Hawks and Doves at the FOMC

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All comments are welcome

Abstract: In this paper we estimate ideal points of Bank Presidents and Board Governors at the FOMC. We use stated preferences from FOMC transcipts and estimate a hierarchical spatial voting model. We find a clear difference between the average Board Governor and Bank President. We find little evidence for difference in ideal points according to the appointing president in case of Bank Governors. Similarly career background has no clear effect on the ideal points. We find that the median ideal point at the FOMC has been fairly stable over our sample period (1989-2007) emphasizing the lack of a political appointment channel. We also show that there was considerable variation in the median ideal point of Bank Presidents and Board Governors, but that these seem to cancel each other out. Also the dispersion of opinions (the spread between the lowest and highest ideal point) varies over time, suggestion variation in agreement at the FOMC.

Keywords: Central Banks; Committees; Transcripts; Ideal Points; FOMC

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1 Introduction

Central bankers at the major central banks increasingly do their job in the spotlight. The press reports extensively on policy meetings and policies are discussed (and criticized) at length. Some central bankers even have obtained a superstar status. Ben Bernanke was in 2009 selected as *Time Person of the Year*. Meanwhile Mario Draghi is routinely referred to as *Super Mario* in economic reporting.
Current reporting about monetary policy bears similarities to reporting about sports or politics. Committee members are divided into camps or ideologies, with the divide indicated by the terms *hawks and doves*. The idea of classifying central bankers into doves and hawks resembles the idea of classifying politicians into left wing or right wing. As in politics, there also exist moderate and extreme versions of these labels e.g. arch-dove versus moderate dove.
This binary view on central bankers is not unique to the press and opinion makers, also academics have used this viewpoint to discuss preferences of, and decisions by central bankers. The central bank profession does not seem particularly enthusiastic about such a framework. Exemplary is the following quote by Mervyn King, former governor of the Bank of England:

> 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. (King (2010))

Mervyn King, as many other central bankers, dislikes being *reduced* to either a dove or a hawk. After all, monetary policy is a complex activity. When reading a transcript of any monetary policy meeting, one quickly senses that central bankers take information of a whole range of economic variables into account. Also in academia some worry about *an oversimplistic categorisation of the outcome to categorise the decision-making process* (Schonhardt-Bailey (2013)). Others look more favorably upon this practice. Morris (2002) defends the single dimension approach by pointing out that a multidimensional approach entails substantial complexity with no apparent payoff: *"Ease and tightness are clearly captured in a single dimension, and it is not obvious what other aspects of monetary policy-making would be captured with additional dimensions.* (Morris (2002), p.38)

In practice classifying remains a popular activity. Central bank watchers tend to classify central bankers on the basis of voting records (if available) or on the basis of quotes by the respective central bankers. In the academic literature, classification is done on the basis of econometric models with central banker specific parameters which can arguably be interpreted as capturing the position of the central banker on a dove-hawk scale. A first goal of this paper is to carry out such an exercise for the FOMC. To do this we employ a methodology originating in other disciplines of which we feel that is an interesting alternative to the prevailing methods in the economic literature. At the same time we investigate whether it is defensible to talk about doves and hawks. Can we describe preferences well with such a classification? After we have classified FOMC members on a dove-hawk scale we investigate the (in-sample) predictive performance of our classification. It turns out that the prediction errors are small suggesting that our unidimensional model is able to describe the observed preferences well. As we explain in this paper, we do not use the official voting records, but we rely on the stated preferences of FOMC members during the meetings. By doing so, we resolve some of the concerns of Schonhardt-Bailey (2013) who rightly points out that: *"[...] self-evident that the preferences of FOMC members are captured only in part by their votes [...]"*. A second goal of this paper is to investigate the determinants of FOMC member preferences. Are there characteristics of FOMC members which robustly predict the latent preference. We think of career backgrounds and an appointment channel. We devote considerable attention to the difference between Board Governors and Bank Presidents and we also study the evolution of preferences of these groups over time.

It is important to note that there does not seem to be wide agreement on a precise, operational definition of doves and hawks. The following quote taken from The Economist is illustrative:

> [...] on whether Janet Yellen (Federal Reserve chair-apparent) is a hawk or a dove. But while both authors have sensible things to say, the discussion mostly demonstrates the weakness of the hawk-dove framework. **The problem is that we don't all go into discussion with a common definition of what it is to be a hawk or a dove**. (Economist (2013))

In this paper we propose to use an ideal points model to pinpoint monetary policy committee members as hawks or doves. We operationalize the idea of hawks and doves within such an ideal points model. Roughly put, a dove would, all other things equal, be more inclined to favor a lower interest rate than a hawk. In the present paper, the ideal points model is stylized. The estimated ideal points are not pure measures of the personal preference but are a mix of different influences and the latent personal preference.

Related literature In this paper we rely on a Bayesian ideal points model. To our knowledge we are the first to examine preferences at the FOMC with such a model. This type of model is heavily used in political science, see for example Clinton, Jackman, and Rivers (2004), Bafumi, Gelman, Park, and Kaplan (2005), Martin and Quinn (2002), Lauderdale (2010). Economic applications are scant and we are only aware of applications related to preferences of monetary policy committee members. Hix, Hoyland, and Vivyan (2010) and Eijffinger, Mahieu, and Raes (2013a) analyzed voting records at the Bank of England, Eijffinger, Mahieu, and Raes (2013b) consider voting records at smaller continental central banks. An important difference with these papers is that we do not use voting records directly but instead we construct *hypothetical votes* from preferences expressed by FOMC members during meetings. This approach follows the work by Meade (2005) who argued that the preferences stated in meetings better reflect the opinions held by monetary policy committee members than the voting records.

Interest in individual policy preferences of FOMC members is not new. An early attempt can already be found in Canterbery (1967) who coded individuals' preferences based on comments recorded as the memoranda, see Chappell, Havrilesky, and McGregor (2000). Until Tootell (1991) researchers compared frequencies of dissent of Board Governors and Bank Presidents, see for example Puckett (1984) or Belden (1989). Tootell (1991) realized that FOMC member actions (i.c. dissents) may have a different meaning across the business cycle and proposed a multinomial logit model with bank dummies to gauge the differences between districts. Chappell, Havrilesky, and McGregor (1993) advanced this literature by devising a method for estimating reaction functions that can vary across individuals. Since then a fertile literature developed with researchers estimating reaction functions for individual monetary policy committee members of different central banks and for various time periods. None of these papers analyze voting behaviour at the FOMC at the individual level. Studying the individual level reduces the risk of confounding individual level and group level determinants, Hix, Hoyland, and Vivyan (2010). An interesting alternative approach is developed in Chang (2001) who proposes a rudimentary approach to infer ideal points. There are some issues with the results provided by her. Morris (2004) finds some of the estimated ideal points difficult to reconcile with what is known about the individuals. Statistically one may worry about the consistency of the estimates given that Chang (2001) works with very small samples while invoking an asymptotic argument. Chang (2001) also does not present errors or confidence intervals for the ideal points which make the results in practice less useful.

Estimating spatial voting models or ideal point models, the route we take in this paper, has a long history in political science and the empirical analysis of legislative bodies, see Poole and Rosenthal (1985). The Bayesian ideal points approach developed by Clinton, Jackman, and Rivers (2004) which led to new applications such as the analysis of social network data, see Barberá (2014). The advantages of the Bayesian ideal points model are its flexibility (as we demonstrate in this paper), the capacity to deal with small samples and the fact that we obtain a joint probability distribution of all individual ideal points. This allows for much richer inference. For example, consider the question who is the most hawkish FOMC member. Given that ideal points are estimated with uncertainty , a rank ordering based on these ideal points is also subject to this uncertainty, see Jackman (2009). It may very well be the case that there are multiple contenders for the spot of most hawkish FOMC member. Who is then the most likely *arch-hawk*? And by what margin? Issues like this are easy to deal with, with the statistical approach we propose in this paper.

Outline This paper is structured as follows. In section 2 we briefly lay out the statistical framework. We briefly discuss the canonical spatial voting model, we discuss a hierarchical extension and then we show how we develop robust versions of these models. In section 3 we discuss our data. We argue why we use preference data, we discuss how we code the preferences and we provide an overview of our sample. In section 4 we present our analysis. We first present and discuss the estimated individual ideal points. Then we discuss the evolution of preferences at the FOMC. We look at the median ideal point as well as the most outspoken preferences. We also compare the evolution of the median ideal point among Bank Presidents and Board Governors. We end this section with one small sanity check. In section 5 we discuss a variety of robustness checks and model checks. These checks show in detail in which areas our model performs well and which aspects leave room for improvement. In section 6 we conclude.

