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*Publication date:*  
2013

[Link to publication in Tilburg University Research Portal](#)

*Citation for published version (APA):*

Eijffinger, S. C. W., Mahieu, R. J., & Raes, L. B. D. (2013). *Inferring Hawks and Doves from Voting Records*. (CentER Discussion Paper; Vol. 2013-024). Economics.

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# Discussion paper

## INFERRING HAWKS AND DOVES FROM VOTING RECORDS

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April 9, 2013

European Banking Center Discussion Paper  
No. 2013-004

This is also a CentER Discussion Paper  
No. 2013-024

ISSN 0924-7815

# Inferring hawks and doves from voting records

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June 20, 2013

**Abstract:** We analyze revealed policy preferences in monetary policy committees. From the voting records of the Bank of England we estimate the policy preferences with spatial models of voting. We analyze systematic patterns in these policy preferences. We find that internal committee members tend to hold centrist policy preferences while pronounced policy preferences are generally held by external members. Committee members with a career in academia and the industry hold more diverse policy preferences whereas committee members with central bank experience exhibit little heterogeneity in preferences. The median voter does not vary systematically according to career background.

**Keywords:** Voting records; Central Banking; Committees; Ideal points

**JEL Classification Numbers:** E58, E59, C11

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\*We would like to thank Willem Buiters, Charles Goodhart, Bjørn Høyland, Thomas Michielsen, Wieland Müller, Lucas Papademos, Christopher Spencer, Steven Verheyen, Nick Vivyan, Wolf Wagner for discussion and advice, as well as seminar discussants at the Tilburg Economic Workshop.

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*Diversity of views drives the Committee to adopt an eclectic approach and thus serves to limit the risk that a single viewpoint or analytical framework might become unduly dominant.* –  
[Bernanke \(2007\)](#)

Most central banks take monetary policy decisions by committee. Committee in this context is not a well-defined organizational concept but refers loosely to a group of people taking decisions. Differences between committees relate to the decision protocol, the (in)formal hierarchy, the size and to the composition. One key difference is the composition of committees. In this paper we focus on the composition and how the diversity of views are related to and influenced by the composition of the committee. Some committees consist mainly of career central bankers who have extensive experience at the central bank, whereas other committees consist mostly of external members recruited outside of the central bank. [Besley, Meads, and Surico \(2008\)](#) argue that the internal-external dichotomy could matter for at least two reasons. First, the selection procedure for internal and external members is in many cases formally different. Second, career concerns could affect incentives. Externals leave after their terms whereas internal members may be building a further career in central banking. Also the backgrounds of committee members differ. Experience in the financial industry, at an NGO or with the government may influence how these committee members approach monetary policy making.

We examine the voting record of the Bank of England. We use the observed votes to infer the policy preferences of the central bankers. With these policy preferences we can compare internals with externals and gauge the impact of career backgrounds. To analyze the voting record we estimate the policy preferences or ideal points of monetary policy committee members. The methodology we use, builds upon a spatial voting model. A spatial voting model is a rational choice model of voting. Utilities are defined as functions of the distance between the preferred outcome and alternatives in a policy space, hence the name spatial voting model. We derive a basic version of this model and discuss how to estimate such a model.

The model we use is unidimensional. The latent dimension on which we classify monetary policy committee members is called a dove-hawk dimension. We present two main results. First we show that internals are not more hawkish than externals (or vice versa). This is related to a debate in the literature on voting at the Bank of England where some researchers claim that internal members tend to be more hawkish whereas other researchers argue that this is not the case. Our results support the latter strand of the literature.<sup>1</sup> However, we find that internals tend to have centrist policy preferences whereas as the most pronounced policy preferences (very dovish or very hawkish) are nearly always held by external members.

Our second result is that the policy preferences are not systematically influenced by career backgrounds. The median voter does not change substantially when we consider monetary policy committee members with different career backgrounds. However, career backgrounds seem to be related to the heterogeneity in policy preferences. We find less variation in policy preferences among monetary policy committee members with a central bank background than among monetary policy committee members with a background in academia or the (non-financial) industry. This result suggests that there are meaningful differences among monetary policy committee members which are driven by career backgrounds. The low heterogeneity in preferences among committee members with a central bank background is suggestive of an organizational consensus.

The methodology in this paper builds upon developments in other disciplines. We devote some space to introduce the standard spatial voting model and we suggest a modification to deal with the data we encounter in our application. We show how spatial voting models can easily be estimated with Bayesian

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<sup>1</sup>This finding is in line with [Besley, Meads, and Surico \(2008\)](#), [Hix, Hoyland, and Vivyan \(2010\)](#) but contradicts [Gerlach-Kristen \(2009\)](#), [Bhattacharjee and Holly \(2010\)](#) and [Hansen, McMahon, and Rivera \(2013\)](#).

methods. Throughout our empirical analysis we demonstrate the flexibility of the methodology when analyzing voting data. It is our hope that economists consider this methodology when analyzing voting data.

The structure of the paper is as follows. The next section discusses the literature. In Section 3 we explain what a spatial voting model is and how such a model can be estimated. We also discuss issues related to identification. In Section 4 we introduce the data. We explain how the dataset was constructed and comment on the raw data. We argue that a modification of the standard approach is needed because the dataset is small which may exacerbate the influence of outliers. In Section 5 we provide the estimation results. We present some model checks which make clear where the model fits well and where the model performs worse. Here we also assess the robustness of the model. In Section 6 we use the estimated ideal points to evaluate some claims in the literature. We compare internal and external monetary policy committee members. In Section 7 we explore whether policy preferences are driven by career backgrounds. In Section 8 we conclude.

## 1 Related literature

This paper fits into the literature on decision taking at central bank committees. The institutional arrangements of monetary policy committees differ considerably across central banks and may have important implications for monetary policy making in practice. These institutional details concern (i) the way decisions are reached, (ii) the transparency of procedures and (iii) the composition of such a committee. Researchers have tried to provide theoretical and empirical arguments for the best institutional design. [Riboni and Ruge-Murcia \(2010\)](#) consider the theoretical and empirical implications of three different voting protocols. They find that the consensus protocol where a level of support is required that exceeds simple majority (super-majority voting), to be the best protocol. This conclusion is in line with [Dal Bo \(2006\)](#) who also suggests super-majority voting as a way to combine flexibility and commitment in monetary policy decision making.

[Sibert \(2003\)](#) finds that not publishing individuals' votes lowers expected social welfare. [Meade and Stasavage \(2008\)](#) investigate the costs associated with transparency on decisions. They find that greater transparency may come at the cost of voters revealing private information less easily when deliberations are behind closed doors. Their theoretical argument, for which they find evidence at the FOMC, builds upon reputational concerns. The potential adverse effects of reputational concerns are also studied by [Visser and Swank \(2007\)](#). [Swank, Swank, and Visser \(2008\)](#) show that increased transparency may induce pre-meetings in order to conceal disagreement.

In this paper we focus on the composition of a monetary policy committee and on the heterogeneity in policy preferences among the individual members. We consider whether different types of members hold systematically different policy preferences.

Existing empirical research on this topic uses mainly one of two approaches. On the one hand researchers estimate aggregate and individual interest rate rules. [Besley, Meads, and Surico \(2008\)](#) estimate reaction functions for the individual committee members and assess the extent to which these capture the heterogeneity in voting patterns. They group the committee members according to career background (e.g. academia vs non-academia) and according to their appointment within the committee (external or internal member). The parameters of the individual members are then compared across groups. The authors find that while there is substantial heterogeneity in voting patterns, the individual reaction functions are fairly homogenous with no significant differences between members according to the background characteristics considered. Other examples of this approach studying the Bank of England are [Riboni and Ruge-Murcia \(2008\)](#) and [Harris and Spencer \(2009\)](#).

The other dominant approach builds upon a regression framework where the dependent variable captures the votes cast by members. This dependent variable is then regressed on relevant meeting characteristics (variables capturing economic conditions) and voter characteristics (backgrounds of the individual voters). As an example, [Harris, Levine, and Spencer \(2011\)](#) examine the frequency and type of dissenting votes in the monetary policy committee at the Bank of England. While they find strong heterogeneity in voting patterns, they only find a weak role for career experience in determining the decision to dissent. These findings stand in contrast to the large literature studying votes at the FOMC suggesting that career backgrounds do matter as well as political influence through appointment, see the discussion in [Harris, Levine, and Spencer \(2011\)](#) and see [Chappell, Havrilesky, and McGregor \(1993\)](#) for early evidence on the appointment channel.

We use an alternative way to investigate voting behavior of monetary policy committee members. The approach builds on methodological advancements in other disciplines where researchers have investigated voting behavior of legislators and judges. We estimate spatial voting models for explaining the voting behavior of members of the monetary policy committee of the Bank of England. Our spatial framework yields the revealed policy preferences (ideal points) of each monetary policy committee member, which can be depicted as points on a latent dove-hawk dimension. Armed with these individual preferences we are able to tackle a variety of questions posed in the literature on decision making in monetary policy committees. The methodology yields a convenient to use and intuitive measure of policy preferences. Moreover, the Bayesian method that we employ yields a joint posterior distribution of all the parameters. This makes our approach much more flexible than the approaches discussed above. We demonstrate this flexibility throughout the paper by investigating and making inference about derived quantities in a way that would be nearly infeasible with the approaches discussed above. While economists have greatly contributed to the development of the theoretical underpinnings of the spatial voting model since the pioneering work by [Black \(1948\)](#), empirical implementations of the spatial voting model remain scant within economics. An early contribution is the paper by [Heckman and Snyder \(1997\)](#) which is an influential methodological contribution with an application to legislative data but by now outdated for the purpose of estimating ideal points, see also [Clinton, Jackman, and Rivers \(2004\)](#). [Henry and Mourifié \(2013\)](#) test the spatial voting model in the context of US national elections. The few empirical papers we are aware of nearly always consider applications in politics and the analysis of judicial votes.<sup>2</sup> In this paper we focus on voting data of monetary policy committees. There is one other paper that empirically investigates voting at a monetary policy committee in a spatial voting framework, see [Hix, Hoyland, and Vivyan \(2010\)](#). Their analysis looks at the voting process through the lens of political economy. Specifically they explore the extent to which the (political) appointment process was able to move the median voter. Our contribution is to connect the ideal point approach with the existing research in (monetary) economics, adapt the methodology and widen the scope of the approach. After presenting a concise introduction to this approach, we show how this methodology can (and should) be adapted to the data available in the study of decisions by monetary policy committees. We subsequently present tools for model checking to assess the robustness of the results.

