Influence and Interactions in Monetary Policy Committees.

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Abstract

Over the last two decades central bank independence has become the default for the conduct of monetary policy. In turn the decision-making process, within a central bank, has become - by design - much more transparent. The governance of this process is generally embedded in some type of committee. In turn, the use of committees to make decisions about interest rates, and other aspects of monetary policy, has increased the amount of information – again deliberately – made available about this decision-making itself. This in turn has generated a large literature on how committees make decisions, how they interact among themselves, and whether or not the outcome reflects the consensus, a majority decision, or perhaps the domination of one or more members of the committee in the decision-making process. This paper offers further insight into how decisions are made within a committee and and proposes a method by which we can detect hidden interactions among members of a committee, once we've conditioned on the factors that influence individual committee member's decisions on interest rates. Using our method we are able to identify directions of influence. In other words, a committee member can influence another committee member, but not necessarily be influenced in return by that member. In other words, that can be considerable asymmetry in the influence committee members have, and how they are influenced in turn by others.

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1 Introduction

Over the last two decades central bank independence has become the default for the conduct of monetary policy. In turn the decision-making process, within a central bank, has become - by design - much more transparent. The governance of this process is generally embedded in some type of committee. In turn, the use of committees to make decisions about interest rates, and other aspects of monetary policy, has increased the amount of information – again deliberately – made available about this decision-making itself. This in turn has generated a large literature on how committees make decisions, how they interact among themselves, and whether or not the outcome reflects the consensus, a majority decision, or perhaps the domination of one or more members of the committee in the decision-making process.

This paper offers further insight into how decisions are made within a committee and and proposes a method by which we can detect hidden interactions among members of a committee, once we've conditioned on the factors that influence individual committee member's decisions on interest rates. Using our method we are able to identify directions of influence. In other words, a committee member can influence another committee member, but not necessarily be influenced in return by that member. In other words, that can be considerable asymmetry in the influence committee members have, and how they are influenced in turn by others.

We apply these methods to 3 different (though sometimes overlapping) groups of committee members for the Bank of England's Monetary Policy Committee. The first is during the period that Eddie George was Governor of the Bank of England. The last two are for the period during which Mervyn King was Governor.

The approach we take draws on the literature on cross-section, or spatial, dependence. Here the dependence is abstract, rather than geographically contiguous. In this literature, at one end are multifactor approaches which assume cross-section dependence can be explained by a finite number of unobserved common factors that affect all units (regions, economic agents, etc.). Estimation of panel data regression models under such factor error structure has been addressed by maximum likelihood (Robertson and Symons, 2000), principal component analysis (Bai and Ng, 2006), common correlated effects (Pesaran, 2006), or interactive fixed effects (Bai, 2009).

An alternative approach, originally developed in the regional science and geography literatures, but with increasing economic applications, is based on spatial weights matrices. The idea is that there are spillover effects across economic agents because of spatial or other forms of local cross-section dependence. Spatial dependence here is structural, rather than factor based, in the sense that dependence between observation units depend solely on the location of these units in geographic or characteristic space. Panel data regression models with spatially correlated error structures have been estimated using maximum likelihood (Anselin, 1988) and generalized method of moments (Kapoor *et al.*, 2007; Kelejian and Prucha, 1999, 2007; Conley, 1999).

While these two approaches to modeling cross-section dependence are conceptually quite different, they are not mutually exclusive (Bhattacharjee and Holly, 2011). Factor models often provide only a partial expanation for cross-section dependence, and it is often observed that residuals from estimated factor models display substantial cross-section correlation. Further, Pesaran and Tosetti (2011) consider a panel data model where both the above sources of cross-section dependence coexist.

While the spatial weights matrix provides an useful way to model cross-section dependence, measurement of these weights has a significant effect on inference (Anselin, 2002; Fingleton, 2003). Measurement of weights vary widely across applications, with multiple possible choices and substantial uncertainty regarding the appropriate selection of distance measures. However, while the existing literature has addressed cross-section dependence in various ways, it has focused mainly on estimation of the regression coefficients in the underlying model, treating the cross-section dependence as a nuisance parameter. Estimation and inferences on the magnitude and strength of spillovers and interactions has been largely ignored. At the same time, there are many applications where inferences about the nature of the interaction is of independent interest. Recent developments in the economics of networks (Goyal, 2007) suggest that the pattern of connections between individual agents shapes their actions and determines their rewards. Understanding, empirically, the precise form of interaction is, in our view, an important counterpart to the development of the theory of networks.

Bhattacharjee and Jensen-Butler (2011) consider estimation of a spatial weights matrix in a spatial error model with spatial autoregressive errors, and show that the estimation problem is only partially identified. Therefore, structural constraints, such as symmetry of the spatial weights matrix, are required for precise estimation. However, such identifying restrictions may be too strong in some applications.

In this paper, we use a GMM based estimation methodology for spatial or *interaction* weights matrices,[1] where identification is achieved through instrument validity and other moment restrictions. The interaction weights are unrestricted except being subject to the validity of the included instruments and other moment conditions. Furthermore, instrument validity can be tested in our framework, in addition to the structural restrictions required for the estimators proposed in Bhattacharjee and Jensen-Butler (2011).

Specifically, we consider a setup where a given set of cross-section units have fixed but unrestricted interactions; these interactions are inherently structural in that they are related to an underlying structural economic model. Further, there exist a set of other cross-section units, correlated with the units under consideration, but which may change over time, expand or even vanish. Motivated by system GMM inference for the dynamic panel data model (Arellano and Bond, 1991; Blundell and Bond, 1998), our estimation methodology uses these additional units to constitute instruments.[2] However, whereas the dynamic panel data literature is largely based on fixed N large T asymptotics, our asymptotic setting is different. We focus on estimating interactions between a fixed number of cross-section units, and allow the number of time periods to increase to infinity. In addition to our basic method based on a multiple regression model with spatial autoregressive errors, we consider three extensions. First, we extend our estimates to the censored regression model. Secondly, we consider a regression model with spatial autoregressive structure in the regressors in addition to cross-section dependent errors. Third, our framework can allow for common factors in addition to idiosyncratic errors with spatial interactions. We evaluate small sample performance of the proposed methods using a Monte Carlo study.

In our application to the Bank of England's Monetary Policy Committee (MPC), we consider a MPC where personalities are important. In our model of committee decision making, personalities are reflected in heterogeneity in the policy reaction functions of different members, as well as in

[1] We prefer to use the term interaction rather than spatial since the latter term denotes some notion of physical proximity when there are many circumstances in which an interaction takes place in a much broader sense.

[2] In our application later in the paper we consider interactions between a subset of the members of the Monetary Policy Committee of the Bank of England. The membership changes over time, so during the period that we study there are members joining and leaving who provide instruments for the subset who remain on the Committee for the whole of the period.

interactions among members that can be strategic or just a reflection of like-mindedness. The application itself draws partly on previous work on cross-member heterogeneity and its impact on decision making within a monetary policy committee (Bhattacharjee and Holly, 2009, 2010), focussing on heterogeneity in the beliefs about the effects of interest rates on output and inflation, in the private information of each committee member and in their differing views on uncertainty. By contrast, the application here examines the network structure and interactions within the committee. Our estimates suggest significant cross-section interactions between members, both positive and negative. There is also substantial asymmetry in these interactions, which highlights the advantage of the proposed methods over Bhattacharjee and Jensen-Butler (2011). Members of the committee can be both influenced by and influencing other members. Also, there are significant changes, over time and committee composition, in the estimated network structure.

One of the estimators proposed here has been used in Bhattacharjee and Holly (2011), in addition to the method in Bhattacharjee and Jensen-Butler (2011) and another method allowing for factor-based interactions, to explain why factor based spatial models are fundamentally different from spatial (or interaction) weights based models. They make the point that, if one were interested in understanding spatial interactions, then the appropriate framework is one based on spatial weights. However, one needs to be wary that spatial dependence may partly be due to hidden factors, that is spatial strong dependence (Pesaran, 2006; Pesaran and Tosetti, 2011); this issue is also important in the empirical application developed here.

The paper is organised as follows. Section 2 develops the basic model and proposed GMM estimator, and report a Monte Carlo study of small sample performance. Two important extensions are developed in section 3 – to a censored regression model and a model with spatial autoregressive structure in the reressors. In section 4, we apply the proposed method based on exogenous censoring intervals to uncover the (static) network structure of 5 selected MPC members under Governor George, and similarly two other committees under Governor King. We compare findings across committees and make inferences on the interactions between members of a committee in a monetary policy setting. Finally, section 5 concludes.