2 Statistical framework

2.1 Canonical Bayesian spatial voting model

In this section we lay out the spatial voting model as put forward by Clinton, Jackman, and Rivers (2004). The methods presented in this section are not new but given that they are seldomly used in economics we present them here briefly. First we discuss the spatial voting model in its canonical form as in Clinton, Jackman, and Rivers (2004), then we show a hierarchical extension. We end by discussing how to we can make these models robust to outliers.

Suppose we have $n = 1, \dots, N$ voters who are faced with $t = 1, \dots, T$ policy proposals. A policy proposal t presents a voter the choice between policies ψ_t and ζ_t. The policies are functions of a wide range of economic variables but they differ only in the proposed policy rate. Let ζ_t be the higher policy rate and ψ_t the lower policy rate. If voter n chooses the hawkish policy choice at time t we observe $y_{nt} = 1$, otherwise we observe $y_{nt} = 0$. The preferred policy of voter n, also called an ideal point, is a scaler number x_n on the real line $\mathbb{R}$. We assume quadratic utility. The utility voter n derives from choosing ζ_t can be written as: $U_n(\zeta_t) = -\|x_n - \zeta_t\|^2 + \nu_{nt}$. Similarly we write $U_n(\psi_t) = -\|x_n - \psi_t\|^2 + \eta_{nt}$. Utility maximization implies that a voter chooses the hawkish policy choice at time t if $U_n(\zeta_t) - U_n(\psi_t) > 0$. We can rewrite this as follows: $U_n(\zeta_t) - U_n(\psi_t) = \|x_n - \psi_t\|^2 - \|x_n - \zeta_t\|^2 + \eta_{nt} - \nu_{nt} = (\psi_t^2 - \zeta_t^2) + 2(\zeta_t - \psi_t)x_n + (\eta_{nt} - \nu_{nt})$. Assuming a type-1 extreme value distribution for the error terms leads to:

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

which is a logit specification with $\beta_t = 2(\zeta_t - \psi_t)$ and $\alpha_t = (\zeta_t^2 - \psi_t^2)$. The x_n are the policy preferences or *ideal points* of voters n, whereas α_t are vote parameters which capture the overall inclination to vote dovish. The parameters β_t are known as discrimination parameters and capture the extent to which the dove-hawk dimension matter in predicting the observed choices. For example, if β_t equals zero, then we have $\beta_t x_n = 0$ and the preferences on the underlying dove-hawk dimension have no impact on the choice between two competing policy options. To identify the parameters we need to put some restrictions on the parameters. There are several possibilities to do this, see Clinton, Jackman, and Rivers (2004). A standard approach is to constrain the ideal points x_n to have mean zero and a standard deviation of one. To fix the left-right ordering we restrict the discrimination parameter to be positive. The restrictions ensure global identification of the parameters, see also the discussion in Eijffinger, Mahieu, and Raes (2013a). This leads to the following priors:

$$
\begin{aligned}
x_n &\sim N(0,1) &(2)\\
\beta_t &\sim N(1,4) \quad \text{truncated at } 0 &(3)\\
\alpha_t &\sim N(0,4). &(4)\\
& &(5)
\end{aligned}
$$

The prior on α_t and β_t are fairly diffuse (given the prior on the ideal points). This choice of priors identifies all parameters and has been employed elsewhere, see for example Hix, Hoyland, and Vivyan (2010). Eijffinger, Mahieu, and Raes (2013a) use a similar setup and present a sensitivity analysis demonstrating that the prior variances have little impact on the estimates of the ideal points.

2.2 Hierarchical extension

To make use of the observable data we have on voters, we extend the model given by equation 1 into the following hierarchical model:

$$
\begin{aligned}
P(y_{nt} = 1) &= \text{logit}^{-1}(\beta_t x_n - \alpha_t) &(6)\\
x_n &\sim N(\mu_x, \sigma_x^2) &(7)\\
\mu_x &= \gamma \boldsymbol{v_n} &(8)\\
\sigma_x &\sim \text{Unif}(0,1) &(9)\\
\gamma &\sim N(0,2) &(10)\\
\beta_t &\sim N(1,4) \quad \text{truncated at } 0 &(11)\\
\alpha_t &\sim N(0,4). &(12)
\end{aligned}
$$

The ideal points x_n are now modeled in such a way that they allow for exogenous explanatory variables $\boldsymbol{v_n}$, to enter the prior mean parameter. The priors on the hyperparameters reflect uncertainty on how the observables $\boldsymbol{v_n}$ are related to the ideal points x_n.

2.3 Robust extensions

Standard ideal point models as in equation 1 may be prone to outliers, see Bafumi, Gelman, Park, and Kaplan (2005). These problems mimic issues with robustness for probit and logit models in general, see Pregibon (1982) and Liu (2004).

Bafumi, Gelman, Park, and Kaplan (2005) modify the canonical ideal point model by adding error probabilities: $P(y_{nt} = 1) = \epsilon_0 + (1 - \epsilon_0 - \epsilon_1)\text{logit}^{-1}(\beta_t x_n - \alpha_t)$. An alternative way to make the model robust follows a sugestion by Liu (2004). This approach, called *robit*, replaces the normal cumulative distribution function of the probit model, with a cumulative distribution function of a **t**-distribution centered at zero, with 7 degrees of freedom and with scale parameter 1.5484. This link function approx-

imates the logistic link, see Liu (2004), but has heavier tail probabilities which makes the model more robust to outliers.
In section 5 we discuss the results of implementing a robit version of the hierarchical models we use in the main part of this paper.

All spatial voting models discussed in this paper are implemented in Stan (see Stan Development Team (2014)), a C++ library with implementations of the No-U-Turn Sampler (abbreviated as NUTS), an extension to Hamiltonean Monte Carlo. The advantage of NUTS is that it converges often quickly to high-dimensional target distributions (as in our case) without the need of user intervention or tuning runs as is needed with regular Hamiltonean Monte Carlo. The results in this paper testify hereto. All results presented in this paper are based on runs of three chains with 15000 iterations. This is in fact much more than often needed to achieve convergence and good mixing, but much less than what is needed to obtain convergence when resorting to Gibbs sampling or slice sampling. We monitored convergence of all models we estimated, by means of the R-statistic as well as a battery of standard convergence tests.

3 Data

When analyzing decisions by monetary policy committees, researchers often rely on voting records. This approach is sensible if voting records are sufficiently informative of the preferences of individual committee members. For the FOMC there are good reasons to doubt this. The dissent rate at the FOMC has historically been lower than at other major banks. This low dissent rate in fact hides differences in opinion of FOMC members. Under Alan Greenspan meetings were often structured in two rounds of discussion. A first round offered participants the possibility to present their views on the state of the economy. Presidents of the Federal Reserve Banks had the possibility to present specific information on developments in their region. The second round was devoted to policy options and culminated in the chairman presenting his views and making a policy recommendation. This was followed by other participants responding and making own recommendations. At the end of the second round Greenspan made a final proposal which was taken to a formal vote, with the chairman first to vote. Meade (2005) read and coded the transcripts of meetings in the period 1989-1997 and showed that participants generally voice an explicit policy preference in the second round. The disparity between the disagreement in *voiced preferences* and the dissent rate in official votes is remarkable. Meade (2005) reports a dissent rate in official votes in her sample of 7.5% whereas the disagreement in voiced rates among voters is 28.2%. Among central bank observers and academics there is a consensus that FOMC voters face a threshold when intending to vote against the proposal of the chairman. The exact nature of this threshold is unsure. There may be a collective believe that dissent weakens the FOMC as institution. Or the chairman could have obtained a status which would induce members to reconsider their opinion or maybe FOMC members feel inclined to support the chairman as he is the one who needs to testify in Congress semi-annually.[1]

The threshold phenomenon described above complicates our empirical analysis as we are interested in the preferences of individual FOMC members. Using the official voting record a lot of disagreement is disguised and consequently lowers variation in the data. To overcome this, we build a dataset of *hypothetical votes*. Construction of this dataset consists of two stages. First, we build a preference dataset extending the work by Meade (2005). Meade (2005) build a dataset with the policy preferences for 72 FOMC meetings from 1989 through 2007. We extend this dataset up until 2007. Second, we recode the preference data in a format amenable to our modeling approach. Our approach consists of estimating

[1]See Meade (2005) for an outline of the arguments and Meade and Sheets (2005) for an empirical paper which incorporates the threshold idea. Blinder (2007) also suggests that voting against the chairman was rare because of informal hurdles.

spatial voting models with binary dependent variables. We now are going to discuss both stages in detail.

