40
297	Russell/Bob	LDem	-0.54	-0.62 -0.46
298	Cann/Jamie	Lab	-0.54	-0.72 -0.38
299	Keen/Ann	Lab	-0.55	-0.75 -0.35
300	Stevenson/George	Lab	-0.55	-0.69 -0.41
301	Clarke/Tom	Lab	-0.55	-0.83 -0.30
302	George/Bruce	Lab	-0.56	-0.76 -0.36
303	Ennis/Jeff	Lab	-0.56	-0.73 -0.39
304	Morgan/Alasdair	SNP	-0.56	-0.70 -0.42
305	Snape/Peter	Lab	-0.56	-0.77 -0.37
306	Moonie/Lewis	Lab	-0.57	-0.76 -0.38
307	Winterton/Rosie	Lab	-0.57	-0.79 -0.36
308	Barron/Kevin	Lab	-0.57	-0.73 -0.41
309	Griffiths/Win	Lab	-0.57	-0.71 -0.44
310	Hepburn/Stephen	Lab	-0.58	-0.74 -0.42
311	Jones/Martyn	Lab	-0.58	-0.74 -0.43
312	Golding/Llin	Lab	-0.58	-0.71 -0.46
313	Colman/Tony	Lab	-0.58	-0.74 -0.43
314	Smith/John	Lab	-0.58	-0.88 -0.30
315	McGrady/Eddie	SDLP	-0.59	-0.73 -0.44
316	Begg/Anne	Lab	-0.59	-0.74 -0.44
317	Levitt/Tom	Lab	-0.59	-0.73 -0.45
318	Wigley/Dafydd	PC	-0.59	-0.70 -0.49
319	Jones/Barry	Lab	-0.60	-0.72 -0.48
320	Ward/Claire	Lab	-0.60	-0.86 -0.37
321	Keeble/Sally	Lab	-0.61	-0.82 -0.40
322	Murphy/Jim	Lab	-0.62	-0.90 -0.36
323	Moran/Margaret	Lab	-0.62	-0.83 -0.42

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Table 2 – continued from previous page

Number	Name	Party	Posterior Mean	95% CCI
324	Dunwoody/Gwyneth	Lab	-0.62	-0.80 -0.45
325	Jones/Nigel	LDem	-0.63	-0.71 -0.54
326	Foster/Derek	Lab	-0.63	-0.82 -0.45
327	Davies/Geraint	Lab	-0.63	-0.80 -0.47
328	Marshall/David	Lab	-0.64	-0.86 -0.43
329	Beard/Nigel	Lab	-0.64	-0.88 -0.42
330	King/Andy	Lab	-0.64	-0.77 -0.51
331	Lewis/Ivan	Lab	-0.64	-0.91 -0.39
332	Morgan/Rhodri	Lab	-0.64	-0.89 -0.42
333	Blizzard/Bob	Lab	-0.65	-0.82 -0.49
334	Pickthall/Colin	Lab	-0.65	-0.81 -0.49
335	Hoyle/Lindsay	Lab	-0.65	-0.74 -0.56
336	Powell/Ray	Lab	-0.66	-0.83 -0.49
337	Ruane/Chris	Lab	-0.66	-0.84 -0.49
338	Healey/John	Lab	-0.66	-0.86 -0.47
339	Connarty/Michael	Lab	-0.66	-0.81 -0.53
340	Grogan/John	Lab	-0.67	-0.87 -0.47
341	Sarwar/Mohammad	Lab	-0.67	-0.88 -0.47
342	Follett/Barbara	Lab	-0.67	-0.89 -0.48
343	Berry/Roger	Lab	-0.68	-0.82 -0.54
344	Davis/Terry	Lab	-0.68	-0.78 -0.58
345	Robinson/Geoffrey	Lab	-0.68	-0.92 -0.45
346	Smith/Geraldine	Lab	-0.68	-0.85 -0.52
347	Twigg/Stephen	Lab	-0.68	-0.82 -0.55
348	Williams/Alan W	Lab	-0.69	-0.90 -0.49
349	McCabe/Stephen	Lab	-0.69	-0.87 -0.51
350	Wise/Audrey	Lab	-0.69	-0.78 -0.60
351	Thomas/Gareth R	Lab	-0.69	-0.86 -0.53
352	Olnier/Bill	Lab	-0.70	-0.85 -0.55
353	Griffiths/Nigel	Lab	-0.70	-0.87 -0.54
354	McWalter/Tony	Lab	-0.70	-0.84 -0.56
355	Woolas/Phil	Lab	-0.70	-0.92 -0.50
356	Curtis-Thomas/Claire	Lab	-0.70	-0.90 -0.51
357	Reed/Andrew	Lab	-0.70	-0.83 -0.58
358	Rapson/Syd	Lab	-0.71	-0.83 -0.59
359	Osborne/Sandra	Lab	-0.71	-0.85 -0.57
360	McWilliam/John	Lab	-0.71	-0.83 -0.59
361	Gunnell/John	Lab	-0.71	-0.86 -0.57
362	Clark/David	Lab	-0.72	-0.87 -0.57
363	Williams/Alan	Lab	-0.72	-0.86 -0.58
364	Todd/Mark	Lab	-0.72	-0.85 -0.59
365	Griffiths/Jane	Lab	-0.72	-0.87 -0.58