2 Base model and GMM estimator

We consider a panel data model with fixed effects and unrestricted slope heterogeneity

$$y_{it} = \eta_i + \alpha_i' d_t + \beta_i' x_{it} + e_{it}, \quad i = 1, 2, \ldots, N; t = 1, 2, \ldots, T \tag{1}$$

$$E(e_{it}) = 0; V(e_{it}) = \sigma_i^2; E(e_{it}.e_{is}) = 0 (t \neq s),$$

where y_i is an observation on the i-th cross-section unit and x_i is a $k \times 1$ vector of observed individual specific regressors for the i-th unit and d is a $n \times 1$ vector of common deterministic components. e_i are the individual-specific (idiosyncratic) errors assumed to be independently distributed of d and x_i. Since our main objective here is to provide estimates of the interactions between the cross-section units, the regression errors are allowed to have arbitrary cross-section dependence.

There are a variety of estimators in the literature for the regression coefficients of the above model. In particular, in the case when N is not large, the SURE method allows for unrestricted correlations across cross-section units, and provides a simple way to test for slope heterogeneity in the regression coefficients.

Our focus is, however, on a problem that has not received much attention in the literature – specifically, on modelling the network between agents $1, 2, \ldots, N$ (N fixed) and the estimation of cross-agent interactions. For this purpose, we propose the spatial error model (Anselin 1988, 2006)

$$\begin{aligned}
e_{1t} &= w_{12}e_{2t} + w_{13}e_{3t} + \ldots + w_{1N}e_{Nt} + u_{1t} \\
e_{2t} &= w_{21}e_{1t} + w_{23}e_{3t} + \ldots + w_{2N}e_{Nt} + u_{2t} \\
&\vdots \\
e_{Nt} &= w_{N1}e_{1t} + w_{N2}e_{2t} + \ldots + w_{N,(N-1)}e_{N-1,t} + u_{Nt},
\end{aligned}$$

or, in compact form

$$e_t = \boldsymbol{W} e_t + u_t, \tag{2}$$

where $\boldsymbol{W}$ is a $(N \times N)$ matrix of interaction weights with zero diagonal elements and unrestricted entries on the off-diagonals. We make the following assumptions.

Assumption 1: *The spatial errors, u_{it}, are iid (independent and identically distributed) across time. However, we allow for heteroscedasticity across* *units, so that* $\mathbb{E}(\underline{u}_t\underline{u}_t') = \boldsymbol{\Sigma} = diag(\sigma_1^2, \sigma_2^2, \ldots, \sigma_N^2)$*, and* $\sigma_i^2 > 0$ *for all* $i = 1, \ldots, N$*.*

The uncorrelatedness of the spatial errors across the units is crucial. **Assumption 1** ensures that all spatial autocorrelation in the model is solely due to spatial interaction described by the spatial weights matrix.

Assumption 2: *The spatial weights matrix* $\boldsymbol{W}$ *is an unknown and possibly asymmetric matrix of fixed constants.* $\boldsymbol{W}$ *has zero diagonal elements and there are no sign restrictions on the off-diagonal elements (i.e., they could be either positive or negative).*

We retain the flexibility of a possibly asymmetric spatial weights matrix, and do not impose a non-negativity constraint on the off-diagonal elements of $\boldsymbol{W}$.

Assumption 3: $(\boldsymbol{I} - \boldsymbol{W})$ *is non-singular, where* $\boldsymbol{I}$ *is the identity matrix.*

This is a standard assumption in the literature, and required for identification in the reduced form.

The interaction weights matrix $\boldsymbol{W}$ is similar to the spatial weights matrix popular in geography, the regional sciences and in the spatial econometrics literature. However, while that literature treats W as exogenous and known *a priori*, at least approximately, our interpretation differs. For us, $\boldsymbol{W}$ is a matrix of interaction weights which is unknown and on which we aim to conduct inferences, based on an asymptotic setting where $T \to \infty$. One way to motivate the framework is network theory (Dutta and Jackson, 2003; Goyal, 2007), where an equilibrium network emerges through interactions between agents.

Pesaran and Tosetti (2011) consider a similar setting, but one where both N and T increase asymptotically. Since $\boldsymbol{W}$ can then vary with sample size, one needs a spatial granularity (stationarity) assumption of bounded row and column norms to ensure weak dependence (structural interactions) rather than strong spatial dependence (factor based interactions); see Bhattacharjee and Holly (2011) and Pesaran and Tosetti (2011) for further discussion. This assumption ensures that, as the number of units grow, no unit becomes dominant. In our context, $\boldsymbol{W}$ is a matrix of fixed constants, and therefore the spatial granularity condition is not required for inference. However, the assumption is useful for interpretation of the estimated interaction weights. In terms of implementation, this necessitates including all common factors contributing to strong dependence as regressors in (1), so that the model for the errors (2) satisfies the spatial granularity condition.

2.1 GMM estimation

We propose GMM based estimators for the above weights. Towards this end, we consider first a somewhat analogous setup from the dynamic panel data literature, where the standard model is described as

$$y_{it} = \eta_i + \alpha y_{i,t-1} + e_{it}, \quad i = 1, 2, \ldots, N; t = 1, 2, \ldots, T \tag{3}$$

$$E(\eta_i) = 0; E(e_{it}) = 0; E(e_{it}.e_{is}) = 0 (t \neq s).$$

Arellano and Bond (1991) considered GMM estimation of the above model based on a sequence of linear moment conditions:

$$E\left(y_i^{(t-2)}. \triangle e_{it}\right) = 0 \quad t = 3, \ldots, T, \tag{4}$$

where $y_i^{(t-2)} = (y_{i1}, y_{i2}, \ldots, y_{i,t-2})$.

The context here is somewhat different. We have lagged endogenous variables as regressors, but the observations are not sampled at equi-spaced points on the time axis. Rather, the economic agents can be thought of as being located in a multi-dimensional, and possibly abstract, space without any clear notion of ordering or spacing between observations. At the same time, one can often imagine that potential non-zero interaction weights imply that $e_{1t}, e_{2t}, \ldots, e_{Nt}$ are regression errors from (1), at time t, on a collection of agents who are not located very far away in space. There may also be, potentially specific to the time period, additional agents who are located further away (similar to higher lags in the dynamic panel data model), who are correlated with the above set of endogenous variables, but not with the idiosyncratic errors $u_{1t}, u_{2t}, \ldots, u_{Nt}$ from the interaction error equation (2).

In social networks agents who have weak ties with other agents may act as instruments for groups of agents that share strong ties (Granovetter, 1973; Goyal, 2005). In panel data on cross-sections of countries or regions, such a set may include other countries not included in the analysis either because of irregular availability of data or because they are outside the purview of the analysis. Similarly, in geography and regional studies, observations at a finer spatial scale may constitute such instruments. We denote such a collection of instruments, specific to a particular time t, by $\overline{e}_i^{(t)} = \left(e_{it}^{(1)}, e_{it}^{(2)}, \ldots, e_{it}^{(k_t)}\right)$, and assume the $\sum_{t=1}^{T} k_t$ moment conditions

$$E\left(\overline{e}_i^{(t)}.u_{it}\right) = 0 \quad i = 1, 2, \ldots, N; t = 1, 2, \ldots, T. \tag{5}$$

Given the nature of our problem, N is fixed. Our main focus is drawing inferences on the spatial dynamics of the system, in contrast to the standard dynamic panel data setting, where dynamics lie along the time dimension. Therefore, our asymptotic setting is one where T is large, as we accumulate evidence on the finite number of cross-section interactions as the number of time periods increase to infinity. This is in direct correspondence with the standard dynamic panel data model, where GMM inference is drawn as N becomes large, while T is held fixed.

Further, and similar to Arellano and Bond (1991), we assume a first order autoregressive structure in the errors of the interactions model:

$$u_{it} = \alpha u_{i,t-1} + \varepsilon_{it} \quad i = 1, 2, \ldots, N; t = 2, 3, \ldots, T,$$

$$E\left(\varepsilon_{it}\varepsilon_{is}\right) = 0 \quad t \neq s,$$

and obtain additional $N(k-1)$ linear moment conditions ($k \geq 2$)

$$E\left(e^{(t-2)}.u_{it}\right) = 0 \quad t = 3, \ldots, T, \tag{6}$$

where $e^{(t-2)} = \left(e_1^{(t-2)}, e_2^{(t-2)}, \ldots, e_N^{(t-2)}\right)$ and $e_i^{(t-2)} = (e_{i,t-k}, e_{i,t-k+1}, \ldots, e_{i,t-2})$ for $i = 1, 2, \ldots, N$.[3]

In the context of a specific application, the potential instrument set (and corresponding moment conditions) would typically be large. First of all, there would be observation units at larger spatial lags (5) – peripheral units in a committee or network setting, observations at finer spatial scales in a spatial setting, or a selection of other countries (such as trade partners) in a cross-country setting. Second, like the dynamic panel literature, one could include temporal lags (6). If endogeneity is an issue, observations further in the past may be appropriate. Third, temporal lags of exogenous variables included in the model are also candidate instruments. Finally, depending on the context of the application, there may be observed shocks that potentially affect some of the units. Instrument validity and potential weak instruments problem are crucial issues here. Therefore, one has to carefully select instruments that are appropriate to an application. The validity of the potentially large number of instruments can be verified using the Sargan-Hansen J-test (Hansen, 1982), and instrument adequacy using the Kleibergen and Paap (2006) r_k Wald test

[3] Following Ahn and Schmidt (1995), one can add further moment conditions under the assumption that u_{it} are homoscedastic over time. Likewise, lags of exogenous regressors can consititute additional moment conditions/ instruments.

for weak instruments. These issues are further discussed in the context of the application considered later.