3.1 Preference data

To construct our preference data we follow Meade (2005) and her sample up until 2007. For each FOMC meeting we read the transcript and coded a preference if a committee member voiced his preference in such a way that there is no doubt about his position. An example is: *Therefore, I can certainly support another increase in the funds rate of 25 basis points today (Yellen, transcripts of June 2006).* For most members during most meetings this is straightforward to do. However, there are some more difficult cases. In these cases we followed the guidelines and approach by Meade (2005). In an appendix to this paper, we provide an overview of the different cases we encountered and how we dealt with these situations. Here we discuss the most difficult, ambiguous cases to code.

A first situation occurs when the committee member states that action should be taken at this meeting without explicit mention what the action might be. If the context clearly describes whether the change is positive or negative and the size of that change, then we code the preference accordingly. If only the direction is mentioned or if the direction is not clear, we do not code this preference. This is very though in this sample. Another difficult (and rare) situation is a situation where a committee member does not express his opinion directly. This situation occurred in two forms. Sometimes a committee member only stated that he agreed with the chairman. In that case we code the preference as equal to the preference of the chairman. The other situation that occurred was that the committee member made clear that (s)he did not share the opinion of the chairman but there was too much uncertainty to be clear on the preferred policy choice. In that case we did not code the preference.

To make sure that there was some consistency in coding, we carried out two additional checks. First, the statements were coded by one of the authors of this paper as well as by one research assistant. The preferences were coded independently of each other and were afterwards compared. Second, both recoded a few yares from the sample coded by Meade (2005) and checked whether the same results were obtained. It turned out that we had coded the preferences in exactly the same way in all cases.

A second step in our data construction consists of recoding the preferences in a format amenable to our methodology, the hypothetical votes. In our analysis we drop meetings with unanimous preferences as these meetings are uninformative for our purposes. The remaining meetings were coded as decisions over two alternatives. The more restrictive alternative is the hawkish alternative and coded as 1, the other alternative is the dovish alternative and coded as 0. Table 1 clarifies this with two examples. In example 1, we have a meeting where two types of preferences were expressed. Three members expressed a preference for an increase of the federal funds rate with 25 basis points, we coded their preference as hawkish or 1. The other FOMC members favored an unchanged federal funds rate and we coded their preference as dovish or 0. In example 2 we have a situation where three FOMC members favor lowering the federal funds rate with 25 basis points, one FOMC members prefers lowering the federal funds rate with 50 basis points, while the other FOMC members favor the status quo. Such a meeting is recoded into two decisions over two alternatives. We code this once as the choice between lowering the federal funds rate by 50 basis points (coded as 0) or lowering the federal funds rate by 25 basis points or keeping the federal funds rate unchanged. We code these preferences a second time as a choice between lowering the federal funds rate (coded as 0) or keeping the federal funds rate unchanged (coded as 1).

To get an idea of how the data looks like we present in Table 2 summary statistics of the hypothetical votes. The table shows for each committee member the number of hypothetical votes (preferences coded) as well as the fraction of hawkish votes. We see substantial variation in the number of observations we have for each voter. We need a minimum number of votes to be able to estimate the ideal

Table 1: Examples of the coding scheme

Example 1: August 8 2006			Example 2: October 6 1992			
Name	Preference	Coded once as	Name	Preference	Coded once as	Coded a second time as
Greenspan	0	0	Greenspan	0	1	1
Plosser	0	0	McTeer	0	1	1
Pianalto	0	0	Kelley	0	1	1
Minehan	+25	1	Lindsey	-25	1	0
Hoenig	0	0	Parry	-25	1	0
Fisher	0	0	Black	-25	1	0
Stern	0	0	Stern	0	1	1
Poole	0	0	Melzer	0	1	1
Yellen	0	0	Corrigan	0	1	1
Lacker	+25	1	Phillips	-50	0	0
Geithner	0	0	Angell	0	1	1
Moskow	+25	1	LaWare	0	1	1
Guynn	0	0				
Kohn	0	0				
Kroszner	0	0				
Bies	0	0				
Warsh	0	0				

This table explains how the preferences were re-coded. The preferences are expressed in basis points. Example 1 shows the situation where there were only two alternatives favored. In Example 2, votes were split among three policy choices. In our dataset we coded all preferences expressed at the FOMC meetings, including preferences by Bank presidents without voting rights.

points and for this reason we remove the voters for which we have five or less coded preferences.

The fraction of votes is already indicative for the ideal points of the committee members. However by estimating ideal points we also take the preferences of the other committee members into account and we obtain an estimate of uncertainty. Moreover the spatial voting model takes the relative voting behavior of a voter with respect to the other voters present in a meeting into account. We could have two committee members with nearly identical voting records but different ideal points because they faced a different voting situation during their tenure at the FOMC.

Table 2: Overview of FOMC members

Name	Affiliation	Period	President	# Preferences	Fraction Dovish
Greenspan, Alan	Board	1987-2006	Ronald Reagan	89	0.70
Keehn, Silas	Chicago	1981-1994		36	0.69
Guffey, J. Roger	Kansas City	1976-1991		23	0.43
Melzer, Thomas C.	St.Louis	1985-1998		57	0.26
Boykin, Robert H.	Dallas	1981-1991		23	0.35
Stern, Gary H.	Minneapolis	1985-2009		98	0.57
Fisher, Richard W.	Dallas	2005-		10	0.40
Boehne, Edward G.	Philadelphia	1981-2000		68	0.74
Syron, Richard F.	Boston	1989-1994		34	0.59
**Corrigan, E. Gerald	New York	1985-1993		29	0.48
Hoskins, W. Lee	Cleveland	1987-1991		23	0.13
Forrestal, Robert P.	Atlanta	1983-1995		38	0.74
Black, Robert P.	Richmond	1973-1992		23	0.35
Parry, Robert T.	San Fransisco	1986-2004		85	0.52
*Lyon, James M.	Minneapolis	2003		0	0
McTeer, Robert D.	Dallas	1991-2005		62	0.79
Rosengren, Eric S.	Boston	2007-		3	0.67
Hoenig, Thomas N.	Kansas City	1991-2011		63	0.59
Jordan, Jerry L.	Cleveland	1992-2003		44	0.61
Donough, William Joseph	New York	1993-2003		53	0.79
Geithner, Timothy F.	New York	2003-2009		10	0.60
*Stewart, Jamie B. Jr.	New York	2003		1	0.00
Broaddus, Alfred J.	Richmond	1993-2004		57	0.33
Minehan, Cathy E.	Boston	1994-2007		60	0.52
Moskow, Michael H.	Chicago	1994-2007		55	0.69
Guynn, Jack	Atlanta	1996-2006		47	0.70
*Rives, W. LeGrande	St. Louis	1998		1	1.00
Poole, William	St.Louis	1998-2008		26	0.26
*Varvel	Richmond	1998		0	0.00
*Stone	Philadelphia	2000		4	0.25
Plosser, Charles I.	Philadelphia	2006-		7	0.71
Pianalto, Sandra	Cleveland	2003-		13	0.54
Santomero, Anthony M.	Philadelphia	2000-2006		12	0.33
*Barron, Patrick	Atlanta	2006		2	1.00
LaWare, John P.	Board	1988-1995	Ronald Reagan	42	0.52
Heller, Robert H.	Board	1986-1989	Ronald Reagan	5	0.80
Johnson, Manuel M.	Board	1986-1990	Ronald Reagan	16	0.75
Seger, Martha R.	Board	1984-1991	Ronald Reagan	23	0.91
Kelley, Edward W. Jr.	Board	1987-2001	Ronald Reagan	83	0.73
Angell, Wayne	Board	1986-1994	Ronald Reagan	35	0.34
Mullins, David W. Jr.	Board	1990-1994	George H. W. Bush	17	0.53
Phillips, Susan M.	Board	1991-1998	George H. W. Bush	44	0.86
Lindsey, Lawrence B.	Board	1991-1997	George H. W. Bush	32	0.72
Evans, Charles L.	Chicago	2007-		3	0.67
Lockhart, Dennis P.	Atlanta	2007-		3	1.00
Blinder, Alan S.	Board	1994-1996	Bill Clinton	11	0.91
Lacker, Jeffrey M.	Richmond	2004-		11	0.18
Yellen, Janet	San Fransisco	2004-2010		32	0.88
Rivlin, Alice	Board	1996-1999	Bill Clinton	22	1.00
Meyer, Laurence	Board	1996-2002	Bill Clinton	35	0.83
Gramlich, Edward	Board	1997-2005	Bill Clinton	24	0.67
Ferguson, Roger W. Jr.	Board	1997-2006	Bill Clinton	16	0.64
Olson, Mark W.	Board	2001-2006	George W. Bush	9	0.44
Bies, Susan	Board	2001-2007	George W. Bush	14	0.50
Bernanke, Ben S.	Board	2002-2005	George W. Bush	14	0.57
Kohn, Donald L.	Board	2002-2010	George W. Bush	15	0.53
Kroszner, Randall S.	Board	2006-2009	George W. Bush	10	0.70
Warsh, Kevin Maxwell	Board	2006-2011	George W. Bush	10	0.70
Mishkin, Frederic S.	Board	2006-2008	George W. Bush	6	1.00