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Table 2 – continued from previous page

Number	Name	Party	Posterior Mean	95% CCI
366	Cousins/Jim	Lab	-0.72	-0.88 -0.57
367	Ruddock/Joan	Lab	-0.72	-0.85 -0.60
368	Banks/Tony	Lab	-0.73	-0.96 -0.49
369	Birmingham/Gerald	Lab	-0.73	-0.88 -0.58
370	Quinn/Lawrie	Lab	-0.73	-0.87 -0.59
371	Coaker/Vernon	Lab	-0.73	-1.00 -0.48
372	Wright/Tony	Lab	-0.73	-0.98 -0.48
373	Corbett/Robin	Lab	-0.74	-0.86 -0.61
374	Clarke/Eric	Lab	-0.74	-0.85 -0.62
375	Rammell/Bill	Lab	-0.74	-0.90 -0.58
376	Sheerman/Barry	Lab	-0.74	-0.96 -0.53
377	Salter/Martin	Lab	-0.74	-0.85 -0.63
378	Strang/Gavin	Lab	-0.74	-0.97 -0.53
379	Taylor/Dari	Lab	-0.74	-0.93 -0.56
380	Marsden/Gordon	Lab	-0.75	-0.87 -0.63
381	Lawrence/Jackie	Lab	-0.75	-0.90 -0.61
382	Rogers/Allan	Lab	-0.75	-0.94 -0.58
383	Iddon/Brian	Lab	-0.76	-0.85 -0.66
384	Flint/Caroline	Lab	-0.76	-1.01 -0.53
385	Murphy/Denis	Lab	-0.76	-0.92 -0.61
386	Morgan/Julie	Lab	-0.76	-0.91 -0.61
387	Pound/Stephen	Lab	-0.77	-0.93 -0.61
388	Kidney/David	Lab	-0.77	-0.93 -0.60
389	Marshall/Jim	Lab	-0.77	-0.99 -0.55
390	Singh/Marsha	Lab	-0.77	-0.88 -0.65
391	Ladyman/Stephen	Lab	-0.77	-0.94 -0.61
392	Brinton/Helen	Lab	-0.77	-0.87 -0.68
393	Cummings/John	Lab	-0.77	-0.88 -0.67
394	McAllion/John	Lab	-0.78	-0.92 -0.64
395	Miller/Andrew	Lab	-0.78	-0.96 -0.60
396	Borrow/David	Lab	-0.78	-0.92 -0.65
397	McDonagh/Siobhain	Lab	-0.78	-1.06 -0.52
398	Crausby/David	Lab	-0.78	-0.91 -0.66
399	O'Neill/Martin	Lab	-0.79	-0.96 -0.63
400	Davies/Ron	Lab	-0.79	-0.97 -0.62
401	Prosser/Gwyn	Lab	-0.80	-0.93 -0.67
402	Whitehead/Alan	Lab	-0.80	-1.02 -0.59
403	Hamilton/Fabian	Lab	-0.80	-1.00 -0.61
404	McIsaac/Shona	Lab	-0.80	-1.02 -0.59
405	Turner/Dennis	Lab	-0.80	-1.01 -0.59
406	Mitchell/Austin	Lab	-0.80	-0.89 -0.71
407	Wright/Anthony	Lab	-0.80	-0.98 -0.63

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Table 2 – continued from previous page