Assumption 4: *We assume moment conditions (5) and (6) and validity of any other instruments included, such as temporal lags of exogenous regressors.*

For the model given in (1) and (2), under assumptions 1–4, we propose a three step estimation procedure as follows. First, we estimate the underlying regression model (1) using an optimisation based method such as maximum likelihood, least squares or GMM, and collect residuals. Next, we estimate the interactions error model (2) using a two-step GMM estimator. The weights matrix is estimated using the outer product from moment conditions evaluated at an initial consistent estimator, which is the GMM estimator using the identity weighting matrix. The validity of multi-step procedures (consistency and asymptotic normality) such as the one proposed here follow from Newey (1984).

2.2 Monte Carlo study[4]

To investigate the small sample performance of the proposed estimator, we conduct a Monte Carlo study with 3 cross-section units and a symmetric interaction matrix $\boldsymbol{W}$. The experimental DGP is the following:

$$\left.\begin{array}{c} y_t = (y_1 : y_2 : y_3)'_t = y_t^* + \lambda \boldsymbol{W} y_t + \varepsilon_t, \\ y_{it}^* = x_{it} + z_{it} + \eta_{it}, i = 1, 2, 3, t = 1, \ldots, T, \\ \varepsilon_{it} \overset{iid}{\sim} N(0,1), \begin{pmatrix} x \\ z \\ \eta \end{pmatrix}_{it} \overset{iid}{\sim} N_3 \left[\begin{pmatrix} 2 \\ 2 \\ 0 \end{pmatrix}, \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0.01 \end{bmatrix} \right], \end{array} \right\} \begin{array}{c} \boldsymbol{W} = \begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \\ 1 & 0 & 0 \end{bmatrix}, \\ \lambda = 0.25, \end{array} \tag{7}$$

with sample sizes of $T = 25, 50, 100$ and 200. The model is estimated using y_{it}^* as an exogenous regressor and x and z as instruments for the endogenous relation between y's. The above experimental model is somewhat different from (1) and (2), and is in fact a hybrid with the mixed regressive spatial autoregressive model considered later in section 3. We choose this model because of two reasons. First, it allows us to examine the performance of our

[4]We are grateful to an anonymous referee for suggesting the Monte Carlo study, which helped us understand the finite sample performance of our estimation strategy much more explicitly.

IV/GMM approach in the presence of an additional exogenous variable, but in a way that avoids sampling variation from the first step of the proposed three-step procedure. Note that the performance in the first step would be inherited from some regression estimator consistent under cross section dependence, and is not central to the inference methods developed here. Second, the above model is a standard spatial autoregressive model and therefore allows easy comparison of the GMM estimator against other standard estimators. We chose 2 such alternate estimators – the SAR-ML and spatial SURE estimators. The SAR-ML estimator uses maximum likelihood to estimate the slope coefficient on y^* and the spatial autoregressive parameter λ under the assumptions of a known $\boldsymbol{W}$ and Gaussian homoscedastic errors, both of which are true under the above DGP. The spatial SURE estimator does not assume knowledge of $\boldsymbol{W}$ or an assumption of homoscedasticity, but assumes Gaussian errors. In our implementation, we also impose the restriction that the slope coefficient is the same across all the 3 observation units; see, for example, Anselin (2006) for further discussion of these two estimators. The GMM estimator makes none of the above assumptions (known $\boldsymbol{W}$, homoscedasticty or Gaussian errors), but assumes that x and z are valid instruments, which is true under the above DGP (7).

$1,000$ Monte Carlo samples from the above DGP are used for the study. Estimation and inferences are carried out in Stata, using the *ivreg2* program for GMM inferences (Baum *et al.*, 2007), the *spatreg* program for SAR-ML estimation (Pisati, 2001), and the core Stata *sureg* program for spatial SURE. There are two objectives of the Monte Carlo study. First, we compare the finite sample performance of the three estimators, in terms of bias and MSE of the spatial parameter(s) and the slope parameter. Estimates of spatial parameters refer to off-diagonal elements of the matrix $\lambda\boldsymbol{W}$. In the case of GMM and spatial SURE estimators, we evaluate estimates of each off-diagonal element of $\lambda\boldsymbol{W}$. In the case of SAR-ML, we first estimate λ, and then evaluate estimates of each off-diagonal element of $\lambda\boldsymbol{W}$ implied by $\widehat{\lambda}$ and the known $\boldsymbol{W}$. In the case of spatial SURE, the slope parameter is constrained to be equal for the three cross-section units. Second, we investigate the nominal size and power of t-tests for the proposed GMM estimator for the spatial parameters. We consider separately the cases when the null hypothesis of zero interaction weight is true ($\lambda w_{13} = \lambda w_{31} = 0$) and false ($\lambda w_{12} = \lambda w_{21} = \lambda w_{23} = \lambda w_{32} = 0.25$). In both cases, we report: (a) the percentage of Monte Carlo samples when the null hypothesis of zero interaction weight is rejected, and (b) the empirical distribution of the standardised test statistic.

Table 1: Finite sample performance of competing estimators
(GMM, spatial SURE and SAR-ML)

Accuracy of estimates	Spatial parameters			Slope parameter		
	GMM	**SURE**	**ML**	**GMM**	**SURE**	**ML**
Bias						
$T = 25$	0.0038	0.0269	0.0175	-0.0125	-0.0928	-0.0096
$T = 50$	0.0020	0.0268	0.0182	-0.0062	-0.0917	-0.0087
$T = 100$	0.0012	0.0269	0.0186	-0.0039	-0.0920	-0.0084
$T = 200$	0.0002	0.0261	0.0189	-0.0009	-0.0901	-0.0068
MSE						
$T = 25$	0.01785	0.02242	0.00166	0.02233	0.02035	0.00761
$T = 50$	0.00828	0.01335	0.00098	0.01019	0.01353	0.00358
$T = 100$	0.00406	0.00971	0.00067	0.00503	0.01106	0.00183
$T = 200$	0.00197	0.00783	0.00053	0.00242	0.00942	0.00092

Of the three competing estimators, the SAR-ML is expected to have the highest efficiency. ML would be most efficient in large samples when the maintained assumptions are true and further, knowledge of the true $\boldsymbol{W}$ is a very large assumption that, if true, is expected to lead to substantial efficiency gains. We also expect the GMM estimator to show small sample bias, for the same reason that the IV estimator is known to be biased. However, the magnitude of the bias relative to the other estimators is ambiguous. The GMM estimator also incorporates an assumption, true for our DGP, that the used instruments are valid. This assumption is weaker than the SAR-ML assumption of a known $\boldsymbol{W}$. Further, to make the proposed GMM estimator comparable with SURE, we compensate for the moment assumption by endowing the spatial SURE estimator with the assumption, true for the chosen DGP (7), that the slope parameter is identical for each cross-section unit.

The Monte Carlo results (Table 1) indicate good small sample performance for the proposed GMM estimator. Somewhat surprisingly, the proposed GMM estimator has the smallest bias of all the three candidate estimators (GMM, spatial SURE and SAR-ML) at all sample sizes. Also, the MSE for the GMM estimator is smaller than the spatial SURE estimator. The MSE of the estimated spatial parameters is 10.74 times that for SAR-ML for small sample sizes ($T = 25$), but this advantage of SAR-ML reduces to 3.75 times when $T = 200$. The MSE for the slope parameter is between 2.5 to 3.0 times that for the SAR-ML estimator at all sample sizes.

Table 2A reports rejection percentages for a standardized z-test that a spatial parameter, using the GMM estimator, is zero. The corresponding sampling distributions for the standardised test statistic are reported in Table 2B. The Monte Carlo experiments show that, when the null hypothesis of zero interaction weight holds, the nominal size for a 1% test is about 0.04 in small sample sizes ($T = 25$), and reduces to 0.02 when $T = 200$; correspondingly, the power in the case when the null is false increases from 0.50 for small sample sizes ($T = 25$) to 1.00 when $T = 200$. This shows acceptable small sample performance. Likewise, the sampling distribution of the standardised statistic is close to the standard normal distribution when the null hypothesis of zero interaction weight is true, and the distribution gets increasingly separated as sample size increases, when the null hypothesis is false.