This Table provides an overview of the committee members in our dataset. Affiliation specifies whether the committee members are at the Board or at a regional Bank. Period mentions during which period they were Board Governor, Federal Reserve Bank President or when they were acting as a replacement (see below). The number of meetings refers to number of coded preferences. As explained in the text, unanimous meetings are dropped and some meetings are coded multiple times. In the final column we present the fraction of dovish votes to total votes. *: Indicates that this person was not a Federal Reserve president but acted as a replacement during a meeting (meetings). **: Gerald Corrigan was president of the Federal Reserve Bank of Minneapolis from 1980 until 1984 and president of the Federal Reserve Bank of New York from 1985 until 1993. Our sample starts in 1989 so we only have observations of Corrigan in his capacity as president of the Federal Reserve Bank of New York.

4 Results

The hierarchical model given by equations 6-12 does not specify what external information we include. We have explored three sources of external information for the ideal points. First we focused on the distinction between Board Governors and Bank presidents. The results can be found in the column labelled *Model 1* in Table 3. The results suggest, that board governors have on average a more dovish ideal point than Bank presidents.

Next, we categorized the board governors according to the appointing president. This allows us to probe for any political patterns in the appointment of board members. The results of this exercise, see *Model 2 in Table 3*, suggest that the differences due to the political colour of the appointing president are much less pronounced than earlier suggested. The information provided by including only a board dummy or dummies for the different appointed presidents is nearly the same and hence the resulting estimation results for the ideal points are the same.

Then we constructed career related variables. We followed Adolph (2013) in constructing career variables. These variables are constructed as the fraction of the pre-FOMC career spent in a certain job category. The job categories are: in the financial industry (Fin. Exp.), with the government (Gov. Exp.), at the U.S. Treasury (FM Exp.), at the Federal Reserve staff (CB Exp.), as an economist (Eco Exp.) or in private business (Bus Exp.). We found none of these background variables to have an influence on the ideal points of FOMC members. In our final specification we included Board affiliation as well as the career variables. Once again, none of the career variables matter while the estimated parameter on for board affiliation remains negative albeit that the 95% confidence interval barely overlaps with zero. We conclude that career variables have no systematic influence on the latent preferences. For this reason, we present only the results of the specification with Board membership as predictor in the vector v_n (equation 8).

The results of estimating the ideal point model over the entire sample are summarized in Figure 1. This Figure shows a ranking according to the ideal points of all FOMC members in our sample. So we are able to rank and compare Thomas Melzer and Donald Kohn, even though they were never colleagues at the FOMC and hence never voted on the same issues. Figure 1 hence provides a historical ranking of FOMC members. The FOMC members at the bottom of the Figure are clearly the most dovish from a historical perspective, whereas the FOMC members at the top are the most hawkish. However, comparative statements of the ideal points of FOMC members are often more relevant when focusing on members who where at the FOMC contemporaneously. In Figure 2 we show ideal points for FOMC members participating in the meeting of February 1997 and December 2007.