Number	Name	Party	Posterior Mean	95% CCI
408	Williams/Betty	Lab	-0.80	-0.94 -0.66
409	Edwards/Huw	Lab	-0.80	-0.94 -0.67
410	Laxton/Bob	Lab	-0.80	-0.97 -0.64
411	Drew/David	Lab	-0.80	-0.92 -0.69
412	Kingham/Tess	Lab	-0.81	-0.93 -0.68
413	Sedgemore/Brian	Lab	-0.81	-0.95 -0.66
414	Wray/Jimmy	Lab	-0.81	-1.00 -0.62
415	Campbell/Ronnie	Lab	-0.81	-0.94 -0.68
416	Hesford/Stephen	Lab	-0.81	-0.94 -0.68
417	Cawsey/Ian	Lab	-0.81	-1.00 -0.63
418	Mackinlay/Andrew	Lab	-0.81	-1.00 -0.63
419	Thomas/Gareth	Lab	-0.81	-0.97 -0.66
420	McCafferty/Chris	Lab	-0.81	-0.98 -0.66
421	Godsiff/Roger	Lab	-0.82	-0.99 -0.64
422	Bradley/Peter	Lab	-0.82	-0.94 -0.70
423	Pollard/Kerry	Lab	-0.82	-0.92 -0.71
424	Stoate/Howard	Lab	-0.82	-0.95 -0.69
425	Southworth/Helen	Lab	-0.82	-1.01 -0.64
426	White/Brian	Lab	-0.82	-0.97 -0.68
427	Russell/Christine	Lab	-0.82	-1.00 -0.65
428	Gilroy/Linda	Lab	-0.82	-0.96 -0.69
429	Lepper/David	Lab	-0.83	-0.96 -0.70
430	Benn/Hilary	Lab	-0.83	-1.07 -0.59
431	Davidson/Ian	Lab	-0.83	-0.96 -0.69
432	Taylor/David	Lab	-0.83	-0.95 -0.71
433	Hinchliffe/David	Lab	-0.83	-1.00 -0.67
434	Hall/Patrick	Lab	-0.83	-1.06 -0.63
435	O'Hara/Edward	Lab	-0.84	-0.94 -0.74
436	Cunliffe/Lawrence	Lab	-0.84	-0.94 -0.74
437	Ashton/Joseph	Lab	-0.84	-1.01 -0.68
438	Atkins/Charlotte	Lab	-0.84	-0.99 -0.70
439	Coleman/Iain	Lab	-0.85	-0.99 -0.70
440	Plaskitt/James	Lab	-0.85	-1.03 -0.68
441	Lewis/Terry	Lab	-0.85	-0.98 -0.72
442	Burgon/Colin	Lab	-0.85	-1.05 -0.66
443	Cunningham/Jim	Lab	-0.85	-0.97 -0.74
444	Ross/Ernie	Lab	-0.85	-1.01 -0.70
445	Humble/Joan	Lab	-0.86	-1.05 -0.68
446	Foster/Michael Jabez	Lab	-0.86	-0.98 -0.75
447	Love/Andrew	Lab	-0.86	-0.97 -0.75
448	Organ/Diana	Lab	-0.86	-1.01 -0.73
449	Trickett/Jon	Lab	-0.87	-1.11 -0.64

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Table 2 – continued from previous page