Table 2: Performance of z-tests for spatial parameters

A: Nominal size and power – Percentage of rejection

Test for $H_0 : w_{ij} = 0$	**Null H_0 true** w_{13}	w_{31}	**Null hyp. H_0 false ($w_{ij} = 0.25$)** w_{12}	w_{21}	w_{23}	w_{32}
1% **signif. level**						
$T = 25$	0.038	0.034	0.473	0.527	0.523	0.480
$T = 50$	0.024	0.026	0.693	0.773	0.771	0.711
$T = 100$	0.028	0.024	0.919	0.969	0.964	0.939
$T = 200$	0.018	0.022	0.998	1.000	0.999	1.000

B: Sampling distributions of z-statistics

Null true/ false	$p_{0.01}$	$p_{0.05}$	**Median**	$p_{0.95}$	$p_{0.99}$	**Mean**
$w_{ij} = 0 : (w_{13}, w_{31})$						
$T = 25$	-2.729	-1.876	-0.086	1.670	2.444	-0.096
$T = 50$	-2.551	-1.766	-0.050	1.580	2.335	-0.064
$T = 100$	-2.520	-1.680	-0.045	1.581	2.315	-0.039
$T = 200$	-2.475	-1.663	-0.030	1.566	2.220	-0.044
$w_{ij} = 0.25 :$ $(w_{12}, w_{21}, w_{23}, w_{32})$						
$T = 25$	-0.399	0.366	2.336	4.627	5.812	2.389
$T = 50$	0.397	1.170	3.118	5.308	6.170	3.160
$T = 100$	1.570	2.362	4.291	6.375	7.393	4.332
$T = 200$	3.370	4.067	6.009	8.051	8.891	6.029
Null dist. $N(0, 1)$	-2.326	-1.645	0.000	1.645	2.326	0.000

3 Extensions

In this section, we consider two useful extensions. The first is to a model where the response variable is interval censored. This is important in the context of the application considered in section 4, where the response – changes in the policy rate – tends to change in multiples of 25 basis points. Our second extension is to a model, similar to Pinkse *et al.* (2002), where in addition to cross-section dependence in the error structure, we also have spatial autoregression in the underlying economic model. In the final subsection, we discuss inferences on the structure of a network.

3.1 Interactions between censored residuals

Consider a DGP where the residuals from the underlying economic model are interval censored: $e_{it} \in [e_{0it}, e_{1it}]$. Such censoring typically arises because the dependent variable, y_{it}, is itself either interval censored or ordinal. Then, for a given cross-section unit i, we have the following model in latent errors

$$e_{it} = \widetilde{e}'_{(-i)t} w_{(i)} + \varepsilon_{it},$$

where $\widetilde{e}_{(-i)}$ denotes the vector of residuals for the cross-section units other than i, $w_{(i)}$ is the i-th row of W transposed (ignoring the diagonal element, which is zero by construction), and observations run over $t = 1, \ldots, T$. Henceforth, for simpler exposition, we omit the reference to subscripts i and t. We discuss estimation of the $w_{(i)}$, an index row of W. The same procedure is repeated for each cross-section unit in turn, and the entire W matrix is therefore estimated.

Then, the censored regression model in the regression errors is more simply written as

$$\begin{aligned} e &= \widetilde{e}\,'w + u \\ \text{Observations} &: \left([e_0, e_1], \widetilde{e}, z\right) \\ P\left(e \in [e_0, e_1]\right) &= 1 \end{aligned} \tag{8}$$

where $\widetilde{e}$ are endogenous regressors with instruments z.

We further assume that

$$\begin{aligned} \widetilde{e} &= z'b + \varepsilon; E\left(z\varepsilon\right) = 0; \\ u &= \varepsilon'\gamma + v; v \perp u, \varepsilon; v \sim N\left(0, \sigma_v^2\right). \end{aligned} \tag{9}$$

An important special case when this holds is when u and ε are jointly normally distributed and independent of z. However, in general, normality of ε is not required. The framework can be further generalised where $\widetilde{e} = h\left(z\right) + \varepsilon$, and the distribution of errors is unknown (Blundell and Powell, 2004). In that case, estimation and inference requires kernel based methods and appropriate measures of choice probabilities. For modelling the choice probabilities, various options are available from the literature: purely nonparametric kernel estimates, average structural functions (Blundell and Powell, 2003) or index choice probabilities (Ichimura, 1993); see Blundell and Powell (2003) for a review and discussion. For simplicity, we assume a linear structure and normality of the instrument equation errors.

Substituting for u, the interval inequalities corresponding to $P\left(e \in [e_0, e_1]\right) = 1$ can be expressed as

$$\begin{aligned} D_0 &= 1\left(-e_0 + \widetilde{e}\,'w + \varepsilon'\gamma + \upsilon \geq 0\right) \quad \text{and} \qquad (10) \\ D_1 &= 1\left(e_1 - \widetilde{e}\,'w - \varepsilon'\gamma - \upsilon \geq 0\right) \qquad (11) \end{aligned}$$

3.1.1 Exogenous censoring intervals

First, let us assume that the boundaries of the censoring intervals (e_0 and e_1) are exogenous. Exogeneity of the censoring interval is natural or otherwise a plausible assumption, in many applications. For example, event studies on firms often focus on a fixed period of time, which then corresponds to an exogenous interval in the age of the firm or an exogenous interval of duration after being subject to a treatment under study. Another example could be the study of exit, investment and acquisition decisions by firms, where the underlying model of Jovanovic and Rousseau (2002) posits four regions of firm efficiencies: the firm exits at levels below a lower threshold, continues without investment in the next, invests only in new capital at higher efficiencies, and expands through organic growth and acquisitions at efficiencies above a high threshold (see also Bhattacharjee *et al.*, 2009). Other applications would arise from data on longitudinal surveys, where economic agents are observed over time, but typically only at fixed time points.

In the above case, $-e_0$ and e_1 can be treated as regressors with positive unit coefficients and the control function approach (Blundell and Smith, 1986) can be applied. Extending Lewbel (2004), we first define

$$\begin{aligned} R_0\left(D_0, e_0, \widetilde{e}, \varepsilon, w, \gamma, \sigma_\upsilon\right) &= D_0 \frac{\phi\left[\left(-e_0 + \widetilde{e}\,'w + \varepsilon'\gamma\right)/\sigma_\upsilon\right]}{\Phi\left[\left(-e_0 + \widetilde{e}\,'w + \varepsilon'\gamma\right)/\sigma_\upsilon\right]} \\ &\quad + \left(1 - D_0\right) \frac{-\phi\left[\left(-e_0 + \widetilde{e}\,'w + \varepsilon'\gamma\right)/\sigma_\upsilon\right]}{1 - \Phi\left[\left(-e_0 + \widetilde{e}\,'w + \varepsilon'\gamma\right)/\sigma_\upsilon\right]}, \text{ and} \\ R_1\left(D_1, e_1, \widetilde{e}, \varepsilon, w, \gamma, \sigma_\upsilon\right) &= D_1 \frac{\phi\left[\left(e_1 - \widetilde{e}\,'w - \varepsilon'\gamma\right)/\sigma_\upsilon\right]}{\Phi\left[\left(e_1 - \widetilde{e}\,'w - \varepsilon'\gamma\right)/\sigma_\upsilon\right]} \\ &\quad + \left(1 - D_1\right) \frac{-\phi\left[\left(e_1 - \widetilde{e}\,'w - \varepsilon'\gamma\right)/\sigma_\upsilon\right]}{1 - \Phi\left[\left(e_1 - \widetilde{e}\,'w - \varepsilon'\gamma\right)/\sigma_\upsilon\right]}, \end{aligned}$$

where ϕ and Φ are the pdf and cdf of the standard normal distribution respectively.

The following moment conditions can then be obtained:

$$E\left[z\left(\widetilde{e}-z'b\right)\right] = 0$$

$$\begin{aligned}
E\left[R_0\left(D_0, e_0, \widetilde{e}, \left(\widetilde{e}-z'b\right), w, \gamma, \sigma_v\right)\widetilde{e}\right] &= 0 \\
E\left[R_0\left(D_0, e_0, \widetilde{e}, \left(\widetilde{e}-z'b\right), w, \gamma, \sigma_v\right)\left(\widetilde{e}-z'b\right)\right] &= 0 \\
E\left[R_0\left(D_0, e_0, \widetilde{e}, \left(\widetilde{e}-z'b\right), w, \gamma, \sigma_v\right)e_0\right] &= 0
\end{aligned} \tag{12}$$

$$\begin{aligned}
E\left[R_1\left(D_1, e_1, \widetilde{e}, \left(\widetilde{e}-z'b\right), w, \gamma, \sigma_v\right)\widetilde{e}\right] &= 0 \\
E\left[R_1\left(D_1, e_1, \widetilde{e}, \left(\widetilde{e}-z'b\right), w, \gamma, \sigma_v\right)\left(\widetilde{e}-z'b\right)\right] &= 0 \\
E\left[R_1\left(D_1, e_1, \widetilde{e}, \left(\widetilde{e}-z'b\right), w, \gamma, \sigma_v\right)e_1\right] &= 0
\end{aligned}$$

Here, z includes instruments $\overline{e}_i^{(t)}$ and $e^{(t-2)}$ corresponding to moment conditions (5) and (6) respectively, as well as lags of exogenous variables as appropriate.