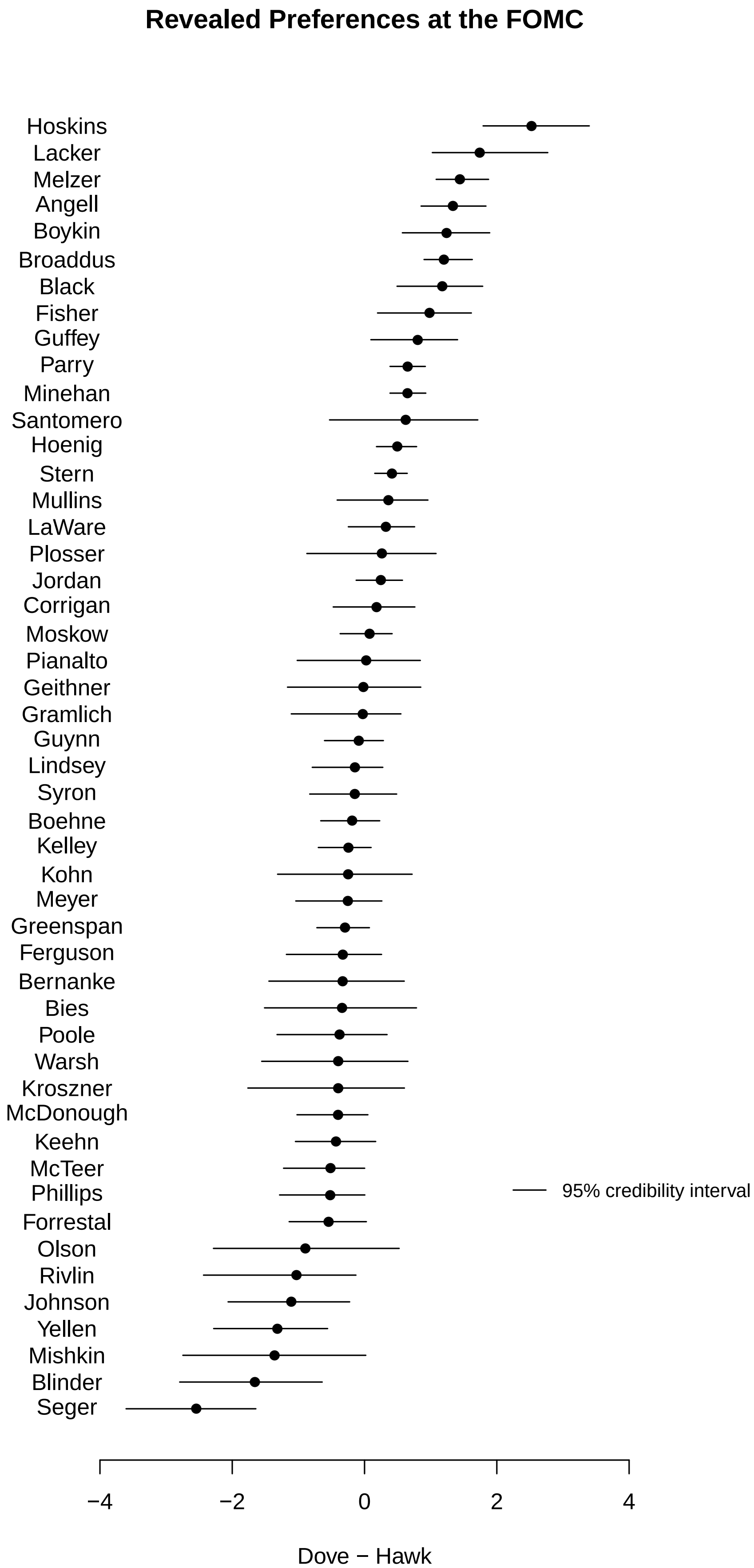


Figure 1: Overview of all ideal points

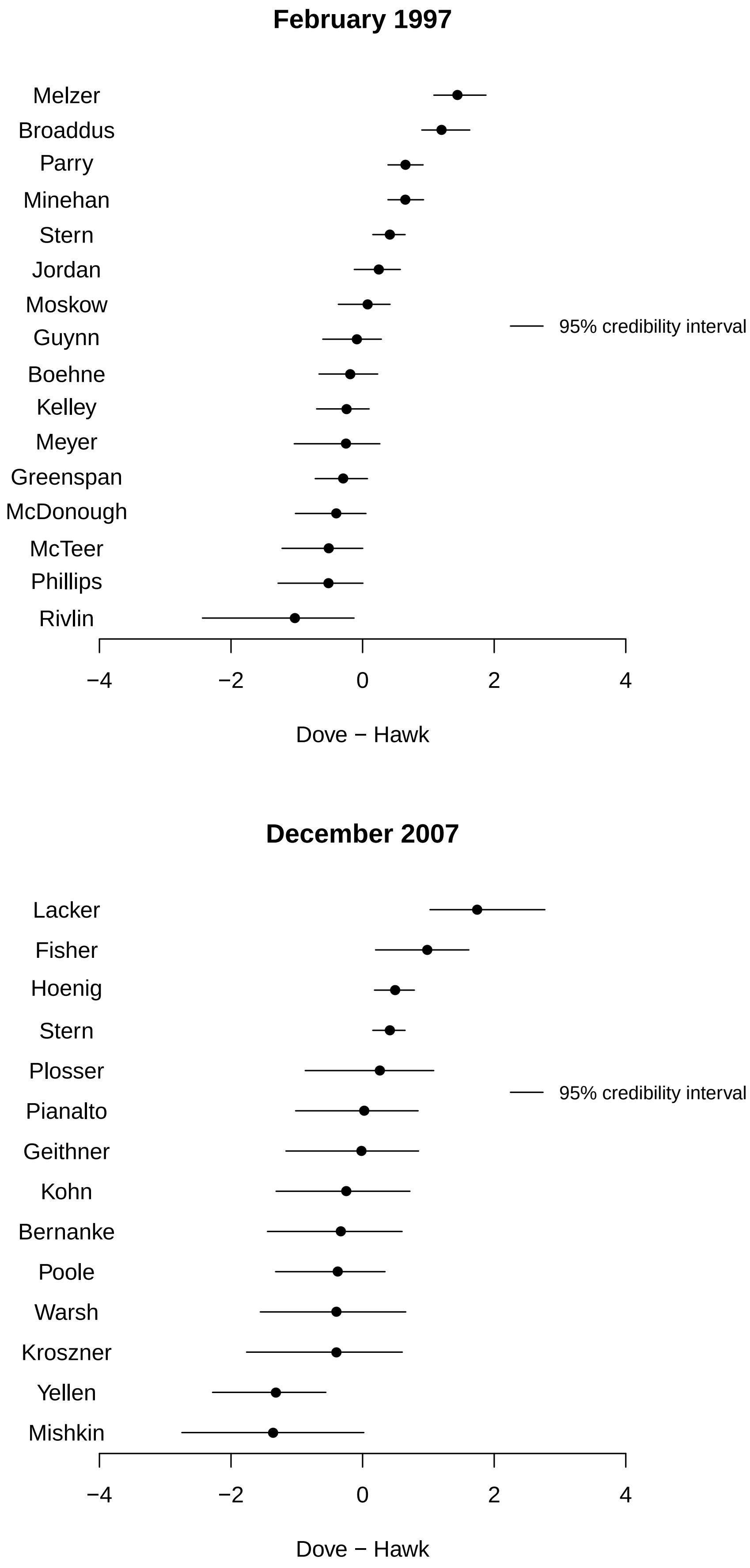


Figure 2: Overview of ideal points of FOMC members in February 1997 and December 2007

Table 3: Overview of the estimated hierarchical parameters in different models

	Model 1	Model 2	Model 3	Model 4
Board Member	-0.856			-0.635
	[-1.41, -0.3]			[-1.32, 0.0579]
	(-1.33, -0.39)			(-1.21, -0.0571)
Reagan		-0.716		
		[-1.56, 0.0673]		
		(-1.43, -0.0331)		
Bush Sr.		-0.331		
		[-1.48, 0.783]		
		(-1.31, 0.606)		
Clinton		-1		
		[-1.97, -0.0446]		
		(-1.83,-0.211)		
Bush Jr.		-1.03		
		[-2.01, -0.016]		
		(-1.84, -0.146)		
Fin. Exp.			0.37	0.227
			[-1.21, 2.02]	[-1.48, 1.83]
			(-0.965,1.74)	(-1.18, 1.57)
Gov. Exp.			-0.746	-0.749
			[-3.34, 1.77]	[-3.26, 1.71]
			(-2.98, 1.39)	(-2.88, 1.3)
FM Exp.			-0.368	-0.683
			[-3.07, 2.09]	[-3.03, 1.87]
			(-2.61 1.78)	(-2.63, 1.51)
CB Exp.			0.588	0.22
			[-0.979, 2.18]	[-1.38, 1.79]
			(-0.701 1.93)	(-1.19, 1.6)
Eco. Exp.			-0.49	-0.356
			[-2.18, 1.2]	[-2.02, 1.36]
			(-1.88, 1.01)	(-1.81, 1.07)
Bus. Exp.			0.409	0.596
			[-1.65, 2.59]	[-1.48, 2.72]
			(-1.32, 2.25)	(-1.16, 2.32)

In this Table we present the estimated *hierarchical* parameters of four different specifications of the model given by equations 6-12. To be specific, the parameter estimates presented here correspond to different parameter vectors $\hat{\gamma}$ in equation 8. In model 1 we only have variable capturing the affiliation with the Board of Governors as hierarchical predictor, in model 2 we have four appointment variables as predictors, in model 3 we have six career background variables and in model 4 we have the same career background variables as well as Board affiliation. Between brackets we display the 95% confidence interval, between parentheses we display the 90% confidence interval.

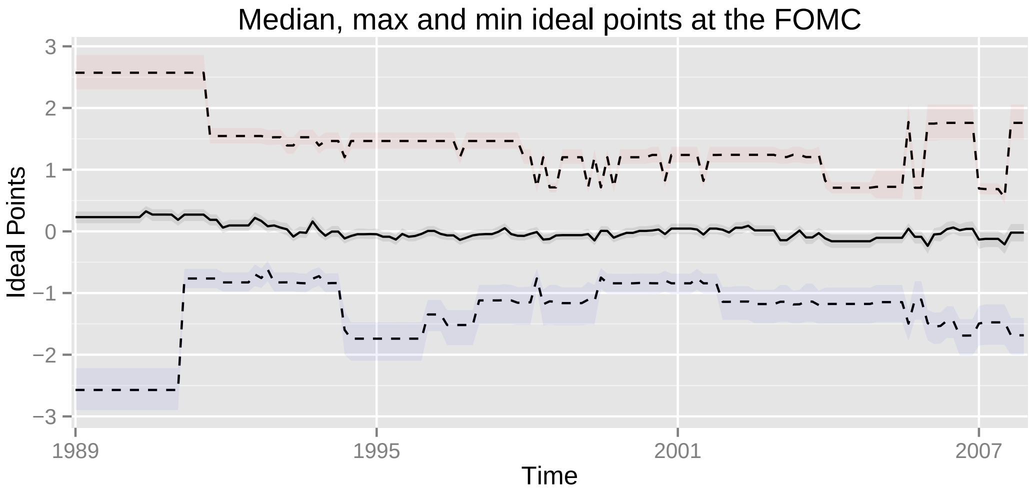
4.1 Evolution over time

Another point of interest is to consider how preferences at the FOMC have evolved over time. In the top graph of Figure 3 we show the evolution of the median ideal point as well as the ideal point of the most dovish and most hawkish member. The median ideal point is remarkably stable over our sample period. This suggests that the rotation of Board governors has not lead to a shift towards a more hawkish or dovish board over time. Above, we expressed doubt about the existence of an effective political appointment channel. This adds evidence to that claim. Even if there would be an effect of political appointment, the median ideal point seems unaffected by this.
The evolution of the most dovish and most hawkish ideal point suggests that the breadth of preferences is not stable over time. At the beginning of our sample we find the largest differences between the most dovish and the most hawkish FOMC member. This difference diminishes as time progresses, only to increase again at the end of our sample.

Our estimation results indicated that the ideal point of a Board Governor is on average more dovish than the ideal point of a Bank president. The bottom graph shows that this results masks variation over time. Sometimes this difference is more pronounced e.g. at the beginning of our sample and in the middle of the nineties. But occasionally roles were reversed such as in the beginning of the nineties, where we briefly find that the median ideal point of Bank presidents was more dovish than the median ideal point of Board Governors. At the end of our sample, the uncertainty on the median ideal point of Board members increases a lot and as a result we have a very imprecise estimate of the median ideal point of the Board Governors, compared to a rather sharp estimate of the median ideal point of Bank presidents.