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<sup>2</sup>Recently, the empirical analysis of voting data regained attention of economists. Authors have proposed different equilibrium models of decision making. The idea is that some of these traditional areas of application (such as voting in supreme courts) have peculiar features (e.g. strategic voting) which require a modified methodology. These papers typically do not build upon a spatial voting model. As an example, [Iaryczower and Shum \(2012\)](#) examine voting behavior in the US supreme court and build an equilibrium model of decision making to quantify the value of information. [Iaryczower, Lewis, and Shum \(2013\)](#) also look at the US supreme courts and investigate the trade-off between politicians and bureaucrats. While the *standard* spatial voting model assumes sincere voting, this assumption can be relaxed. In the application we consider in this paper there is no particular reason why strategic voting would be an issue. This is also discussed in [Blinder \(2007\)](#). Explicitly allowing for strategic voting in our framework could be done along the lines of [Clinton and Meiorowitz \(2004\)](#).

## 2 Voting records and ideal point estimation

The approach presented in this paper starts from voting records from central bank committee deliberations. Our goal is to estimate the policy preferences of each member. To do so, we borrow from statistical methods developed for analyzing political roll calls and decisions at judicial courts. These methods are rooted in the psychometric literature and in educational research but can be motivated by a spatial voting model. The spatial voting model itself has its roots in political economy, see [Black \(1948\)](#), but was further developed in political science, see [Enelow and Hinich \(1984\)](#).

### 2.1 Ideal points and a spatial voting model

The data we analyze consist of voting records of monetary policy deliberations. For a given central bank we observe the votes casted on a policy rate. The data consist of monetary policy committee members to whom we refer as voters  $n = 1, \dots, N$  voting on policy choices  $t = 1, \dots, T$ . Each policy choice  $t$  presents voters with a choice between a *dovish* position  $\psi_t$  and a *hawkish* position  $\zeta_t$ , locations in a one-dimensional Euclidean policy space  $\mathbb{R}$ . A voter  $n$  choosing the hawkish position  $\zeta_t$  on policy choice  $t$  is denoted as  $y_{nt} = 1$ . If voter  $n$  chooses the dovish position  $\psi_t$ , we code this as  $y_{nt} = 0$ .

It is important to realize that both choices  $\zeta_t$  and  $\psi_t$  are functions of a policy rate and of variables capturing the contemporaneous economic conditions prevailing at policy choice  $t$ . However both choices differ only in the policy rate with  $\zeta_t$  being the more restrictive choice i.e. the higher policy rate of the two. Assume that voters have quadratic utility functions over the policy space such that  $U_n(\zeta_t) = -\|x_n - \zeta_t\|^2 + \eta_{nt}$  and  $U_n(\psi_t) = -\|x_n - \psi_t\|^2 + \nu_{nt}$ , where  $x_n \in \mathbb{R}$  is the *ideal point* or the underlying monetary policy preference of voter  $n$  and  $\eta_{nt}, \nu_{nt}$  are the stochastic elements of utility and  $\|\cdot\|$  denotes the Euclidean norm.<sup>3</sup> Utility maximization implies that  $y_{nt} = 1$  if  $U_n(\zeta_t) > U_n(\psi_t)$  and  $y_{nt} = 0$  otherwise.

To derive an item response specification, we need to assign a distribution to the errors. Assuming a type-1 extreme value distribution leads to a logit model with unobserved regressors  $x_n$  corresponding to the ideal points of the voters:<sup>4</sup>

$$\begin{aligned}
 P(y_{nt} = 1) &= P(U_n(\zeta_t) > U_n(\psi_t)) \\
 &= P(\nu_{nt} - \eta_{nt} < \|x_n - \psi_t\|^2 - \|x_n - \zeta_t\|^2) \\
 &= P((\nu_{nt} - \eta_{nt}) < 2(\zeta_t - \psi_t)x_n + (\psi_t^2 - \zeta_t^2)) \\
 &= \text{logit}^{-1}(\beta_t x_n - \alpha_t)
 \end{aligned} \tag{1}$$

The last line follows from substituting  $2(\zeta_t - \psi_t)$  with  $\beta_t$  and substituting  $(\zeta_t^2 - \psi_t^2)$  with  $\alpha_t$ . To understand these coefficients, start by considering the situation where  $\beta_t$  equals 1. Then the model reduces to:

$$P(y_{nt} = 1) = \text{logit}^{-1}(x_n - \alpha_t). \tag{2}$$

[Figure 1 about here.]

Figure 1 provides an illustration of the simplified model ( $\beta_t = 1$ ) as shown in equation 2 with two voters and two meetings. Voter 1 has an ideal point  $x_1$  slightly smaller than zero, whereas Voter 2 has

<sup>3</sup>This framework is readily extended to a multidimensional policy space  $\mathbb{R}^d$  with d-dimensional ideal points and positions. All methods presented here are valid in the multidimensional case. However the intuition quickly becomes more difficult and identification harder as we discuss in subsection 2.2. We return to the choice for one latent dimension in detail later on.

<sup>4</sup>The logit specification seems to be the more popular approach but we could just as well have assumed a joint normal distribution for the errors which results in a probit specification with unobserved regressors  $x_n$ . An example of the latter approach is [Clinton, Jackman, and Rivers \(2004\)](#). Substantially this does not matter.

an ideal point  $x_2$  larger than two. The dove-hawk dimension runs from dovish to hawkish and so  $x_2$  would be a clear hawk here. Both voters have an ideal point larger than the vote-difficulty parameter  $\alpha_1$  associated with Meeting 1. This implies that both voters are more likely to vote for the hawkish policy option in this meeting since for  $n = 1, 2$  we have that  $\text{logit}^{-1}(x_n - \alpha_1) > 0.5$ . However, the ideal point of Voter 2 is larger than the ideal point of Voter 1 so the predicted probability of voting hawkish is larger for Voter 2. Now consider Meeting 2. For this meeting we have  $x_1 = \alpha_2$ , the ideal point of Voter 1 and the vote-difficulty parameter of this meeting are equal. We find that  $\text{logit}^{-1}(x_1 - \alpha_2) = \text{logit}^{-1}(0) = 0.5$ . There is an equal probability that Voter 1 chooses the hawkish or the dovish option in this meeting. Once again, Voter 2 has an ideal point larger than  $\alpha_2$  and so we give this voter a higher probability of voting for the hawkish policy choice. These examples show that the vote-difficulty parameter captures meeting characteristics and determines how likely it is a priori that voters vote for the dovish or the hawkish policy choice.

Now consider the effect of  $\beta_t$  or the *discrimination parameter*. This parameter captures the extent to which preferences in the dove-hawk dimension determine the choice between two competing policy rate proposals. Say we find that for a certain meeting  $t$ ,  $\beta_t$  equals zero. Then  $\beta_t x_n$  equals zero and the preferences in the underlying dove-hawk dimension do not have an impact on the choice between competing policy proposals. Analogously, a negative  $\beta_t$  implies that doves (hawks) have a higher probability of choosing the hawkish (dovish) policy choice. A Voter  $n$  is as likely to choose the dovish as the hawkish choice if his ideal point  $x_n$  equals  $\alpha_t/\beta_t$ . This ratio is referred to as the cutpoint, the point in the policy space where voters are indifferent between two policy choices presented in meeting  $t$ . We return to the intuition behind these parameters in 4.1 where we discuss estimates of this parameter in the context of our empirical application.

We acknowledge that voting could depend on a whole range of influences: personal preferences, group preferences (e.g. through an organizational consensus, varying reputational concerns). Identifying each of these requires considerably more data and/or assumptions. The measures of revealed policy preferences we propose in this paper, represented by the ideal points, are therefore a mix of these influences on monetary policy voting rather than a literal measure of policy preference.<sup>5</sup> In our opinion these serve as a useful summary of policy preferences and could aid researchers analyzing monetary policy votes.

## 2.2 Identification

Identification of the parameters requires some special attention. There are two identification issues with the model as presented in equation 1. As can be seen in Figure 1, the probabilities depend on the relative position of ideal points and vote-difficulty parameters. We could add a constant to  $\beta_t x_n$  and to  $\alpha_t$  and the predictions would not change. This is referred to as additive aliasing. Analogously we could multiply  $\beta_t$  by a constant and divide  $x_n$  by the same constant. This is referred to as multiplicative aliasing. In a unidimensional spatial context, identification is easier resolved than in a multidimensional model, see Rivers (2003) for a detailed description of the issues involved in general spatial models. In a unidimensional model two linearly independent a priori restrictions are sufficient. For example we could simply fix two ideal points at arbitrary positions, e.g. one voter at -1 and another voter at +1. Fixing two voters in this way forces the model to position the ideal points of the other votes relative to these two voters. However, the results may be hard to interpret depending on the choice of ideal points which were fixed.<sup>6</sup>

Another, more often used approach is to constrain the ideal points to have mean zero and a standard

<sup>5</sup>See also the discussion in Jackman (2009) p.458-459.