A GMM estimator based on the above moment conditions is simple to implement. Typically, such a method based on control functions would be applicable only if the endogenous variables are continuous (not limited dependent); the assumption $E(z\varepsilon) = 0$ is typically violated otherwise.

3.1.2 Ordered choice with fixed intervals

Exogeneity of the censoring intervals can be a strong assumption. However, in many applications, the intervals are fixed in repeated sampling. This is often because the DGP allows measurement of the response in integer intervals; for example, education or business longevity measured in years, business cycle duration in quarters, income in thousands of currency units, and so on. In this paper, we consider an application to monetary policy decision making, where preferred changes are in multiples of 25 basis points. In such situations, the underlying censoring scheme can be characterised by a sequence of $K+1$ intervals

$$I_k = \left[\alpha_{k-1}, \alpha_k\right], k = 1, \ldots, K+1,$$

where α_0 and α_{K+1} may be finite, or set to $-\infty$ and ∞ respectively, and the intervals may be considered as open or closed at either threshold. In this setup, interval censored data imply observing a sequence of discrete decision functions D_k and the resulting discrete choice variable D, where

$$\begin{aligned} D_k &= 1\left(\alpha_k + \widetilde{e}\,' w + u \geq 0\right); \\ D &= \sum_{k=1}^{K} D_k \in \{0, 1, 2, \ldots, K\}. \end{aligned} \tag{13}$$

This is a variant of the usual ordered choice model, with the difference that the interval boundaries are fixed by design and therefore do not need to be estimated. Although the underlying censoring intervals of the latent response variable here clearly depends on $\widetilde{e}$, the censoring scheme itself is exogenous. Lewbel (2000) has developed estimates of the ordered choice model in the case when one of the regressors is "very exogenous".[5]

Here, the censored regression problem is cast as one where K decision functions are sequentially evaluated for each individual. The interval corresponding to each single decision is fixed a priori, in a way that is independent of the regression error u. Following Blundell and Smith (1986) and Lewbel (2004), we set up the problem as in (9), with moment conditions:

$$\begin{aligned} E\left[z\left(\widetilde{e} - z'b\right)\right] &= 0 \\ \\ E\left[R_0\left(D_1, -\alpha_1, \widetilde{e}, \left(\widetilde{e} - z'b\right), w, \gamma, \sigma_v\right)\right] &= 0 \\ E\left[R_0\left(D_1, -\alpha_1, \widetilde{e}, \left(\widetilde{e} - z'b\right), w, \gamma, \sigma_v\right) \widetilde{e}\right] &= 0 \\ E\left[R_0\left(D_1, -\alpha_1, \widetilde{e}, \left(\widetilde{e} - z'b\right), w, \gamma, \sigma_v\right) \left(\widetilde{e} - z'b\right)\right] &= 0 \\ E\left[R_0\left(D_1, -\alpha_1, \widetilde{e}, \left(\widetilde{e} - z'b\right), w, \gamma, \sigma_v\right) \alpha_1\right] &= 0 \\ &\vdots \\ E\left[R_0\left(D_K, -\alpha_K, \widetilde{e}, \left(\widetilde{e} - z'b\right), w, \gamma, \sigma_v\right)\right] &= 0 \\ E\left[R_0\left(D_K, -\alpha_K, \widetilde{e}, \left(\widetilde{e} - z'b\right), w, \gamma, \sigma_v\right) \widetilde{e}\right] &= 0 \\ E\left[R_0\left(D_K, -\alpha_K, \widetilde{e}, \left(\widetilde{e} - z'b\right), w, \gamma, \sigma_v\right) \left(\widetilde{e} - z'b\right)\right] &= 0 \\ E\left[R_0\left(D_K, -\alpha_K, \widetilde{e}, \left(\widetilde{e} - z'b\right), w, \gamma, \sigma_v\right) \alpha_K\right] &= 0. \end{aligned} \tag{14}$$

[5] Intuitively, a "very exogenous regressor" has three properties. First, it is a regressor in the latent variable model and has coefficient unity. Second, conditional on all other endogenous, exogenous and instrumental variables in the model for the regression errors (8), it is independent of the error term u. Third, it has a support large enough to counterbalance the effect of other regressors and the errror. The second condition is similar to exogeneity but stronger – exogeneity requires conditioning only on the exogenous variables in the model. The regressor must also take both positive and negative values, which is easily achieved by location shifts.

The instruments z are defined as before, based on our moment conditions (5), (6) and thoe implied by any other suitable instruments.

There are two important observations to note. First, all the K individual decisions are applied to each individual. Second, as discussed earlier, the choice of endogenous variables is somewhat limited in this approach. This is particularly important for our application where the endogenous regressors are also interval censored.

We address the second problem using an error in variables approach. Specifically, we explicitly model the DGP of the endogenous variables and replace the censored observations with estimates of their expectations conditional on their censoring interval. This way, the measurement errors are mean zero and the error in variables problem here is in no way different from that addressed in the standard instrumental variables literature; see, for example, Wansbeek and Meijer (2001). The effectiveness and validity of these instruments are empirical issues specific to each individual application, and can be judged in standard ways within the proposed GMM framework.

A more general nonparametric approach to instrumental variables estimation of the censored regression model, under the conditional median assumption $median(\varepsilon|z) = 0$, has been proposed by Hong and Tamer (2003). We do not adopt this approach for two reasons. First, the method involves kernel based estimation, which is often difficult to implement in high dimensions. Second, the GMM based approach proposed here can be easily combined with other maximum likelihood, or least squares, or method of moments estimation procedures to obtain efficient two stage or three stage estimators (Newey, 1984). This is particularly useful in the application considered in this paper.

3.2 Spatial autoregressive model with spatial autoregressive errors

Case (1991) and Pinkse *et al.* (2002), among others, have considered models where there is spatial dynamics in the response variable, in addition to spatial dependence in the errors. Specifically, we consider a model

$$y_t = \eta + W_1 y_t + A d_t + \beta' X_t + e_t, \quad t = 1, 2, \ldots, T \tag{15}$$

where y_t and e_t are $N \times 1$ vectors, and X_t is a $N \times k$ matrix of regressors, and η is the $N \times 1$ vector $(\eta_1, \eta_2, \ldots, \eta_N)'$ of fixed effects, and d_t is a $p \times 1$ vector of observed common factors. While cross-section dynamics in y_t is described by the weights matrix W_1, dependence in the errors is modeled as

$$e_t = W_2 e_t + u_t, \tag{16}$$

where W_2 is a (potentially) different matrix of cross-section or network interactions. Our objective is to estimate both W_1 and W_2.

Moment conditions corresponding to the errors are similar to those described earlier. Analogous to the model for e_t, we can develop moment conditions for dynamics in y_t. Specifically, the moment conditions based on spatial time lags of y_t can be given by

$$\begin{aligned} E\left(\overline{y}_i^{(t)}.e_{it}\right) &= 0, \quad \overline{y}_i^{(t)} = \left(y_{it}^{(1)}, y_{it}^{(2)}, \ldots, y_{it}^{(k_t)}\right); \text{ and} && (17) \\ E\left(y^{(t-2)}.e_{it}\right) &= 0, \quad y^{(t-2)} = \left(y_1^{(t-2)}, y_2^{(t-2)}, \ldots, y_N^{(t-2)}\right), && (18) \\ y_i^{(t-2)} &= \left(y_{i1}, y_{i2}, \ldots, y_{i,t-2}\right), t = 3, \ldots, T. \end{aligned}$$

We propose a sequential GMM estimation strategy, first estimating (15) under moment conditions (17) and (18), collecting residuals, and then using the residuals to estimate (16) under moment conditions (5), (6) and other lagged exogenous regressors. Validity of the sequential method follows from Newey (1984).