4.2 One sanity check

The results above are obtained through the estimation of a fairly advanced model. It is a good habit to compare results from elaborate estimation procedures with results obtained in a more straightforward manner. We compare our ideal point estimates with a batting average in a similar spirit as Hix, Hoyland, and Vivyan (2010). In Figure 4 we plot both measures. The batting average is here simpy the number of hawkish preferences we recorded divided by the total number of preferences we recorded. We see a positive correlation between both measures which is reassuring. The batting average measure does not take economic conditions at the time of the meeting into account. All meetings carry an equal weight. This measure also disregards whether a policy member expressed a preference alone versus an otherwise united committee (e.g. an *extreme* opinion) or whether there were groups of opinions. A last issue is that this method does not provide uncertainty estimates. It is hard to judge from the batting average when two members have a truly different latent preference or whether they fall within a margin of error, see also the discussion in Hix, Hoyland, and Vivyan (2010).



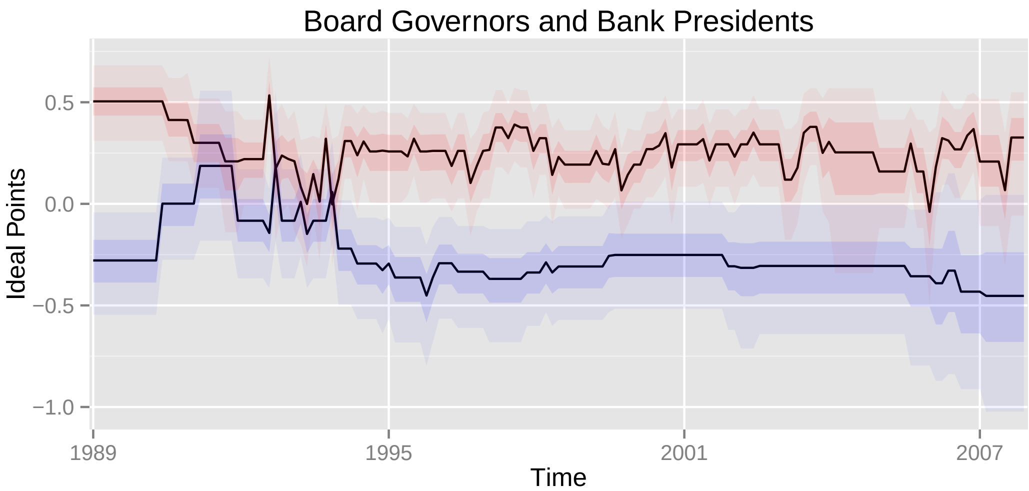


Figure 3: Top: Evolution of the median ideal point, as well as the most dovish and most hawkish ideal point. Bottom: Evolution of the median preference among Board Governors and among Bank presidents at the FOMC.

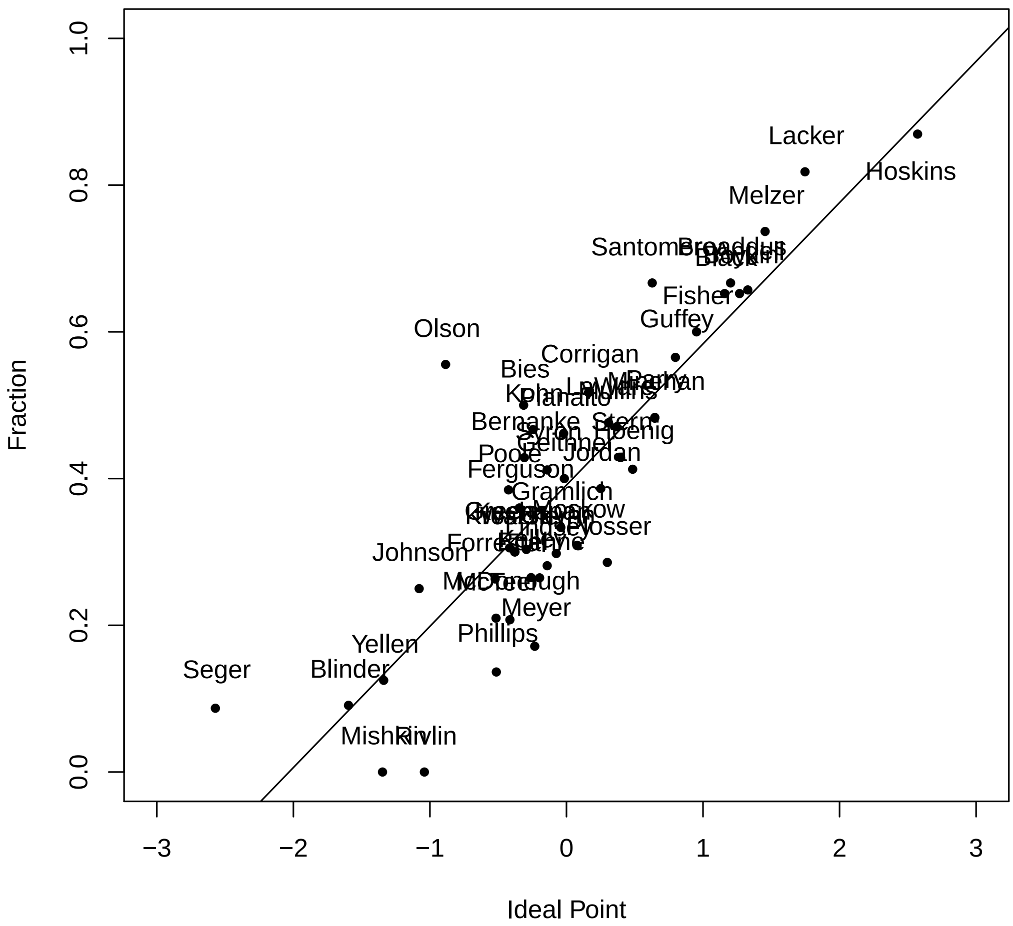


Figure 4: Comparison of our estimated ideal points with a batting average. The line in the figure is the simple linear regression line.

5 Robustness and model checks

In this section we summarize a variety of model checks and sensitivity analyses. These checks show us how well the model performs, in which aspects it does well and in which aspects it performs worse. Additionally these checks help us to understand the extent to which our results hinge on the assumptions we made throughout our analysis. We have carried out the following model checks:

1. Overall prediction errors and the excess error rate for individual FOMC members.
2. Sensitivity analysis of the priors.
3. Stability of the ideal points.

5.1 Prediction errors

Prediction errors are a useful way to evaluate the in-sample predictive performance of an ideal points model. The approach we outline here follows the recommendations by Bafumi, Gelman, Park, and Kaplan (2005). For a model with a binary outcome, a prediction error *pe* occurs when one observes 1 when the model predicts 0 and vice versa. Formally:

$$\begin{aligned} pe_{nt} &= 1 \quad \text{if} \quad \mathbb{E}(y_{nt}) > 0.5 \text{ and } y_{nt} = 0, \text{ or } \mathbb{E}(y_{nt}) < 0.5 \text{ and } y_{nt} = 1 \\ &= 0 \quad \text{otherwise.} \end{aligned} \tag{13}$$

Combining the prediction errors we obtain the error rate, which for our model is 8.7%. This low error rate is not that surprising since our model is parameter rich. Individual prediction errors can also be used to construct excess error rates. The excess error rate is the proportion of errors beyond the errors we expect if the model would be true: $\mathbb{E}(e_{nt}) = \min(\text{logit}^{-1}(\beta_t x_n - \alpha_t), 1 - (\text{logit}^{-1}(\beta_t x_n - \alpha_t)))$. The excess error ee_{nt} is then: $ee_{nt} = pe_{nt} - \mathbb{E}(e_{nt})$. The excess error rates for the different FOMC members are summarized in Table 4. To have an intuition on the size of excess error rates, we can compare with results reported in Bafumi, Gelman, Park, and Kaplan (2005) and Eijffinger, Mahieu, and Raes (2013a). The former paper reports excess error rates mostly between -0.2 and +0.2, with an occasional outlier over 0.5. The latter paper, focusing on the ideal points of monetary policy committee members at the Bank of England, report excess error rates between -0.22 and +0.25. The results here are comforting. The realized excess rates are in general not too large (in absolute sense). We also calculate reference excess error rates. These are excess error rates calculated from observations simulated from our parameter estimates. These reference errors show what we could expect if the model were true. We find that the ideal points of Olson, Geithner, McTeer, Boykin, Jordan, Angell, Hoenig, Lacker, Fisher have elevated excess error rates. Ideal points at the extremes tend to be a bit harder to estimate, because there are fewer possibilities to anchor these from both sides. Especially Fisher and Angell seem to be less accurate. In the case of Fisher we also have relatively few observations (10) which may help to explain the excess error rate. However in general we do not find the excess error rates too worrisome.