Number	Name	Party	Posterior Mean	95% CCI
450	Pike/Peter	Lab	-0.87	-1.01 -0.73
451	Winnick/David	Lab	-0.87	-1.10 -0.65
452	Abbott/Diane	Lab	-0.87	-0.99 -0.75
453	Gordon/Eileen	Lab	-0.87	-1.06 -0.70
454	Ellman/Louise	Lab	-0.87	-1.05 -0.70
455	McNamara/Kevin	Lab	-0.87	-0.97 -0.77
456	Drown/Julia	Lab	-0.87	-1.01 -0.74
457	Perham/Linda	Lab	-0.87	-1.02 -0.73
458	Watts/Dave	Lab	-0.88	-1.07 -0.69
459	Clark/Paul	Lab	-0.88	-1.13 -0.65
460	King/Oona	Lab	-0.88	-0.98 -0.78
461	Cook/Frank	Lab	-0.88	-1.01 -0.76
462	Starkey/Phyllis	Lab	-0.88	-1.04 -0.73
463	Walley/Joan	Lab	-0.89	-1.00 -0.77
464	Fitzsimons/Lorna	Lab	-0.89	-1.05 -0.73
465	Kemp/Fraser	Lab	-0.89	-1.04 -0.75
466	Barnes/Harry	Lab	-0.89	-0.97 -0.81
467	Galloway/George	Lab	-0.89	-1.05 -0.74
468	Foster/Michael John	Lab	-0.90	-1.05 -0.75
469	Wareing/Robert	Lab	-0.90	-1.03 -0.77
470	Chaytor/David	Lab	-0.90	-0.99 -0.80
471	Stewart/Ian	Lab	-0.90	-1.07 -0.74
472	Sawford/Phil	Lab	-0.91	-1.05 -0.77
473	Atherton/Candy	Lab	-0.91	-1.11 -0.72
474	Butler/Christine	Lab	-0.91	-1.05 -0.77
475	Flynn/Paul	Lab	-0.91	-1.00 -0.82
476	Linton/Martin	Lab	-0.91	-1.16 -0.68
477	Jones/Helen	Lab	-0.91	-1.08 -0.75
478	Blackman/Liz	Lab	-0.92	-1.14 -0.70
479	Shaw/Jonathan	Lab	-0.92	-1.06 -0.77
480	Turner/Desmond	Lab	-0.92	-1.06 -0.78
481	Moffatt/Laura	Lab	-0.92	-1.06 -0.78
482	Steinberg/Gerry	Lab	-0.92	-1.08 -0.77
483	Henderson/Ivan	Lab	-0.93	-1.08 -0.78
484	Canavan/Dennis	WW	-0.93	-1.10 -0.77
485	Stinchcombe/Paul	Lab	-0.93	-1.07 -0.80
486	Clarke/Tony	Lab	-0.93	-1.11 -0.77
487	Grant/Bernie	Lab	-0.93	-1.16 -0.71
488	Gerrard/Neil	Lab	-0.94	-1.07 -0.81
489	Norris/Dan	Lab	-0.94	-1.15 -0.73
490	Cox/Tom	Lab	-0.94	-1.05 -0.83
491	Smith/Llew	Lab	-0.94	-1.09 -0.79

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Table 2 – continued from previous page

Number	Name	Party	Posterior Mean	95% CCI
492	Marshall-Andrews/Robert	Lab	-0.94	-1.08 -0.79
493	Illsley/Eric	Lab	-0.94	-1.06 -0.83
494	Gardiner/Barry	Lab	-0.94	-1.07 -0.82
495	Truswell/Paul	Lab	-0.94	-1.10 -0.80
496	Naysmith/Doug	Lab	-0.95	-1.10 -0.80
497	Godman/Norman	Lab	-0.95	-1.05 -0.84
498	Best/Harold	Lab	-0.95	-1.09 -0.81
499	Dawson/Hilton	Lab	-0.95	-1.07 -0.83
500	Wyatt/Derek	Lab	-0.95	-1.07 -0.83
501	Hope/Phil	Lab	-0.95	-1.14 -0.77
502	Worthington/Tony	Lab	-0.96	-1.21 -0.72
503	Efford/Clive	Lab	-0.96	-1.10 -0.82
504	Cryer/John	Lab	-0.97	-1.09 -0.85
505	Jones/Lynne	Lab	-0.97	-1.08 -0.87
506	Chisholm/Malcolm	Lab	-0.97	-1.19 -0.76
507	Clwyd/Ann	Lab	-0.99	-1.13 -0.86
508	Dean/Janet	Lab	-1.00	-1.16 -0.85
509	Prentice/Gordon	Lab	-1.01	-1.13 -0.88
510	Khabra/Piara	Lab	-1.01	-1.16 -0.86
511	Kumar/Ashok	Lab	-1.01	-1.15 -0.88
512	Smith/Angela	Lab	-1.01	-1.17 -0.86
513	Shipley/Debra	Lab	-1.02	-1.21 -0.83
514	Davey/Valerie	Lab	-1.02	-1.18 -0.87
515	Caton/Martin	Lab	-1.03	-1.18 -0.89
516	Dismore/Andrew	Lab	-1.03	-1.13 -0.93
517	Pond/Chris	Lab	-1.03	-1.21 -0.85
518	Dobbin/Jim	Lab	-1.03	-1.16 -0.91
519	Fyfe/Maria	Lab	-1.04	-1.18 -0.91
520	Buck/Karen	Lab	-1.04	-1.24 -0.86
521	Brown/Russell	Lab	-1.05	-1.19 -0.91
522	Wood/Mike	Lab	-1.05	-1.25 -0.86
523	Darvill/Keith	Lab	-1.05	-1.27 -0.85
524	Palmer/Nick	Lab	-1.06	-1.20 -0.92
525	Simpson/Alan	Lab	-1.08	-1.17 -0.99
526	Gibson/Ian	Lab	-1.08	-1.19 -0.96
527	Eagle/Maria	Lab	-1.08	-1.28 -0.88
528	Austin/John	Lab	-1.08	-1.17 -0.98
529	Keen/Alan	Lab	-1.08	-1.26 -0.91
530	Mahon/Alice	Lab	-1.09	-1.19 -0.98
531	Livingstone/Ken	Lab	-1.10	-1.20 -0.99
532	McDonnell/John	Lab	-1.12	-1.21 -1.03
533	Mallaber/Judy	Lab	-1.14	-1.34 -0.94