Pesaran (2006) distinguished between spatial dependence due to the effect of latent factors (spatial strong dependence) and that arising from the positions of units in space (spatial weak dependence), and proposed the common correlated effects approach for estimation of panel data regression models in the presence of both kinds of dependence. Under this approach, the effect of latent factors is captured by including cross-section averages of the dependent variable and all independent variables as additional regressors. Estimation of a model similar to (15), with the effect of unobserved factors modeled by cross-section averages, would be similar to teh above. However, while the common correlated effects approach is in principle attractive, its use in the empirical application discussed in the following section presented major challenges. Nevertheless, the distinction between strong and weak dependance is useful for interpretation. We discuss this issue in further detail later.

3.3 Inferring on network structure

The GMM estimation framework adopted in this paper relies crucially on the validity and adequacy of the assumed moment conditions. The issues related to this are well understood in the literature; see, for example, Hall (2004). Throughout our empirical exercise, we test for overidentifying restrictions using the Sargan-Hansen J-statistic (Hansen, 1982), and test for weak instruments using the Wald test in Kleibergen and Paap(2006)..

The more interesting tests in our setup relate to network structure. To emphasize, our main assumption in this paper is that interactions in social networks and committees are endogenous outcomes of the strategic behaviour of agents. This is in sharp contrast to the view in the spatial econometrics literature where interaction weights are fixed by design, known at least approximately, and have no special informational content beyond accounting for cross-section dependence in the underlying economic model. We, however, conduct inference on the weights matrix specifically to understand the strength (and nature) of interactions, and to study the pattern of links evolving from network interactions by economic agents.

Recent literature on network theory (see, for example, Goyal (2005, 2007), Goyal and Vega-Redondo (2007) and references therein) point to a variety of equilibrium network structures arising from rational agents' bargaining strategies, and crucially depend on payoffs and incentives. Theory suggests that certain simple network architectures, such as a star or a cycle, may emerge as equilibrium solutions, while structures such as hybrid cycle-star may be less stable. Further, there are important roles for asymmetric networks.

In our framework, evaluating that the network structure has a particular simple architecture reduces to testing for simple parameter restrictions in the interaction weights. Various tests have been proposed within the GMM framework, and issues relating to testing are well understood; see, among others, Newey and West (1987) and Hall (2004).In our application, we use LR type tests for evaluating network structures.

4 Application

We develop the methodological approach described above in the context of a particular form of interaction. In this case it is the decisions that a Committee makes on interest rates for the conduct of monetary policy.

4.1 A model of a MPC

A standard way of understanding how a committee comes to a decision is that each member reacts independently to a 'signal' coming from the economy and makes an appropriate decision in the light of this signal and the particular preferences/expertise of the member. A voting method then generates a decision that is implemented. In practice there are also various forms of cross committee dependence. Before a decision is made there is a shared discussion of the state of the world as seen by each of the members. In this section we model the possible interactions between members of a committee as one in which interaction occurs in the form of deliberation. Views are exchanged about the interpretation of signals and an individual member may decide to revise his view depending upon how much weight he places on his own and the views of others.

This process can be cast as a simple signal extraction problem within a highly stylised framework. Let the j-th MPC member formulate an initial (unbiased) estimate of, say, the output gap (y_t), where $j = 1, \ldots, m$ members are a subset of a Committee of N members. Then the underlying model for the j-th member is:

$$y^j_{t,in} = \beta'_j x^j_t + \eta^j_t \text{ with } \omega^j_t \backsim N(0, \sigma^2_{\eta^j}) \text{ and } E\left(y^j_{t,in}\right) = \beta'_j x^j_t = y_t, \text{ for } j = 1, \ldots, m, \tag{19}$$

where x^j_t represent a collection of macroeconomic variables that the j-th member uses to obtain his own forecast for current output gap, $y^j_{t,in}$.

The internal process of deliberation between the members of the Committee reveals to everyone individual views of the output gap brought to the meeting.[6] The j-th member then optimally combines his estimate with the estimates of the others, attaching a weight to each. The members, however, do not know the true variances of forecast errors, $\sigma^2_{\eta^j}$. Therefore, the weight depends on the j-th member's (subjective) evaluation of the usefulness of the forecasts of others. For example the j-th member's view of the (unbiased) estimate of the output gap of the k-th member is:

$$y^k_{t,in} = y_t + \eta^k_t \text{ with } \eta^k_t \backsim N(0, \sigma^2_{jk}), \text{ for } k = 1, \ldots, m, \tag{20}$$

[6] Austin-Smith and Banks (1996) point out that we need each committee member to be open in revealing his estimate of the output gap and sincere in casting a vote for an interest rate decision that corresponds to the infomation available. Although we consider only the one period problem here, in a multi-period context we assume that reputational considerations are sufficiently powerful to ensure fair play.

including his own forecast y_t^j. In addition, each member holds beliefs on the covariances between the forecast errors. A diffuse prior, σ_{jk}^2, in the Bayesian sense, suggests little confidence in the forecast of the k-th member's estimate relative to the estimate of the j-th member himself and the estimates of the rest of the Committee.

In other words, each member observes the initial estimates $\mathbf{y}_t = \left(y_{t,in}^1, y_{t,in}^2, \ldots, y_{t,in}^m\right)'$, but his views on the accuracy of these forecasts are based on a private belief, denoted $\mathbf{S}_j$, of the covariance matrix of the $(m \times 1)$ vector of errors, $\eta_t = (\eta_t^1, \eta_t^2, \ldots, \eta_t^m)'$. The updated (and optimal in the mean squared error sense) estimate of the output gap for the j-th member is then a weighted average (with the weights summing to one) of the m members:

$$y_{t,up}^j = \mathbf{v}_j'\mathbf{y}_t, \text{ for } j = 1, \ldots, m, \tag{21}$$

where $\mathbf{v}_j$ is a $(m \times 1)$ vector of weights (that sum to one) given by

$$\mathbf{v}_j = \mathbf{e}'\mathbf{S}_j^{-1}/\mathbf{e}'\mathbf{S}_j^{-1}\mathbf{e}, \text{ for } j = 1, \ldots, m,$$

and $\mathbf{e}$ is a $(m \times 1)$ unit vector.[7] The weights that members attach to the estimate of the output gap can in principle be negative if there is a sufficiently large negative covariance, or larger than one if there is a large positive covariance. Therefore, deliberation implies an updated, or revised, $(m \times 1)$ vector of estimates of the output gap: $\mathbf{y}_t^r = (y_{t,up}^1, y_{t,up}^2, \ldots y_{t,up}^m)$. This vector in turn maps into an interest decision through:

$$i_{jt} = \pi_{t|t} + \frac{1}{\alpha_j \beta_{2j}}(\pi_{t+1|t} - \pi^*) + \frac{\beta_1}{\beta_{2j}} y_{t,up}^j \quad \text{for } j = 1, ..., m. \tag{22}$$

Further, substitituting from (21) and (19), we have

$$\begin{aligned} i_{jt} &= \pi_{t|t} + \frac{1}{\alpha_j \beta_{2j}}(\pi_{t+1|t} - \pi^*) + \frac{\beta_1}{\beta_{2j}} \beta_j' x_t^j + \frac{\beta_1}{\beta_{2j}} \mathbf{v}_j' \eta_t \\ &= \pi_{t|t} + \frac{1}{\alpha_j \beta_{2j}}(\pi_{t+1|t} - \pi^*) + \frac{\beta_1}{\beta_{2j}} \beta_j' x_t^j + \varsigma_{jt}, \end{aligned} \tag{23}$$

where x_t^j also potentially includes the forecast of current output gap $y_{t|t}$. In the above, π^* is the inflation target, $\pi_{t+1|t}$ the forecast of inflation at time

[7] This is the standard formula for the optimal combination of linear signals and was first introduced into economics by Bates and Granger (1969) as a way of combining forecasts.

period $t+1$ based on information available in period t, and likewise for $\pi_{t|t}$ and $y_{t|t}$, and the subscript $t|t$ indicates that current realisations of the output gap and inflation may well be imperfectly observed, and need to be forecasted.[8] Being linear combinations of member specific forecast errors, $\left\{\eta_t^j : j = 1, \ldots, m\right\}$, the error terms ς_{jt} are correlated across members. The corresponding weighting matrix, obtained by stacking the row matrices of optimal weights, is denoted by

$$\mathbf{V} = \left[\begin{array}{cccc} \frac{\beta_1}{\beta_{21}}\mathbf{v}_1 : & \frac{\beta_1}{\beta_{22}}\mathbf{v}_2 : & \ldots : & \frac{\beta_1}{\beta_{2m}}\mathbf{v}_m \end{array} \right]'_{(m \times m)},$$

where the linear combinations are given by the rows of $\mathbf{V}$. Thus, the cross-member error vector for the interest rate rule (22) is:

$$\varsigma_t = (\varsigma_{1t}, \varsigma_{2t}, \ldots, \varsigma_{mt})' = \mathbf{V}\eta_t.$$

Define $\mathbf{D} = diag\,(d_1, d_2, \ldots, d_m)$ as the diagonal matrix with entries as the diagonal elements of $\mathbf{V}^{-1}$, and let $\Gamma = \mathbf{VD}$. It follows that

$$\varsigma_t = \Gamma\eta_t^*; \eta_t^* = \left(\frac{1}{d_1}\eta_t^1, \frac{1}{d_2}\eta_t^2, \ldots, \frac{1}{d_m}\eta_t^m\right)',$$

where η_t^* is a vector of independent but heteroscedastic vectors. Further, Γ^{-1} has unit diagonal elements, so that

$$\varsigma_t = \boldsymbol{W}\varsigma_t + \eta_t^*, \tag{24}$$

and $\boldsymbol{W} = \boldsymbol{I} - \Gamma^{-1}$ is an interaction weights matrix with zero diagonal elements.[9] Our inferences on the network structure within the MPC focus on this interaction weights matrix, with (23) as the underlying regression model and (24) as the model for dependent errors; corresponding to (1) and (2) respectively.