<sup>6</sup>For example if we would fix two ideal points of voters who have a very dovish voting record to be -1 and +1. Then the other ideal points would be stretched out below -1 or above +1 and it would be hard to figure out when ideal points become centrist or hawkish.



deviation of one (when using normal priors on the ideal points). This facilitates interpretation but ensures only local identification, see [Clinton, Jackman, and Rivers \(2004\)](#). The left-right direction can still be reversed. To achieve (global) identification one needs to fix the direction. To achieve global identification we explore two different approaches. One approach builds upon the way we coded the data and restricts the discrimination parameters. The other approach we use as a robustness check and involves restricting the support of the priors on some ideal points. We present these after having discussed the data.

### 3 The data

We study the voting records of the monetary policy committee of the Bank of England. This committee is classified as individualistic in the classification scheme of [Blinder \(2007\)](#). Such an individualistic committee is characterized by members who express their opinions and vote accordingly. The important advantage for our purposes is that *"the vote of an individualistic committee conveys genuine information"* ([Blinder \(2007\)](#)). This facilitates our analysis as we can safely assume that the votes are in fact a reflection of the preferences of the voting members. Given the individualistic nature of the monetary policy committee, the voting records are characterized by a fairly high degree of dissent. In over 60% of the 190 Monetary Policy Committee meetings held between June 1997 and February 2013, a decision was taken by non-unanimous votes.

In this paper we drop the unanimous votes as these are uninformative for our purposes. The remaining votes were coded as decisions over two alternatives. [Table 1](#) clarifies the coding with two examples. Example 1 is the situation where there were only two policy choices to vote on in a given meeting. Nickell voted in that particular meeting for a lowering of the interest rate with 25 basis points, whereas the other voters preferred to keep the interest rate unchanged. In this case Nickell chose for the dovish option so his vote is coded as 0, whereas the others chose the hawkish choice and therefore their vote is coded as 1. If a meeting involved a choice with more than two interest rates, we coded these as a series of choices over pairwise alternatives. Consider Example 2 in [Table 1](#). At this meeting, Walton voted in favor of raising the policy rates by 25 basis points, Nickell voted in favor of lowering the policy rate by 25 basis points and the other voters preferred to keep the rate unchanged. We coded these once as a choice between lowering or maintaining the interest rate (coded as 0) and raising the interest rate (coded as 1). We coded these votes a second time but now as a choice between lowering the interest rate (coded as 0) and maintaining or raising it (coded as 1).

[Table 1 about here.]

The unprocessed dataset contains the votes of 32 Monetary Policy Committee members at 190 meetings. We recoded the recorded votes in the way described above. We dropped the unanimous meetings. Subsequently we dropped voting records of the Monetary Policy members we observe less than three times. This leaves us with 117 meetings and 29 Monetary Policy Committee members, henceforward referred to as voters.<sup>7</sup> Not all voters vote at each meeting. Since the Monetary Policy Committee contains at most nine voters, we can at most observe nine votes at each meeting. The 29-by-117 matrix of votes is in fact mostly empty and only 1038 entries are filled.

[Figure 2 about here.]

In [Figure 2](#) on the horizontal axis we have the total votes cast and on the vertical axis the number of votes we coded as dovish for a given voter. The straight line indicates the combinations where exactly

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<sup>7</sup>From here onwards we use the term meeting for one recorded voting session in our dataset. This means that a *real* monetary policy meeting could occupy two meetings in our dataset when three policy choices were considered. The uncoded data did not contain records of votes where four or more policy choices were considered.

half of the votes is coded as being hawkish and half the votes is coded as being dovish. The graph shows that there is a wide variation in the number of votes we observe for the different voters. We have 117 votes of Mervyn King in our data set while we have only 10 votes of David Walton. In the graph we labeled five voters which we use as a reference throughout this paper. As mentioned, King has the largest number of votes of which more than half are classified as hawkish. Santance is another example of someone who has voted predominantly hawkish, Blanchflower on the other hand voted exclusively dovish. Nickell and Buiter seem to have a centrist voting record.

### 3.1 Outliers and few observations: a robust modification

Before proceeding to the empirical analysis we would like to motivate and present a modification of the standard spatial model. The model we presented in 2.1 has quickly become the standard approach for estimating ideal points of legislators.<sup>8</sup>

The data we have in the context of Monetary Policy Committees are more limited than the roll call data available to researchers investigating votes in the U.S. Senate or Congress for which these methods were developed. Consider for example the seminal article by Clinton, Jackman, and Rivers (2004) where the authors fit the standard spatial voting model to the roll calls from the 106th U.S. House of representatives. This gives the authors 444.326 individual voting decisions. Compare this with our sample of only 1038 individual voting decisions and the substantial variation in number of observed votes for each voter.

But there is another problem. Logit and probit models are not robust to outliers. This was already shown by Pregibon (1982) and more recently by Liu (2004). In this context the term outlier refers to an observation of an outcome that is highly unexpected given the linear predictor. Bafumi, Gelman, Park, and Kaplan (2005) provide the following example. Say we have estimated a logit model  $P(y_i = 1) = \text{logit}^{-1}(X_i\beta)$  and we have for a particular observation  $i$ ,  $X_i\hat{\beta} = 10$ . Then  $\text{logit}^{-1}(10) = 0.99995$  so the observation  $y_i = 0$  would be an outlier. The many missing entries in our votes matrix and the fact that we observe only a limited number of votes for some voters potentially aggravate the problem of outliers. Only a few outliers could substantially bias our parameter estimates.

A modification to the standard voting model to become more robust against outliers (in the sense explained earlier) is proposed in Bafumi, Gelman, Park, and Kaplan (2005). To understand this, consider the basic model we derived earlier (see equation 1). Bafumi, Gelman, Park, and Kaplan (2005) propose to add a level of error  $\epsilon_0$  and  $\epsilon_1$  as follows:

$$P(y_{nt} = 1) = \epsilon_0 + (1 - \epsilon_0 - \epsilon_1)\text{logit}^{-1}(\beta_t x_n - \alpha_t). \quad (3)$$

Now, every voter has an immediate probability of success  $\epsilon_0$  and of failure  $\epsilon_1$ . The initial item-response model applies then to the remaining outcomes. This simple modification makes the standard spatial voting model more robust and is straightforward to implement. When we do model checking (see 4.2) we are going to explicitly compare the performance of this modified model presented here with the standard spatial voting model we presented earlier.

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<sup>8</sup>The canonical method for inferring ideal points was based on an unfolding procedure called NOMINATE developed in Poole and Rosenthal (1985) and subsequent work. In recent years the Bayesian approach of estimating ideal points has become the preferred method. Without going into detail on the comparison we mention two important reasons for choosing the Bayesian approach. First of all, the NOMINATE algorithm requires us to drop certain voters and meetings because they are inappropriate for the algorithm (too few votes or too lopsided meetings). So this approach yields a less complete picture in the application we consider. Second the Bayesian approach facilitates inference over derived quantities. We make use of this in further sections of this paper. A classic introduction to the Bayesian statistics of the standard spatial model as presented here is Clinton, Jackman, and Rivers (2004).

## 3.2 Priors

Our approach is Bayesian. In the literature on ideal points the *local identification* approach as we outlined earlier is considered to be the least restrictive. We follow this approach and choose therefore standard normal priors for the ideal points. However we then still need to fix the dove-hawk direction, see our discussion in 2.2. We propose two different ways of doing this so we can compare the resulting ideal points and ensure that our empirical analysis is not sensitive to the assumptions we make in order to achieve global identification. The two different sets of priors are summarized in Table 2.

[Table 2 about here.]

Our preferred choice of priors to which we refer to as the *baseline* prior choice ensures that the discrimination parameters  $\beta_t$  cannot be negative. Remember that we coded votes as 0 or 1 where in each given meeting a vote coded as zero was the most dovish (the least restrictive) of two proposed policy rates. Restricting  $\beta_t$  to nonnegative values then makes sense. It implies that we explicitly model the directionality of each vote which is clear in this application. We restrict  $\beta_t$  to be nonnegative by choosing for each  $\beta_t$  a diffuse normal prior with a positive mean, but which is truncated at zero.<sup>9</sup> When we present different model checks, we show a straightforward way to check this assumption (see subsection 4.1). For the vote-difficulty parameters  $\alpha_t$  we also choose diffuse priors. The prior choice for  $\epsilon_0$  and  $\epsilon_1$  follow the recommendations of Bafumi, Gelman, Park, and Kaplan (2005). This prior choice restricts the values of these parameters to lie in the interval  $[0, 0.1]$ . This is not restrictive because if we would find values which are close to 0.1, suggesting an immediate chance of success or failure of 10%, then a logit-type model should not even be used as an approximation, see Bafumi, Gelman, Park, and Kaplan (2005).