5.2 Sensitivity analysis

Our choice of priors was motivated by previous research. To find out how sensitive our results are to our prior choice, we have re-estimated our model with five different sets of priors. We have estimated the model with a larger variance for the parameters α, β_t, γ and ω as well as with a prior on β_t centered on 3. A summary of these different sets of priors for the sensitivity analysis is given by Table 5. The results of this exercise is summarized in Figure 5. Graphs in the left column plot the ideal points we

Table 4: Overview of prediction errors

	Realized excess error rates	Reference excess error rates	Difference (in absolute value)
Syron	0.03	0.03	0
Corrigan	-0.06	-0.06	0
Geithner	-0.1	-0.1	0
Seger	-0.03	-0.03	0
Kelley	-0.03	-0.03	0
Mullins	0.04	0.04	0
Yellen	0	0	0
Rivlin	0	0	0
Kohn	-0.04	-0.04	0
Warsh	0.05	0.05	0
Mishkin	-0.01	-0.01	0
McDonough	-0.04	-0.03	0.01
LaWare	0	-0.02	0.02
Phillips	0.05	0.03	0.02
Stern	0.01	-0.02	0.03
Boehne	0.03	0.06	0.03
Moskow	0	-0.03	0.03
Meyer	-0.02	0.01	0.03
Guffey	0.02	0.06	0.04
McTeer	0.06	0.02	0.04
Guynn	0.02	-0.02	0.04
Poole	0.03	-0.01	0.04
Melzer	-0.01	0.04	0.05
Black	0.07	0.02	0.05
Bernanke	-0.01	-0.08	0.07
Forrestal	0.08	0	0.08
Broaddus	0.04	-0.04	0.08
Ferguson	-0.06	0.02	0.08
Greenspan	-0.06	0.03	0.09
Parry	0.06	-0.03	0.09
Lindsey	0.09	0	0.09
Blinder	-0.04	0.05	0.09
Hoskins	0.07	-0.02	0.09
Minehan	0.06	-0.04	0.1
Kroszner	0.05	-0.05	0.1
Keehn	-0.06	0.05	0.11
Olson	-0.17	-0.06	0.11
Jordan	0.13	0	0.13
Johnson	0.08	-0.05	0.13
Plosser	0.09	-0.05	0.14
Bies	-0.1	0.04	0.14
Pianalto	-0.09	0.06	0.15
Hoenig	0.17	0.01	0.16
Gramlich	0.08	-0.08	0.16
Boykin	0.12	-0.05	0.17
Santomero	-0.03	0.14	0.17
Lacker	0.18	0	0.18
Angell	0.16	-0.07	0.23
Fisher	0.25	-0.05	0.3

This Table reports prediction errors. This Table reports the realized excess error rates, the reference error rates and the difference between both. Realized error rates are excess error rates calculated using the real data. The reference excess error rate is the excess error rate we calculate from *replicated votes*. These are generated by randomly drawing observations y_{nt} from a binomial distibution with $n = 1$ and $p = \text{logit}^{-1}(\hat{\beta}_t \hat{x}_n - \hat{\alpha}_t))$ with $\hat{\beta}_t, \hat{x}_n, \hat{\alpha}_t$ the estimated parameters we use to calculate the excess error rates in the first place. The reference excess error rates provide a benchmark to compare the realized error rates against. See also Bafumi, Gelman, Park, and Kaplan (2005). The third column shows the difference (in absolute values) between both and thus shows how much the realized excess error rates differ from the reference error rates. This gives us a quick feel for which ideal points are best predicted (with the reference error rate as benchmark). We ranked the FOMC members according to the difference (third column).

Table 5: Overview of different sets of priors in the sensitivity analysis

Parameter	Default	Alternative 1	Alternative 2	Alternative 3	Alternative 4	Alternative 5
α_t	$\sim N(0,4)$	$\sim N(0,8)$	$\sim N(0,4)$	$\sim N(0,4)$	$\sim N(0,4)$	$\sim N(0,4)$
β_t	$\sim N(1,4)$	$\sim N(1,4)$	$\sim N(1,8)$	$\sim N(3,4)$	$\sim N(1,4)$	$\sim N(1,4)$
γ	$\sim N(0,2)$	$\sim N(0,2)$	$\sim N(0,2)$	$\sim N(0,2)$	$\sim N(0,4)$	$\sim N(0,2)$
ω	$\sim N(0,1)$	$\sim N(0,1)$	$\sim N(0,1)$	$\sim N(0,1)$	$\sim N(0,1)$	$\sim N(0,3)$

This Table presents different sets of priors we used to analyze the sensitivity of the posterior distribution of the ideal points to the priors. The column default presents the priors we use throughout this paper.

obtained under the default prior choice with estimates obtained from the same model but with different priors. Graphs in the right column plot the corresponding uncertainty estimates. The main takeaway is that our results are not particularly sensible to the priors we specified.

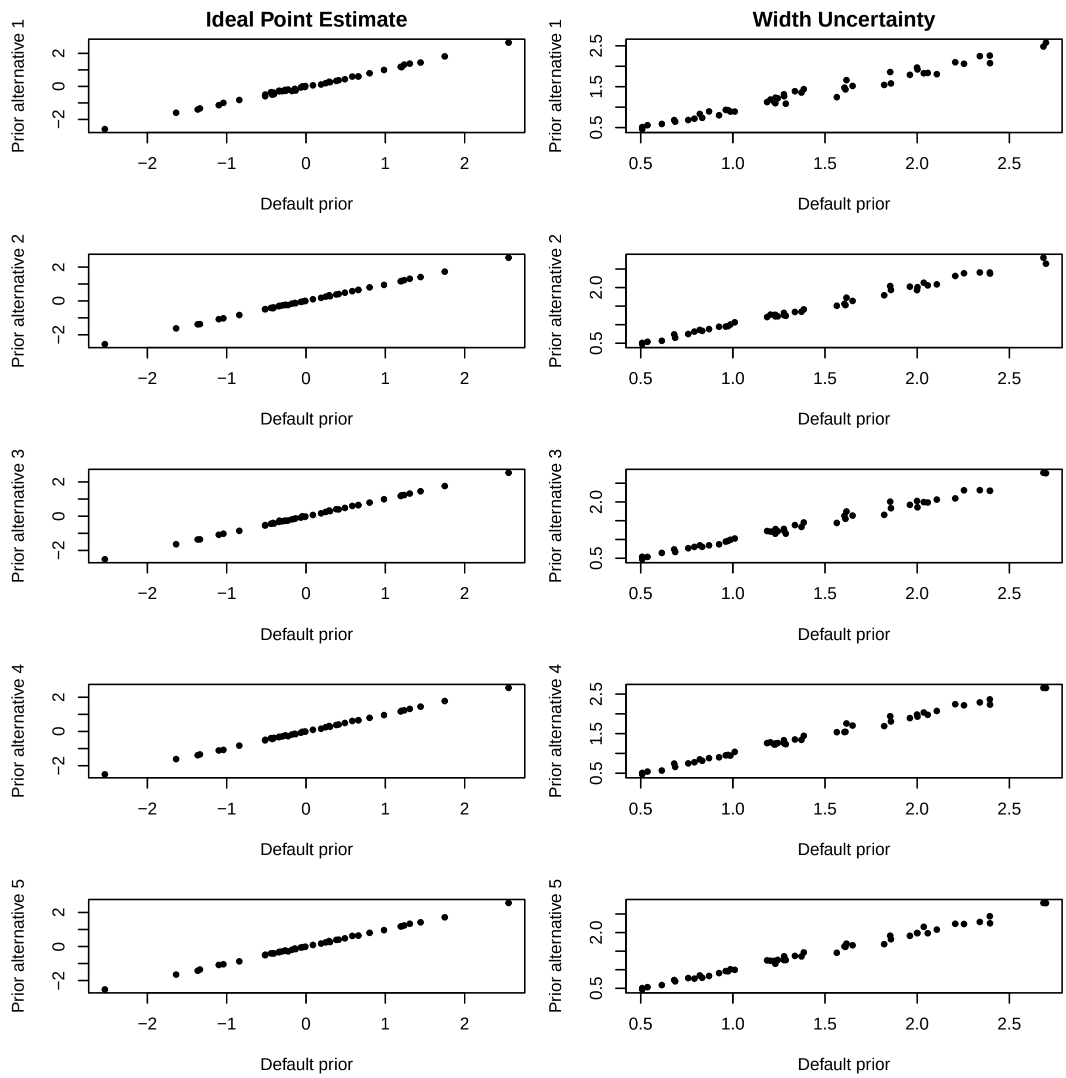


Figure 5: The left column compares the ideal points estimated with our preferred prior choice (see text) with some alternatives. If the estimates are exactly equal then all dots should lie on the 45 degree line. The right column compares the width of the 95% uncertainty intervals. If the intervals are the same under different prior choices, then the dots should lie on the 45 degree line.