[8] The derivation of the above inflation 'feed forward' rule (22) is based on Svensson (1997), where the policymaker only targets inflation, and the central bank can (in expectation) use the current interest rate to hit the target for inflation two periods hence; for further details, see Bhattacharjee and Holly (2009, 2010).

[9] Two assumptions are made in the above derivation. First, the rows of $\mathbf{V}$ are linearly independent, so that $\mathbf{V}^{-1}$ exists. Intuitively, this implies that each of the selected MPC members ($j = 1, 2, \ldots, m$) hold beliefs on accuracy of the initial forecasts that are different from each other. Second, none of the MPC members put zero weight on their own forecast, or technically speaking, all diagonal cofactors of $\mathbf{V}$ are nonzero. This ensures that diagonal elements of $\mathbf{V}^{-1}$ are not zero. Given that the selection of members is made from a group of internal and external experts it would be unlikely that any Committee member attached no credence to his own opinions.

4.2 Interactions among members of the Committee

Covariances between forecast errors imply interactions between members over and above the sharing during deliberation of individual estimates of the output gap.[10] One form of interaction may involve strategic voting by a subgroup of the Committee seeking to influence the interest rate decision.[11] However, it is well known that when the median is used to determine an outcome it will be invariant to attempts to act strategically. Interactions can be asymmetric. Some members are more influenced by others than they in turn influence, while other members may be more influencial and less influenced by others.

However, it is possible that there are commonalities among members of a committee that can be thought of as a form of likemindedness. Some members share a common background or experiences and happen to share a common view of the world. In this case there will be positive covariances between the forecast errors of groups of members who share common views. Similarly, there may be conflicts between preferences of other members. The current literature on political economy emphasizes several channels through which significant interactions may arise; see Gerling *et al.* (2005) for further discussion.

Grüner and Kiel (2004) analyze collective decision problems in which individual bliss points are correlated but not identical. Like our setup here, all agents obtain private information about their most desired policy, but the individually preferred decision of a group member does not only depend on his own private information but also on the other group members' private information. They find that for weak interdependencies, the equilibrium strategy under the median mechanism is close to truth-telling, whereas the mean mechanism leads to strong exaggeration of private information. This is similar to our arguments here. However, in a setting with interdependencies, pre-vote communication may affect equilibrium behaviour - an issue not yet addressed clearly in the literature. Our analysis in this paper suggests that limits to information sharing (only a single revision in our case) may reflect interdependencies, both positive and negative, in the final votes though not necessarily in the median outcome.

[10] The pooling of information avoids any of the complications that arise in Townsend's (1983) model of 'forecasting the forecasts of others'.

[11] As before we assume openness and sincerity in providing information about what the output gap is.

Matsen and Røisland (2005) highlight the fact that members of a Committee may represent different constituents (countries or regions, sectors etc.) where interest rate changes may have different effects. Asymmetric shocks and differing transmission mechanisms may then induce members to engage in strategic voting. In this case, there may be positive or negative interactions originating from unobserved factors which are specific to sub-groups within the Committee. This is similar to the likemindedness view discussed above.

Li *et al.* (2001) analyse small-committee decisions when members have partially conflicting interests and possess private information, but preferences are common knowledge. Their main finding is that information cannot be fully shared and voting procedures arise as the equilibrium method of information aggregation. Further, Felgenhauer and Grüner (2008) show that transparency in publishing voting behaviour may have unintended consequences in settings where external influence is high. Specifically, benefits from strategic voting increase in this case, not only for the pivotal voters, but also for extreme hawks or doves.

Recent literature on endogenous network formation also point to important roles for strategic information sharing and links (Goyal, 2007). First, transmission of information may be unidirectional or bidirectional. Granovetter (1973) interprets unidirectional transmission as a weak link and bidirectional as a strong link. Secondly, the quality of links may vary quite a lot, and network formation endogenously depends on the quality (Goyal, 2005). Third, certain forms of network architecture often emerge as equilibrium solutions, while others are not stable. For example, a periphery-sponsored star is a Nash equilibrium in Goyal (2005), while under capacity constraints Goyal and Vega-Redondo (2007) find a cycle network more meaningful. In the context of interactions between Committee members, this suggests two important aspects. First, a network where all members try hard to obtain private information from others is often not an equilibrium solution. Second, the architecture of networks which emerges in equilibrium is useful for understanding the nature of information aggregation and constraints. Our framework for inference on cross member interactions within the MPC will inform both these aspects.

Finally, within a MPC setting, Sibert (2002, 2003) points to the important role for reputational effects and strategic behaviour. Specifically, she shows that the behaviour of new members may be different from that of veterans, and this difference can depend on the balance of power and size of the committee. Since, under transparency, voting behaviour is the main signal for reputational effects, this line of research also has potential implications for our model of MPC interactions; see also Riboni and Ruge-Murcia (2010) and Alesina and Stella (2011).

4.3 Data and sample period

Above we presented a model of committee decision making based on an inflation forecast rule which accommodated heterogeneity across policy makers and allowed interaction between their individual decisions. Now, we turn to an empirical examination of decision making within the Monetary Policy Committee of the Bank of England. The primary objectives of the empirical study is to understand cross member interaction in decision making at the Bank of England's MPC, within the context of the model of committee decision making presented in the previous section. Importantly, our framework allows for heterogeneity among the MPC members and the limited dependent nature of preferred interest rate decisions. Votes of individual members of the MPC constitute our dependent variables. The source for these data are the minutes of the MPC meetings.

Since mid-1997, when data on the votes of individual members started being made publicly available, the MPC has met once a month to decide on the base rate for the next month.[12] Over most of this period, the MPC has had 9 members at any time: the Governor (of the Bank of England), 4 internal members (senior staff at the Bank of England) and 4 external members. External members were usually appointed for 3 to 4 years with the possibility of reappointment for a further period. Because of this turnover, the composition of the MPC has changed reasonably frequently. There have also been periodic changes in the internal members. Because of frequent changes in the Committee, the data are better suited for static, rather than dynamic analysis. Thus, the data are well matched for the methods proposed in this paper, which are rich in the analysis of cross-sectional dynamics, rather than temporal dynamics. We use these data for studying network structure within chosen compositions of the MPC, focussing on static committee structure, and use variation across different compositions to infer on temporal dynamics.

[12] The MPC met twice in September 2001. The special meeting was called after the events of 09/11.

To facilitate the study of heterogeneity and interaction within the MPC - as well as changes over time - we focus on 3 time periods.[13] For each of these periods, we designated a subset of MPC members as the "core" committee. First, the 33 month period September 1997 to May 2000, with a core committee of 5 members (Governor George, internal members Clementi and King, and external members Buiter and Julius); second, the 35 month period July 2003 to May 2006, with the core committee comprising Governor King, internal members Bean and Lomax, and external members Barker and Nickell; and third, the 44 month period October 2006 to May 2010, with the 5 member core committee Governor King, internal members Bean and Tucker, and external members Barker and Sentance. The core committee consists of 5 members in each case, including the Governor, 2 internal and 2 external members. There are two reasons why we do not consider a larger core committee for any period. First, this would reduce the number of time periods (months) when these individuals as a group would have served on the MPC. Given that the number of time periods in each case is only moderately long, between 33 and 44 monthly meetings, this would have led to significant reduction in sample size. Secondly, and most importantly, the main identification strategy here is through moment conditions, where we use the data for the 4 remaining members of the MPC in a given month to construct instruments. This is analogous to the standard approach in dynamic panel data models of using data at higher lags as instruments.

The question therefore arises as to which individual MPC members should be designated as constituting the "core". We take an empirical view on this matter. Since data on the excluded individuals are used as instruments for the votes of included members, we judge the appropriateness of the core by empirical validity of corresponding moment conditions.