The *alternative* prior choice relaxes the assumption on the discrimination parameters. We do not truncate the normal distribution and so the discrimination parameters could take on negative values. To achieve global identification we restrict the support of the priors of certain ideal points of voters which are *obvious* candidates for being hawk or dove. Specifically we restrict the ideal points of Wadhvani and Blanchflower to be negative and the ideal points of Large and Sentance to be positive. This seems reasonable since we coded 22 of the 24 votes by Wadhvani in our dataset as 0 and all 26 votes by Blanchflower. At the other hand we coded 38 of the 40 votes by Sentance and 22 of the 24 votes by Large as 1. Just as with the baseline prior, we can check the reasonableness of this prior. In the appendix to this paper we also present results of a thorough sensitivity analysis where we look at the sensitivity of our findings to alternative prior choices. We do this by starting with our preferred model (equation 3) with the baseline prior choice and then specifying different priors for the parameters. We re-estimate the model with four alternative specifications. We conclude from these tests that our results are robust.

Simulation from the posterior is done by means of slice sampling, see Neal (2003), as implemented in the MCMCpack package, see Martin, Quinn, and Park (2011) for details. The MCMC algorithm ran for 330,000 iterations. We discarded the first 30,000 draws and thinned the remaining iterations by a factor 30 to keep 10,000 draws. Standard convergence tests suggested convergence and good mixing. In the appendix to this paper we report these diagnostics.

## 4 Ideal points at the Bank of England

We start by estimating the ideal points of the Monetary Policy Committee members with the robust model (see equation 3) and the baseline constraints. Figure 3 presents the ideal points of the 29 voters along with the uncertainty in the estimates.

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<sup>9</sup>Cromwell's rule states that if a particular region of the parameter space has zero prior probability then it also has zero posterior probability, see Jackman (2009). So by restricting the support of the prior to the positive real line we have in fact restricted the  $\beta_t$  parameters to be nonnegative.

Inspection of the figure shows that we could roughly classify the monetary policy members as follows. For Blanchflower, Wadhvani, Julius, Allsopp and Nickell we find that the 95% intervals do not overlap with zero and so we would classify them as doves. Likewise the group of hawks consists of Sentance, Besley, Large, Budd, Weale, Dale, King, Buiters and Vickers. For the latter two we find 95% intervals. The other voters are classified as centrist. In this group we find that for Fisher, Posen, Miles and Bell the 95% credible interval overlaps barely with zero and we would be inclined to label these as dovish as well.

[Figure 3 about here.]

Before we proceed with exploring various ideas on the voting behavior of the monetary policy committee members it is important to verify that the estimation results pass some checks. These checks give an insight in how well the model fits the data and what the impact of certain assumptions are. Moreover the model checks may enhance the understanding of the ideal-point methodology. The idea of model checking is not unique to Bayesian data analysis and has been used by researchers working with complex stochastic models in a variety of fields.<sup>10</sup>

In the following subsection we undertake three checks. We start by gauging the impact of the identifying constraints (the constraint on the discrimination parameters) in our preferred specification. We find that the constraints are reasonable and do not contrast with the data. Then we compare the model specification we prefer, that is the simple modification as given in Equation 3, with the standard spatial model. We show that the robust modification gives results which are less sensitive to the prior choice. This check shows that our results do not depend on the identifying assumption we make. Additionally it provides evidence in favor of our specification choice over the standard spatial model. Both these checks give an insight in respectively the impact of our prior and our model choice. Then we investigate prediction errors. These provide a more rigorous idea of the model fit.

#### 4.1 The constraints on the priors

Our baseline prior constrains  $\beta_t$  to be positive. This constraint on the discrimination parameter is justified from a theoretical point of view.<sup>11</sup> In our framework, when given the choice between a lower and a higher policy rate, someone who is more hawkish should be more inclined to choose the higher policy rate than someone who is less hawkish. Here we check whether this is supported by the data. There are two reasons why we could find a negative discrimination parameter when we would *not* explicitly constrain the discrimination parameter as we do in our baseline prior choice. First of all we could have miscoded the data. As such investigating the negative discrimination parameters under the alternative prior offers an additional check of the data. Secondly, negative discrimination parameters may result because of *switching coalitions*. When hawkish voters vote in the dovish direction or dovish voters vote in the hawkish direction this situation can arise. In Figure 4 we plot the posterior estimates of the discrimination parameters. In the left graph we plot the estimates from our model with the baseline prior and in the right graph from the model under the alternative prior choice. The left graph shows that a few discrimination parameters are close to zero under the baseline prior choice. The right plots reveals which discrimination parameters are suspect in particular. We see that when we put a constraint on the discrimination parameters, some would take on negative values. The graph shows that these negative discrimination parameters are clustered. Most of the negative discrimination parameters fall

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<sup>10</sup> An insightful reference discussing the philosophical aspects and containing plenty of references is Gelman and Shalizi (2013). Practical advice and specific procedures on which we draw in this paper are described in Gelman, Goegebeur, Tuerlinckx, and Van Mechelen (2000), Gelman, Carlin, Stern, and Rubin (2003) and Bafumi, Gelman, Park, and Kaplan (2005).

<sup>11</sup> See also the discussion on constraining the discrimination parameter in Hix, Hoyland, and Vivyan (2010).

in a period which coincides with the tenure of Willem Buiter. After having developed a more hawkish voting profile, he voted in a number of meetings for the dovish choice whereas the majority of the other members, including those who tend to be more dovish, voted for the hawkish option. This explains why the discrimination parameter is negative in the unconstrained specification. Our baseline specification does not allow for negative discrimination parameters and puts a value close to zero on these particular meetings. The interpretation is that in this model the votes in these meetings do not reflect the latent policy preferences of the voters. Overall, this graph tells us that the constraint on the discrimination parameter is not in conflict with the data. When unconstrained, few discrimination parameters take on a substantial negative value.

[Figure 4 about here.]

## 4.2 Comparing the robust and standard spatial model

To check whether our results do not depend on our prior choice and identification scheme we compare the estimated ideal points under both identifying prior choices. We do this once for the robust modification and once for the standard model. In the left graph of Figure 5 both prior choices are compared for the robust model. When we obtain the exact same estimates for the ideal points, all dots should lie on the diagonal. We find that the estimated ideal points are close to the diagonal except for the ideal point of Willem Buiter. His ideal point depends on the specific prior choices although it remains positive.

[Figure 5 about here.]

We do the same check and compare the ideal points found under both prior choices when we estimate the standard spatial model. These results can be found in the right graph of Figure 5. We see that in the standard spatial voting model (without the small modification) the estimates are far less stable. Several dots lie relatively far away from the diagonal, indicating that the ideal points change according to the identifying assumption. Some even switch from clearly dovish to clearly hawkish. This supports our choice for the robust modification.

## 4.3 Prediction errors

To assess how well our model fits we can inspect prediction errors.<sup>12</sup> Define a prediction error  $pe_i$  as:

$$\begin{aligned} pe_i &= 1 && \text{if } \mathbb{E}(y_i) > 0.5 \text{ and } y_i = 0, \text{ or } \mathbb{E}(y_i) < 0.5 \text{ and } y_i = 1 \\ &= 0 && \text{otherwise.} \end{aligned} \tag{4}$$

Using the prediction errors we can quickly check the *error rate* or the proportion of times the prediction is wrong. The error rate for our preferred model is slightly over 8%. This can be compared to the error rate of the null model, the model where we give each outcome a probability equal to the proportion of 1's in our dataset. The error rate of the null model is 46% so our model fits considerably better.

We can also use the prediction errors to consider the *excess error rate* i.e. the proportion of errors beyond what is expected. If the model is true, the probability of error is:

$$\mathbb{E}(e_i) = \min(\epsilon_0 + (1 - \epsilon_0 - \epsilon_1)\text{logit}^{-1}(\beta_t x_n - \alpha_t), 1 - (\epsilon_0 + (1 - \epsilon_0 - \epsilon_1)\text{logit}^{-1}(\beta_t x_n - \alpha_t))) \tag{5}$$

which is the minimum of the model's prediction and 1 minus the prediction. The excess error  $ee_i$  is then:

$$ee_i = pe_i - \mathbb{E}(e_i). \tag{6}$$

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<sup>12</sup>This model check follows the suggestions in [Bafumi, Gelman, Park, and Kaplan \(2005\)](#) closely.

To be able to interpret the prediction errors, we consider averages of errors as these offer 0 as a baseline [Bafumi, Gelman, Park, and Kaplan \(2005\)](#).

[Table 3 about here.]

In [Table 3](#) we show the excess error rate for the voters. The excess error rates are low suggesting that we can estimate the ideal points well.<sup>13</sup> The ideal points for Buitter and Walton have the highest excess error rates. We find for both an error rate which is 25% higher than what we would expect if the model were true. We commented earlier on the voting record of Buitter and so this result should not come as a surprise. Walton on the other hand is the voter for which we have the fewest observations in our recoded sample. The posterior distribution of his ideal point was consequently wide and the excess error rate reflects this uncertainty.

#### 4.4 Data on Asset Purchases

Since March 2009 the Monetary Policy Committee of the Bank of England also votes on asset purchases financed with central bank reserves. We can integrate these voting data in our framework by coding the votes in a similar way as we did for the policy rate votes. These new vote data provide additional information to identify the ideal points of the voters. However some remarks are in order. First, we only have voting data on asset purchases for a limited period, hence only for a subset of voters. Second, we assume that a vote on the asset purchase program and the policy rate can be used more or less on equal footing in our spatial voting model. While our model is flexible and gives different weights to votes in different meetings, this assumption underlies the data construction.