5.3 Stability of the ideal points

In Figure 6 we present the stability of our ideal point estimates. To create this graph we have estimated the model described in equations 6-12 using only information from our first two meetings. We collected the estimated ideal points in a vector $\hat{x}^{(t=\{1,2\})}$. Then we re-estimated the same model but this time with the dataset extended to include the next meeting as well, again collecting the ideal points in a vector $\hat{x}^{(t=\{1,2,3\})}$. We re-estimated the model each time extending the dataset with one meeting until we arrived at the full dataset. Figure 6 shows then the trajectories of the ideal points as the dataset expands until we arrive at the full dataset with all the meetings.

The trajectories show that with only two meetings, the ideal points are concentrated +1 and -1. This results is driven by the hierarchical model where board affiliation works as an informative prior. As the sample grows we see that the importance of board affiliation as a predictor diminishes. At the same time we see that individual ideal point trajectories start to diverge. Most of these seem to stabilize, although a few make some wild jumps. Note that all trajectories have an equal length while we have different amounts of observations for the ideal points of individual members. The Bayesian approach provides us with an estimate of each ideal point at the beginning of the different trajectories, even for the members of which we have not yet observed a preference. When we start to observe preferences the ideal point may diverge sharply from the previous path because up until that point the trajectory of the ideal point was entirely driven by the prior. One notable example is the trajectory of the ideal point of Jeffrey Lacker. This is the trajectory which shows a very large upward spike at the end and ends up being the second largest ideal point. Lackers trajectory followed the cluster starting at +1 on the left of the graph. Lacker became voting member in 2006 and became known for being the only dissent (in favor of tightening) during the FOMC meetings of August, September, October and December 2006. Our dataset contains 11 preferences of Lacker, of which 9 are hawkish. This track record explains why we can have sharp swings in the trajectory. Note that we also have a fairly wide uncertainty region for the ideal point of Lacker, see Figure 1.

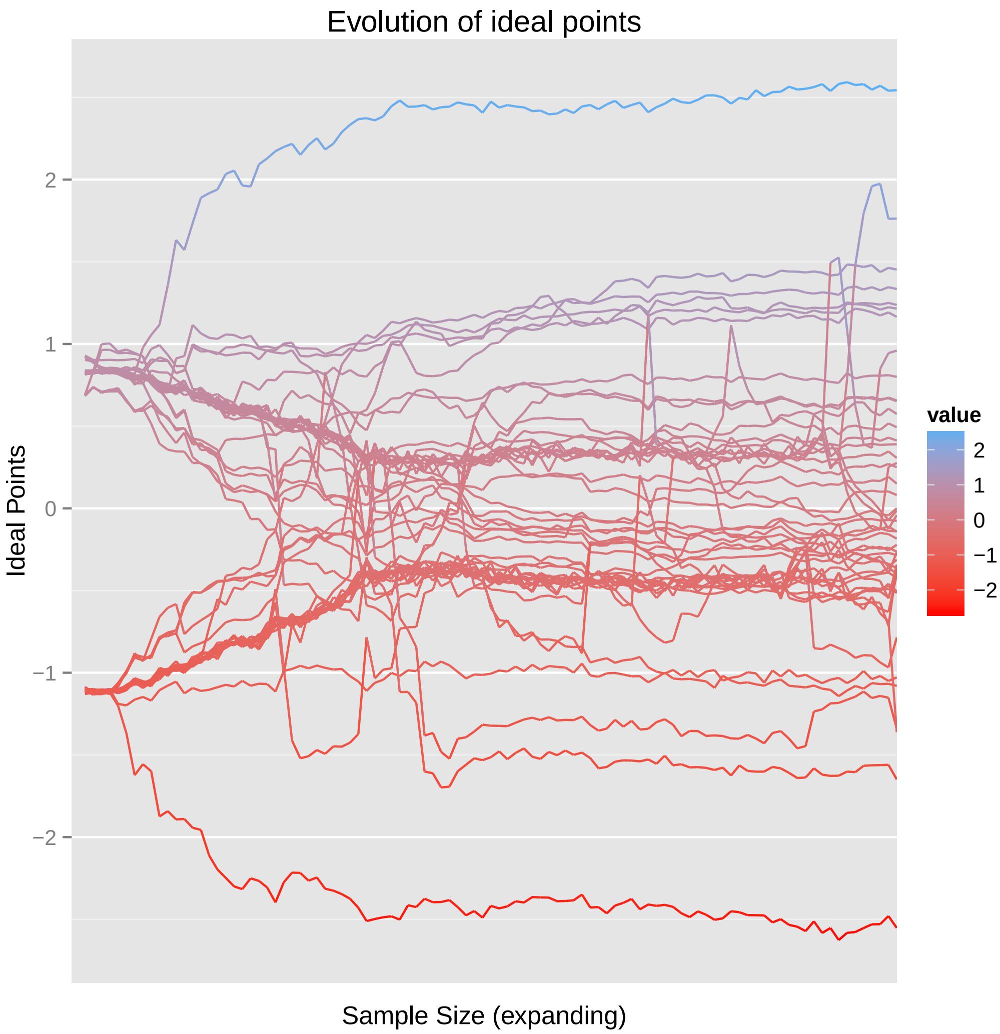


Figure 6: This graph shows how the estimated ideal points change as we expand the dataset. We start at the left with a dataset consisting of the first two meetings. We re-estimate our model, each time adding a meeting until we arrive at our full dataset (the data we use in the paper). The estimated ideal points using the entire dataset are on the right. The lines show the trajectories of the estimated parameters as the dataset increases.

6 Conclusion

In this paper we proposed to use Bayesian spatial voting models to infer and analyze preferences of FOMC members. These models are fairly flexible and can be adapted to the needs of the researcher. We constructed *hypothetical votes* from preferences stated by FOMC members.

At this stage, our sample, starts in 1989 and ends in December 2007. As such, it contains the onset of the financial crisis but not the interesting years thereafter. We intend to extend this data sample further. From 2009 onwards, the transcripts are not yet available given the five year time lag in publication -2009 should become available soon.

While this work is still in progress, so far the findings suggest the following. First, a dove-hawk classification in a unidimensional model works. If we consider the in-sample predictive performance i.e. how well we predict (hypothetical) votes based on the estimated parameters, then we predict $> 90\%$ of these votes correctly. As we discussed in the introduction, we understand the objections against such a classification exercise. However, we feel that one can try to classify monetary policy makers without trivializing the decision making process. If one would want to do so, we feel that using spatial voting models is a better approach than competing methods (reaction functions, averaging votes, frequencies of dissent, etc.). Second, we find few robust determinants for the preferences of FOMC members. The literature has made various suggestions on what predicts votes (and by implication preferences) at the FOMC. Our key finding is that on average, Board Governors seem to have more dovish preferences than Bank Presidents. Evidence on the differences between Board Governors due to the appointing president seems less compelling. Related to this is our result on the evolution of the median ideal point. We find that in the period 1989-2007 the median ideal point has remained remarkably stable. This suggests that even if there would be a political dimension in the appointment of Governors, this does not seem to have a caused shifts in the median ideal point of the FOMC board as a whole. In this paper, we do not try to answer *why* it is the case that Bank Presidents seem on average to hold more hawkish preferences.

While the median ideal point of the FOMC board as a whole was fairly stable, this was less the case for the group of presidents and the group of governors. Over time there has been more variation in the median ideal points of these groups. Also the most outspoken preferences (most dovish and most hawkish member at the board) show substantial evolution over time.

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