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Table 2 – continued from previous page

<b>Number</b>	<b>Name</b>	<b>Party</b>	<b>Posterior Mean</b>	<b>95% CCI</b>	
534	Benn/Tony	Lab	-1.14	-1.27	-1.01
535	Cohen/Harry	Lab	-1.14	-1.26	-1.02
536	Jones/Jenny	Lab	-1.14	-1.28	-1.01
537	Clapham/Michael	Lab	-1.15	-1.25	-1.05
538	Hopkins/Kelvin	Lab	-1.17	-1.29	-1.05
539	Campbell-Savours/DN	Lab	-1.18	-1.35	-1.00
540	Corbyn/Jeremy	Lab	-1.19	-1.28	-1.11
541	Fitzpatrick/Jim	Lab	-1.20	-1.36	-1.05
542	Cryer/Ann	Lab	-1.3	-1.42	-1.18
543	Vis/Rudi	Lab	-1.33	-1.47	-1.20
544	Skinner/Dennis	Lab	-1.34	-1.51	-1.18
545	Etherington/Bill	Lab	-1.36	-1.49	-1.23
546	Michie/Bill	Lab	-1.55	-1.70	-1.41

## References

- Clinton, Joshua, Simon Jackman and Douglas Rivers. 2004. “The Statistical Analysis of Roll Call Data.” *American Political Science Review* 98:355–370.
- Gelman, Andrew, John B. Carlin, Hal S. Stern and Donald B. Rubin. 2004. *Bayesian Data Analysis*. 2nd. ed. Boca Raton, Florida: Chapman and Hall/CRC.
- Martin, Andrew D. and Kevin M. Quinn. 2002. “Dynamic Ideal Point Estimation via Markov Chain Monte Carlo for the U.S. Supreme Court, 1953–1999.” *Political Analysis* 10:134–153.
- Neal, Radford M. 2003. “Slice Sampling.” *Annals of Statistics* 31:705–767.

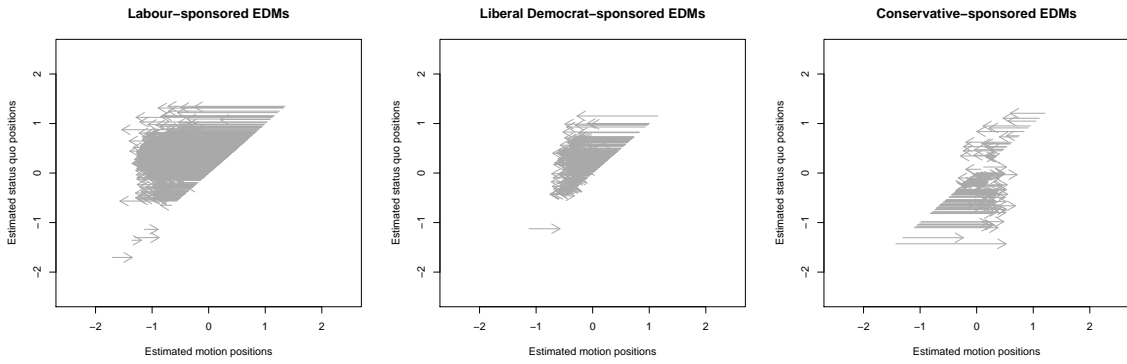


Figure 5: Implied policy shifts of EDMs sponsored by major party MPs