The results of the combined dataset can be found in the appendix to this paper. The most noticeable changes are related to Miles, Fisher and Posen. The additional votes allow us to discriminate among these three more clearly. Posen becomes an outspoken Dove. Miles and Fisher are now more centrist with Fisher leaning more towards the hawkish side than Miles. This makes sense when we look at the vote data on asset purchases. Posen voted in about 85% of the occasions for the dovish option in asset purchase decisions (more asset purchases) whereas Fisher did so only about 15% of the time. Miles voted half the time for the dovish choice and half the time for the hawkish choice.

When we incorporate the data vote data on asset purchases, we find even more support for the empirical claims we discuss in the remainder of this paper. We choose to present results only based on the votes with respect to the policy rate to remain conservative. We refer the interested reader to the online appendix to this paper where we comment in detail on the the results when vote data on asset purchases are also used.

## 5 Internals and Externals

The model checks in the previous section suggest that the model fits well. In this section we use our results to investigate whether groups of members systematically differ in their policy preferences. First we consider the differences between internals and externals, that is internal members who have a full-time executive position at the Bank and external members who have no executive responsibilities. [Besley, Meads, and Surico \(2008\)](#) make the same distinction. [Harris, Levine, and Spencer \(2011\)](#) split the monetary policy committee members in three groups distinguishing between external members, internal

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<sup>13</sup>For a reference on the size of error rates we can expect, see [Bafumi, Gelman, Park, and Kaplan \(2005\)](#) where the authors report excess error rates varying from -0.20 to +0.20 with outliers over 0.5. Additionally we could use the estimated parameters to generate reference excess errors based on replicated data. Such an exercise is reported in the appendix to this paper. The results of the comparison of the realized errors to the reference errors confirm the conclusion that only the ideal points of Buitter and Walton have a remarkable excess error rate.



members who are politically appointed and internal members who are not politically appointed. In Table 4 we provide an overview of all the monetary policy committee members we consider in our analysis as well as some information on career backgrounds. The info in this table comes from [Harris, Levine, and Spencer \(2011\)](#) which we updated for the monetary policy committee members who joined after 2007.<sup>14</sup> The classification requires some judgement calls. We tried to only take major appointments into account and so we disregarded consulting roles or special advisory positions.

[Table 4 about here.]

At first sight it seems that externals and internals do not seem to be easily classified as either dovish or hawkish. As can be seen in Figure 3, outspoken doves such as Blanchflower and Wadhvani as well as clear hawks such as Sentance and Besley both belong to the external group. What does seem to be the case is that the internals tend to take the centrist position. Of the politically appointed internal members only Large and King are hawks. Also the other internally appointed members tend to take the centrist position and only Dale has a hawkish ideal point. Remarkably all the doves belong to the external group. These conclusions all stem from looking at Figure 3. To verify that indeed the external members have the most outspoken ideal points, we want to infer the *ranks* of the estimated voting scores. Our Bayesian simulation results facilitate this analysis. As explained in [Jackman \(2009\)](#), given the joint posterior density over the ideal points  $\mathbf{x} = (x_1, \dots, x_{29})$  we can induce a posterior density over any quantity of interest that is a function of the  $\mathbf{x}$ .

## 5.1 The most dovish and hawkish voters

To obtain a posterior density over the order statistics for each voter we use the following procedure.<sup>15</sup> For each MCMC draw  $k = 1, \dots, K$ , we order the ideal points  $\mathbf{x}_n^{(k)} = x_1^{(k)}, \dots, x_{29}^{(k)}$  and assign a rank  $r$  to the sampled ideal points. Denote the ranks  $r$  at each iteration of the MCMC algorithm as  $\mathbf{r}^{(k)} = (r_1^{(k)}, \dots, r_{29}^{(k)})'$ . Each element of  $\mathbf{r}^{(k)}$  is an integer  $r_n^{(k)} \in \{1, \dots, 29\}$ . The probability that voter  $n$  occupies rank  $r$  is thus  $\frac{1}{K} \sum_{k=1}^K \mathbb{1}_{\{r\}} r_n^{(k)}$ . By computing these ranks over the iterations of our sample, we compute a posterior mass function over the possible ranks.

We now consider only rank 1 and rank 29 we obtain the probability of being the *most* dovish and the *most* hawkish for each voter. Table 5 reports all the voters for whom we find a non-zero probability of being the most dovish or the most hawkish. If we consider the voters with a probability of being the most dovish than we see that only Fisher does not belong to the group of external members. Similarly we find that for the group of voters who have non-zero probability of being the most hawkish, only Vickers and Large are internal members. Taken together our analysis suggests that the most dovish and most hawkish members at the monetary policy committee of the Bank of England so far were externals. Internal members tend to occupy more the middle ground.

[Table 5 about here.]

To our knowledge this observation is new in the literature. Moreover it sheds light on a topic which has been heavily discussed in the literature. In line with what we have found, [Besley, Meads, and Surico \(2008\)](#) and [Hix, Hoyland, and Vivyan \(2010\)](#) could not classify external or internal members as either more dovish or more hawkish. Our ideal point estimates and rank estimations make clear why. In contrast some studies do claim systematic differences internal and external members. In particular that internals tend to be more hawkish than external members. [Bhattacharjee and Holly \(2010\)](#) found that internals are hawkish. However this difference in findings is attributable to the data they use. Their sample ends

<sup>14</sup>We thank Christopher Spencer for providing background on the original classification and advice on the update.

<sup>15</sup>See also [Jackman \(2009\)](#), chapter 9.

in 2005 and does not contain the voting records of external voters we found to be very hawkish such as Tim Besley or Andrew Sentance. Also [Gerlach-Kristen \(2009\)](#) suggests that external members are more dovish but here results also rest on shorter sample. Recent work by [Hansen, McMahon, and Rivera \(2013\)](#) suggests that internals make more precise assessments of the economy and that they tend to be more hawkish. Our analysis does not shed light on the precision of their assessments but the claim that internals are more hawkish cannot be confirmed by our analysis.

The estimated ideal points for our clear doves and hawks are well separated from zero and so we are confident that the conclusions hold. Internals do not vote systematically more hawkish or dovish than externals. But externals do tend to have members among their ranks with more outspoken policy preferences. This finding resonates with the views expressed in [Gerlach-Kristen \(2003\)](#) and [Harris and Spencer \(2009\)](#) that differences between internals and externals could arise because of an organizational consensus among internals. Related to this, there may be career concerns among internals which are less relevant for external members. [Gerlach-Kristen \(2003\)](#) suggests that externals may even be incentivized to gain media attention. Our analysis does not focus on the act of dissenting per se but rather on the revealed policy preferences. Our results do suggest that internals indeed tend to have policy preferences which are less heterogenous.

## 6 Career backgrounds

Related to the differences between internals and externals, we are also interested in career background effects. The intuition is that career backgrounds may persistently influence the policy preferences of monetary policy committee members. This notion comes from the literature investigating voting at the FOMC where such effects have been suggested. The aforementioned study by [Harris, Levine, and Spencer \(2011\)](#) only finds *weak* (often counterintuitive) influences of career backgrounds when analyzing the records of dissents. [Besley, Meads, and Surico \(2008\)](#) consider fewer career background characteristics when comparing coefficients of reaction functions. They do not find a meaningful pattern.

We investigate the differences in policy preferences by comparing the entire group of voters and the voters with experience in (1) the finance industry (including banks), (2) industry in general (excluding the financial industry), (3) government (civil service or working for any government), (4) academia (only an appointment post doctoral education counts; most voters have obtained a Ph.D.), (5) at the Bank of England, (6) at an NGO. An overview is provided in [Table 4](#). These groups overlap so some voters belong to multiple groups.

We compare these groups by comparing the median voters within each group. For each iteration  $k$  in the MCMC algorithm we rank the voters within the different groups and select the median voter of group  $l = 1, \dots, 7$  (the six subgroups listed above and the entire group of voters). Let  $x_{l,med}^{(k)}$  denote the ideal point of the median voter of group  $l$  in iteration  $k$ . We then have for each group  $l$  a sample of 10.000 simulation draws of the ideal point of the median voter. Similar to our earlier inferences we can construct an estimate of the median voter ideal point and corresponding uncertainty. In the left graph of [Figure 6](#) we present the ideal points of the seven median voter ideal points. The median voters of the six subgroups we listed above and the median voter of the entire group (all voters in our dataset). The figure reveals that the median voter from the group with industry experience is more hawkish than the median voters of the other groups, including the overall median voter. Monetary Policy Committee members with NGO experience tend to be a bit more dovish but they are only distinguishable from the group with industry experience. [Harris, Levine, and Spencer \(2011\)](#) found that industry experience and work experience at the Bank of England promote tightness dissents -both findings were deemed to be counterintuitive. Our findings suggest while we find a more hawkish policy preference among those with



industry experience, those with work experience at the Bank of England do not hold more hawkish policy preferences. Experience in government, academia or in finance does not seem to systematically shift the policy preferences. These results are in line with [Harris, Levine, and Spencer \(2011\)](#) and [Besley, Meads, and Surico \(2008\)](#) who could not find systematic differences in the estimated parameters of reaction functions when comparing voting members with academic experience and without.

We also consider the heterogeneity in policy preferences in the different groups. To do this we estimate the dispersion of ideal points in the different groups with a procedure similar to our estimations of the median voters in each group. For each iteration  $k$ , we calculate for each group  $l$  the standard deviation of ideal points,  $std_l^{(k)}$ . The results can be found in the right graph of [Figure 6](#).

[Figure 6 about here.]

We find that there is a larger heterogeneity among the monetary policy committee members with a background in the industry and academia than those with career experience in a central bank or at the government. To estimate the probability that the heterogeneity in group A,  $std_A$ , is larger than in group B,  $std_B$ , we can generate a binary variable  $D_{A>B}^{(k)}$  which takes the value of 1 when  $std_A > std_B$  and zero otherwise. We can then compute the probability that the heterogeneity in group A is then larger than in group B:  $P(std_A > std_B) = \frac{1}{K} \sum_{k=1}^K D_{A>B}^{(k)}$ . The results of this calculation indicate that the heterogeneity among voters with an academic background is larger than the heterogeneity among (i) voters with a background at a central bank (> 99%), (ii) voters with a career background at the government (> 99%), (iii) voters with an NGO background (> 98%), (iv) voters with a background in the financial industry (> 93%). The heterogeneity among the voters with a background in the industry is the largest but it should be noted here that this group is very small compared to the other groups. These findings align well with the findings on internal and external members. Voters with an academic background are predominantly found among the external members. Earlier we showed that this group tends to have more extreme policy preferences. When we look at the background of the voters ([Table 4](#)) mentioned in [Table 5](#) we find that these are often voters with an academic background. One explanation could be that academics may have developed an own, idiosyncratic view on what monetary policy should do and are subsequently more pronounced in their opinions and preferences. Voters with other career backgrounds, be it in government, at a central bank or in the financial industry, may share a sort of consensus view and hence have less heterogenous policy preferences.

## 7 Conclusion

The spatial voting model provides an appealing way of inferring policy preferences from voting records. This approach has widespread acceptance in research outside of economics. This paper introduces a Bayesian approach to estimate the spatial voting model and to study the voting behavior of the monetary policy committee of the Bank of England. We start by focusing on the differences between internals and externals, a topic which has been discussed in many papers. We find that it is not the case that internals are more hawkish than externals (or vice versa). This finding is in line with the results reported by [Besley, Meads, and Surico \(2008\)](#), [Hix, Hoyland, and Vivyan \(2010\)](#) but contradicts [Gerlach-Kristen \(2009\)](#), [Bhattacharjee and Holly \(2010\)](#) and [Hansen, McMahon, and Rivera \(2013\)](#). Our ideal point estimates strongly suggest that the most dovish and the most hawkish positions on the dove-hawk dimension are occupied by externals. This stands in contrast to the above cited papers who find that internals tend to be more hawkish than externals. We also investigate whether voting members with different career backgrounds tend to hold different policy preferences. To evaluate this, we divide all monetary policy members in different categories according to their career backgrounds. We compare the

median voter policy preference for each category of the monetary policy committee members. We find that the median voter in each of these categories is very similar (and similar to the overall median voter) except for those with career experience in the industry. We subsequently compare the heterogeneity in policy preferences in different groups. We find that monetary policy committee members with a background in academia and the industry exhibit a large heterogeneity in policy preferences. In contrast, monetary policy committee members with a central bank background exhibit the lowest heterogeneity in preferences. An overview of the literature on voting at central banks by [Sibert \(2006\)](#) suggests that central banks committees should be designed such that members do not act as part of a group, perhaps by including members from outside the central bank. Our findings resonate with this suggestion as we find that indeed members with career experience at the central bank tend to exhibit the lowest heterogeneity in preferences. In contrast, academics (predominantly found among externals) have more differing policy preferences than other groups (except for those with an industry background), a finding which is new to our knowledge. These results are important in the debate on the relevance (or advantage) of having externals in a central bank committee. The Bank of England is known to be an individualistic monetary policy committee. Our results suggest that within our sample, the academics have the highest degree of individualism in central bank committees. In so far this is desirable in the constitutional design of central bank committees our findings can be helpful.

The methodology is versatile. We can modify the model in a variety of ways. In the paper we proposed a small modification to make the model more robust but other modifications are conceivable and may provide avenues for further research.

Another modification to deal with unpredictable voters was suggested by [Lauderdale \(2010\)](#). It is also possible to relax some of the assumptions of the spatial voting model. The model can be made dynamic as in [Martin and Quinn \(2002\)](#) although this poses some demands on the data which may be hard to satisfy. Another extension considers more than one dimension to score central bank committee members. A justification for an additional latent dimension, e.g. a gradualism-activism dimension lies in the notions of instrument costs and fear of reversals.<sup>16</sup> Instrument costs arise when extensive use of the policy instrument (changing the policy) is perceived to be costly. Fear of reversals refers to the notion that cutting the policy rate and raising it the month afterwards (or vice versa) shows lack of consistency or suggests that the policy change in the previous month was a mistake. Both instrument costs and fear of reversals induce a central banker to proceed cautious. In our analysis of the Bank of England we restricted ourselves to one latent dimension. We are aware that many central bankers oppose to the dove-hawk view often held by central bank watchers. [King \(2010\)](#) makes this feeling explicit: *Indeed, for ten years, I was, to my frustration, regularly described as a hawk. But I am neither hawk nor dove. Everyone on the Committee votes according to his or her judgement of the outlook for the economy.* It is understandable that central bankers oppose to a reduction to a simple dove-hawk story. However our statistical analysis suggests that the voting process is well described by a single dove-hawk dimension. The unidimensional model presented in this paper, predicts the observed votes at the Bank of England with an accuracy of nearly 92%. In terms of fit, the room for improvement is low. Increasing the number of latent dimensions seems appealing but it makes modeling the voting process more complex while there is limited scope for improving the classification of votes. The individual error rates enforce this viewpoint. The record of most voters is near perfectly classified using a single dimension. The model is however stylized and the ideal points on the single latent dimension are thus to be interpreted as a mix of different influences which combine into a useful summary of the policy preference of voters. Exploring additional latent dimensions may come at the cost of additional identifying assumptions and a proliferation of parameters which obscures interpretation.

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<sup>16</sup>We thank Willem Buiter for an insightful discussion on these matters.

The Bayesian ideal-point methodology delivers the joint probability of all parameters and hence we can quickly devise tests and explore ideas. As an example, in this paper we investigated whether the heterogeneity varies in groups of voters with different career backgrounds. We could estimate the heterogeneity (measured by the standard deviation of ideal points) while accounting for the uncertainty in the estimates of ideal points. We obtained uncertainty in this measure of heterogeneity and could quickly verify whether the heterogeneity in one group is larger than in another group. The underlying idea is easily amenable to explore other hypotheses.

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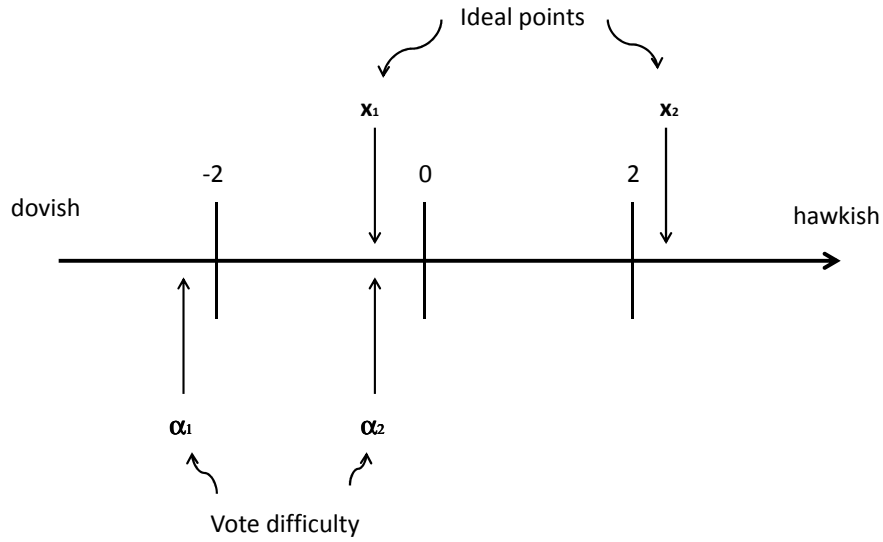


Figure 1: This figure illustrates equation 2. On the latent dove-hawk dimension two ideal points  $x_1, x_2$  (voters) and two vote-difficulty parameters  $\alpha_1, \alpha_2$  (meetings) are shown. If the ideal point of Voter  $n$  is larger than the vote-difficulty parameters  $\alpha_t$ , then it is more likely that Voter  $n$  votes for the hawkish policy choice. In this example, Voter 1 is as likely to vote hawkish as to vote dovish on the policy choice represented by  $\alpha_2$ .

### Votes by individual voters: overview

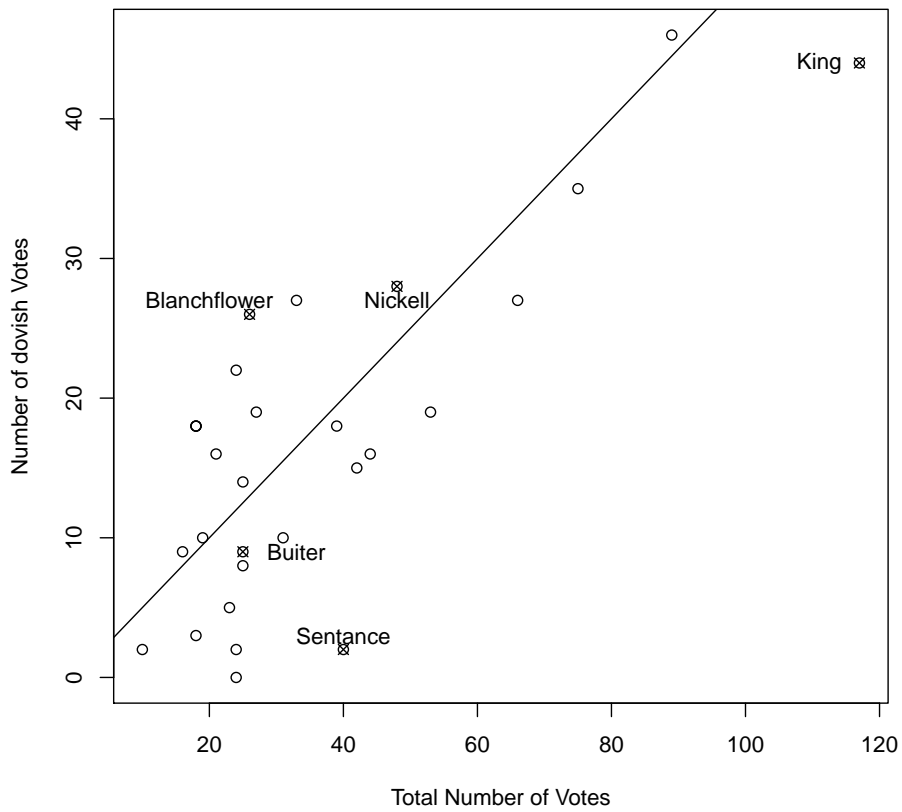


Figure 2: Here we present for each voter the total number of votes (horizontal axis) versus the number of votes coded as the dovish choice. The straight line indicates the combinations where exactly 50% of the total votes is coded as being dovish and 50% as being hawkish.

### Revealed Preferences in the MPC

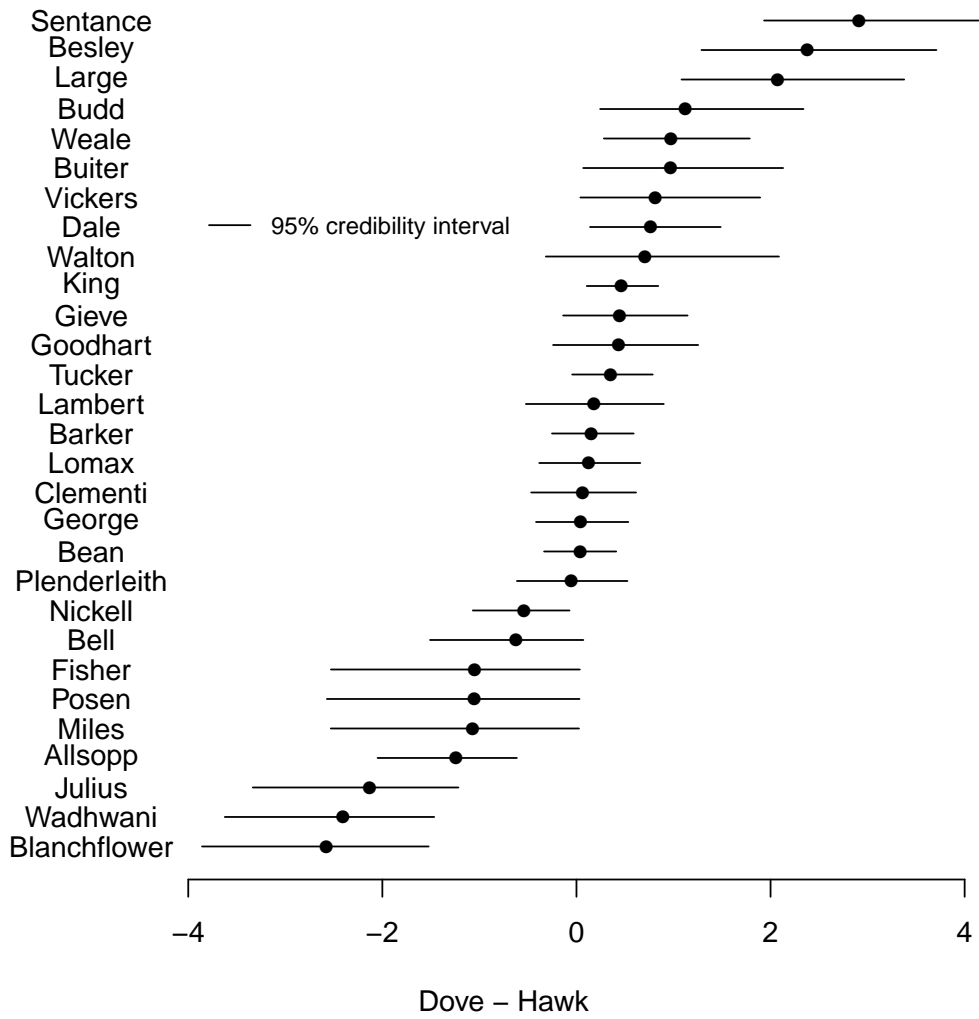


Figure 3: This figure is a graphical representation of the estimated ideal points of the monetary policy committee members. A point indicates the estimate of the ideal point, the thin line represents the 95% credible interval.



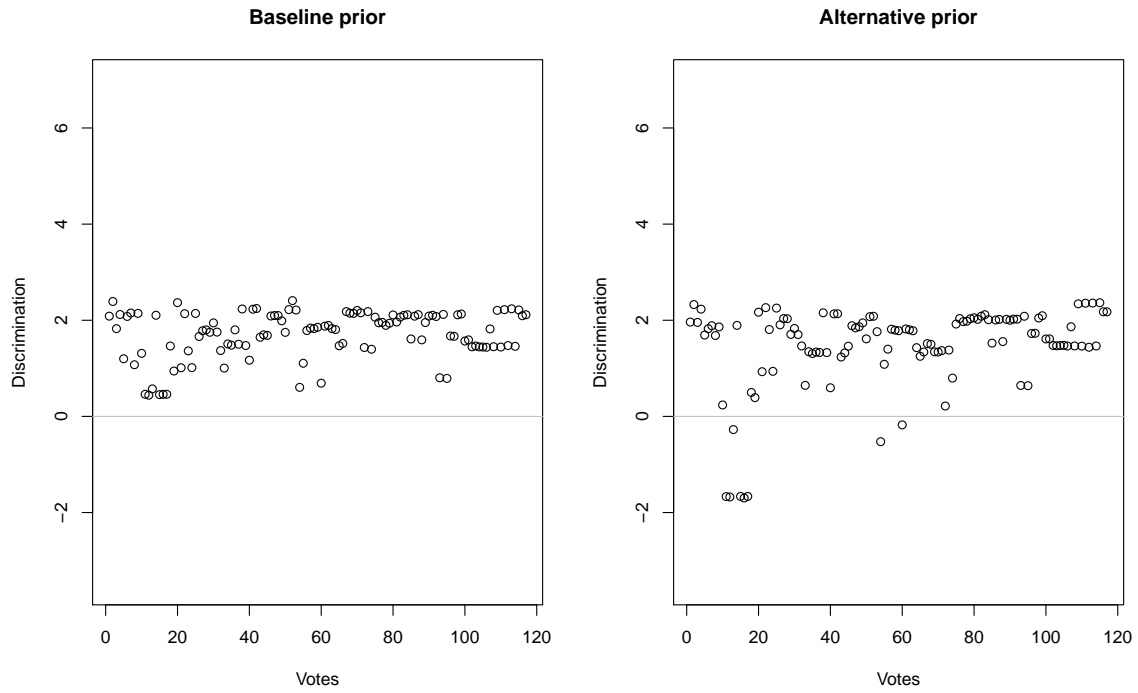


Figure 4: These graphs presents the estimates of the discrimination parameters  $\beta_t$ , plotted across meetings. The left graph shows the estimates under the baseline prior choice and the right graph under the alternative prior choice. Under the alternative prior choice, the discrimination parameters are not constrained to take on nonnegative values. In this case we see two clusters of negative discrimination parameters.

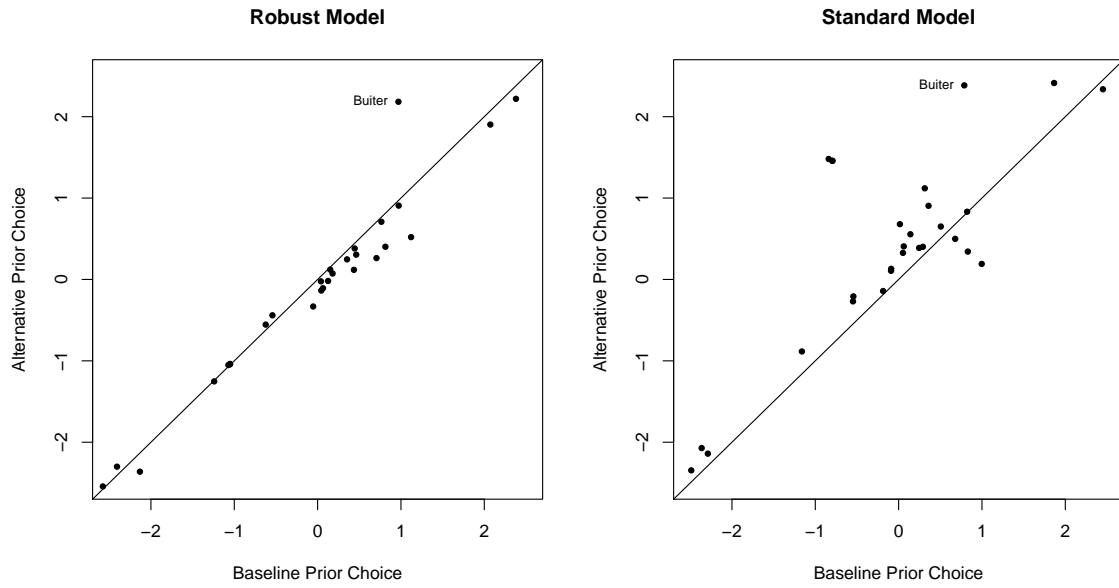


Figure 5: In these graphs we compare the ideal points found under the baseline prior choice (horizontal axis) and the alternative prior choice (vertical axis). When the ideal points are exactly the same under both prior choices, the dots should all lie on the 45 degree line. The further away from this line, the more the estimate is sensitive to the choice of prior. In the left graph this comparison is presented for the robust spatial voting model. All dots are close to the diagonal line except for the ideal point of Buiters. The right graph displays the comparison for the standard spatial voting model. We see that the estimates are far less stable.

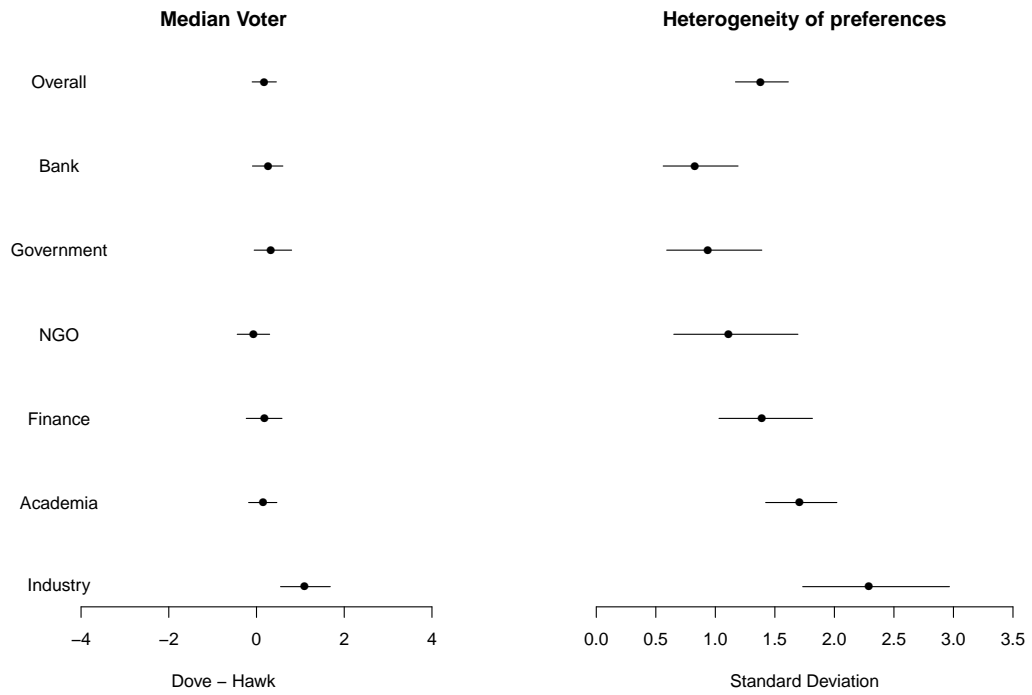


Figure 6: In the left graph we present the ideal point of the median voter of different groups of voters. In the right graph we present the dispersion of ideal points. The dot represents the median of the posterior distribution, the line represents the 95% credible interval. The groups of voters are constructed according to the career backgrounds displayed in Table 4. Voters may belong to multiple groups.

Example 1: April 6 2006			Example 2: May 4 2006		
Name	Vote Casted	Coded once as	Vote Casted	Coded once as	Coded a second time as
King	+0	1	+0	0	1
Lomax	+0	1	+0	0	1
Tucker	+0	1	+0	0	1
Bean	+0	1	+0	0	1
Barker	+0	1	+0	0	1
Nickell	-0.25	0	-0.25	0	0
Walton	+0	1	+0.25	1	1
Gieve	+0	1	+0	0	1

Table 1: This table explains how the data were coded. Example 1 shows the situation where there were only two alternatives favored. In Example 2, votes were split among three policy choices.

Parameter	Baseline Prior	Alternative Prior
$\epsilon_0$	$\sim \text{Uniform}(0, 0.1)$	$\sim \text{Uniform}(0, 0.1)$
$\epsilon_1$	$\sim \text{Uniform}(0, 0.1)$	$\sim \text{Uniform}(0, 0.1)$
$\alpha_t$	$\sim N(0, 4)$	$\sim N(0, 4)$
$\beta_t$	$\sim N(1, 4)$ truncated at 0	$\sim N(1, 4)$
$x_n$	$\sim N(0, 1)$	$\sim N(0, 1)$ with $x_{\text{Blanchflower}}, x_{\text{Wadhvani}}$ truncated above at 0 with $x_{\text{Large}}, x_{\text{Sentance}}$ truncated below at 0

Table 2: This table provides an overview of the two sets of prior choices we work with throughout the paper. Our preferred choice is labeled as baseline prior. The alternative prior serves as a check.

Voter	Excess error rate	Voter	Excess error rate	Voter	Excess error rate
George	-0.13	King	-0.09	Lomax	-0.07
Large	-0.09	Tucker	-0.07	Bean	-0.14
Barker	-0.07	Nickell	0.04	Allsopp	-0.16
Bell	-0.02	Lambert	-0.18	Budd	-0.12
<b>Buiter</b>	<b>0.25</b>	Goodhart	-0.16	Vickers	-0.11
Julius	-0.07	Wahwani	-0.01	Plenderleith	-0.04
Clementi	-0.13	<b>Walton</b>	<b>0.25</b>	Gieve	-0.03
Blanchflower	-0.03	Besley	0.03	Sentance	-0.08
Dale	-0.22	Fisher	-0.02	Miles	-0.02
Posen	-0.02	Weale	-0.21		

Table 3: This table reports the excess error rates for the voters as defined in the text. An excess error rate refers to the proportion of errors beyond what would be expected given the the parameter predictions of the model. The largest excess error rates (Buiter and Walton) are in bold.

Name	Internal or External	Political or Non-political	Finance	Industry	Government	Academia	Bank	NGO
George, Eddie	Internal	Political	N	N	N	N	Y	Y
King, Mervyn	Internal	Both	N	N	N	Y	Y	N
Clementi, David	Internal	Political	Y	N	N	N	N	N
Large, Andrew	Internal	Political	Y	Y	Y	N	N	N
Lomax, Rachel	Internal	Political	N	N	Y	N	N	Y
Gieve, John	Internal	Political	N	N	Y	N	N	N
Plenderleith, Ian	Internal	Non-political	N	N	N	N	Y	Y
Dale, Spencer	Internal	Non-political	N	N	N	N	Y	N
Fisher, Paul	Internal	Non-political	N	N	N	N	Y	N
Vickers, John	Internal	Non-political	N	N	N	Y	N	N
Bean, Charles	Internal	Non-political	N	N	Y	Y	N	N
Tucker, Paul	Internal	Non-political	Y	N	N	N	Y	N
Buiter, Willem	External	Political	N	N	N	Y	N	N
Goodhart, Charles	External	Political	N	N	Y	Y	Y	N
Julius, DeAnne	External	Political	N	Y	N	Y	N	Y
Budd, Sir Alan	External	Political	Y	N	Y	Y	N	N
Wadhvani, Sushil	External	Political	Y	N	N	Y	N	N
Nickell, Stephen	External	Political	N	N	N	Y	N	N
Allsopp, Christopher	External	Political	N	N	N	Y	Y	N
Barker, Kate	External	Political	N	Y	N	N	N	N
Bell, Marian	External	Political	Y	N	Y	N	N	N
Lambert, Richard	External	Political	Y	N	N	N	N	N
Walton, David	External	Political	Y	N	N	N	N	N
Blanchflower, David	External	Political	N	N	N	Y	N	N
Besley, Tim	External	Political	N	N	N	Y	N	N
Sentance, Andrew	External	Political	N	Y	N	Y	N	N
Weale, Martin	External	Political	N	N	N	Y	N	N
Miles, David	External	Political	Y	N	N	Y	N	N
Posen, Adam	External	Political	N	N	N	Y	Y	N

Table 4: The information provided in this table draws upon tables provided by [Harris, Levine, and Spencer \(2011\)](#) and [Hansen, McMahon, and Rivera \(2013\)](#) which we updated for members who joined the monetary policy committee after May 2007. Y (N) stands for Yes (No) and means that the monetary policy member does (not) have career experience in that sector. Some classifications required judgement calls. In particular we classified Weale and Posen to have academic experience. Weale spent time at the NIESR which we consider to be an academic institution. Similarly we labeled Posen’s experience at the Peterson Institute, combined with his publication record as academic experience.

Voter	Probability of being the most dovish	Voter	Probability of being the most hawkish
Blanchflower	$\sim 47\%$	Sentance	$\sim 65\%$
Wadhvani	$\sim 32\%$	Besley	$\sim 23\%$
Julius	$\sim 16\%$	Large	$\sim 11\%$
Fisher	$< 2\%$	Budd	$< 1\%$
Miles	$< 2\%$	Buiter	$< 1\%$
Posen	$< 2\%$	Walton	$< 1\%$
Allsopp	$< 1\%$	Vickers	$< 1\%$
Bell	$< 1\%$		

Table 5: This table reports the probability of being the most dovish and being the most hawkish. Policy preferences are estimated with uncertainty. Small voting histories and lop-sided voting records induce uncertainty. Our ranking of voters incorporates this and for each rank we have a probability mass distribution. In this table we report the voters for which we found a non-zero probability of being the most dovish or the most hawkish, based on our preferred model and 10,000 draws from our MCMC algorithm.