The voting pattern of these selected MPC members suggest substantial variation; see, for example, Table 1 in Bhattacharjee and Holly (2010) and further discussion in Bhattacharjee and Holly (2011). Corresponding to the above periods, we collected information on the kinds of data that the MPC looked at for each monthly meeting. Importantly, we conditioned only on

[13] We thank an anonymous referee for valuable suggestions that encouraged us to extend our analysis of the MPC network structure to the Governor King period. This enabled us to examine issues of changes in the network over time, the role of the Governor, and the effect of entry and exit of members. Further, this helped us clarify the important issue of strong versus weak spatial dependence in the context of the MPC.

information actually available at the time of each meeting.[14] The data used were: (a) Unemployment: year-on-year change in International Labor Organization (ILO) rate of unemployment, lagged 3 months (Source: Office of National Statistics (ONS) Labour Force Survey); (b) Housing prices: year-on-year growth rates of the Nationwide housing prices index (seasonally adjusted) for the previous month (Source: Nationwide); (c) Share prices: year-on-year growth rate of the FTSE 100 share index at the end of the previous month; (d) Exchange rates: year-on-year growth of the effective exchange rate at the end of the previous month (Source: Bank of England); (e) Current inflation: year-on-year growth rate of RPIX inflation lagged 2 months for the Governor George period, and CPI inflation for the Governor King period (Source: ONS); (f) Inflation expectations: 4 year ahead forward yield curve estimates (5 year ahead estimates for the Governor King period) obtained from index linked bonds (Source: Bank of England and ONS, respectively); (g) Current output: annual growth of 2-month-lagged monthly GDP (Source: National Institute of Economic and Social Research); (h) Output expectations: model based one-year-ahead modal quarterly forecasts implied by fan charts (Source: Bank of England); and (i) Uncertainty: standard deviation of the one-year-ahead forecast of GDP growth (Source: Bank of England). For further discussion of these data, see Bhattacharjee and Holly (2010, 2011).

The collection of explanatory macroeconomic variables for estimating member specific interest rate rules was expanded for the two Committees in the Governor King regime. This was because GMM estimates from our model of interaction weights for these periods suggested a potential violation of the spatial granularity (stationarity) condition (Pesaran and Tosetti, 2011). Based on the distinction between spatial strong and weak dependence (Pesaran, 2006), this would suggest the presence of strong dependence, potentially driven by hidden time-specific factors. The common correlated effects methodology (Pesaran, 2006) suggests modelling such latent factor effects using cross-sectional averages of the dependent and independent variables. This approach presented major challenges in our application. First, our explanatory variables are macroeconomic and therefore offer no cross-section variation. Second, the average response variable is meaningful in this context, since it should be a proxy for the majority voting outcome. However,

[14] On the issue of using real-time data rather than ex post revised data for analysing monetary policy decisions, see, for example, Orphanides (2003) and Bhattacharjee and Holly (2011).

it did not appear to be successful in mopping up strong dependence in any significant way. One reason could be that the spatial lag of the response variable was already included in the RHS, and this average contained very little additional information. Third, the common correlated effects methodology is designed to work well in large N and T settings. However, N is fixed in our case, which may have mitigated against its effective use as an approximation for the unobserved factor(s).[15]

Nevertheless, the intuition behing the above approach suggested that we were potentially missing some time-specific common factors in our underlying model. This led us to examine the minutes of MPC meetings and speeches by MPC members to try and identify such latent factors. We found suggestions that during the Governor King period, monetary policy was increasingly affected by world developments, and policy itself may also have been co-ordinated across central banks. Therefore, we included as additional explanatory factors several international economic variables: specifically, a measure of global GDP growth (Source: IfW, Kiel Institute for the World Economy) and US interest rates and US inflation (Source: Federal Reserve). This eliminated strong dependence in every case, and aided interpretation of network structure.

4.4 The empirical model

We start with the model of individual voting behaviour within the MPC (23) developed in the previous section. The model includes individual specific heterogeneity in the fixed effects, in the coefficients of inflation and output gap, in the effect of forecast uncertainty, and features of labour, housing and financial markets, as well as the international economy that specific MPC members may have paid attention to. We estimated this model in a form where the dependent variable is the j-th member's preferred change in the (base) interest rate. In other words, our dependent variable, v_{jt}, represents the deviation of the preferred interest rate for the j-th member (at the meeting in month t) from the current (base) rate of interest r_{t-1}:

$$v_{jt} = i_{jt} - r_{t-1}.$$

Therefore, we estimate the following empirical model of individual deci-

[15] We thank an anonymous referee for pointing this issue out to us.

sion making within the MPC:

$$\begin{aligned} v_{jt} &= \phi_j + \beta_j^{(r)}.\triangle r_{t-1} + \beta_j^{(\pi 0)}.\pi_t + \beta_j^{(\pi 4)}.\pi_{t+4|t} + \beta_j^{(y0)}.y_{t|t} \\ &\quad + \beta_j^{(y1)}.y_{t+1|t} + \beta_j^{(\sigma)}.\sigma\left(y_{t+1|t}\right) + \underline{\lambda}_j'.\underline{Z}_t + e_{jt}, \end{aligned} \tag{25}$$

where $\underline{Z}_t$ represents current observations on the change in unemployment, the change in FTSE index, the change in house prices and the chagne in the exchange rate. The standard deviation of the one-year ahead forecast of output growth is denoted by $\sigma\left(y_{t+1|t}\right)$; this term is included to incorporate the notion that the stance of monetary policy may depend on the uncertainty relating to forecasted future levels of output and inflation. As discussed in Bhattacharjee and Holly (2010), increased uncertainty about the current state of the economy may bias policy towards caution in changing interest rates.

Further, we also, conditioned the MPC member specific decision rules on world GDP growth, the interest rate decision of the Federal Reserve and US inflation rate. As discussed in the previous section, these additional explanatory variables were included to ensure validity of the spatial granularity condition. The above regression model was combined with a model for interaction between the error terms for different members

$$e_t = \boldsymbol{W} e_t + u_t, \tag{26}$$

where $\boldsymbol{W}$ is a $(N \times N)$ matrix of interaction weights with zero diagonal elements. Previously we developed a model where decision making within the MPC implied a matrix, $\mathbf{V}$, of weights that each member attaches to his own forecast and to those of other members. We related $\mathbf{V}$ to a corresponding interaction weights matrix $\boldsymbol{W}$, with zeroes on the diagonal and unrestricted entries on the off-diagonals, such that $(\boldsymbol{I} - \boldsymbol{W})$ is non-singular. In addition to interaction effects because of information sharing and deliberation within the MPC, strategic elements may also be important in determining the network structure.

We applied the model (25) and (26) to data on votes by the Bank of England's MPC members. Our analysis placed special attention to highly clustered interval censored response variable and interaction between errors for the different members.

4.4.1 Interval censored votes

Votes of MPC members are highly clustered, with a majority of the votes proposing no change in the base rate. The final decisions on interest rate changes are all similarly clustered. Thus, votes on interest rate changes are not oberved on a continuous or unrestricted scale, but represent a non-continuous or limited dependent variable. Moreover, changes in interest rates are in multiples of 25 basis points. Therefore, following Bhattacharjee and Holly (2010), we use an interval regression framework for analysis.

Then, the observed dependent variable in our case, $v_{jt,obs}$, is the truncated version of the latent policy response variable of the j-th member, v_{jt}, which we model as

$$\begin{aligned}
v_{jt,obs} &= -0.25 \quad \text{if} \quad v_{jt} \in [-0.375, -0.20) \\
&= 0 \qquad\;\; \text{if} \quad v_{jt} \in [-0.20, 0.20] \\
&= 0.25 \quad\;\, \text{if} \quad v_{jt} \in (0.20, 0.375]\,, \text{ and} \\
v_{jt} &\in (v_{jt,obs} - 0.125, v_{jt,obs} + 0.125] \;\text{ whenever }\; |v_{jt,obs}| > 0.325
\end{aligned} \tag{27}$$

The wider truncation interval when there is a vote for no change in interest rates (*ie.*, for $v_{jt,obs} = 0$) may be interpreted as reflecting the conservative stance of monetary policy under uncertainty with a bias in favour of leaving interest rates unchanged.

4.4.2 Inference methods

Under the maintained assumptions that (a) regression errors are uncorrelated across meetings, and (b) the response variable is interval censored, estimation of the policy reaction function for each member (25) is an application of interval regression (Amemiya, 1973). In our case, however, we have an additional feature that the errors are potentially correlated across members. If we can estimate the covariance matrix of these residuals, then we can use a standard GLS procedure by transforming both the dependent variable and the regressors by premultiplying with the symmetric square root of this covariance matrix. However, the dependent variable is interval censored and has to be placed at its conditional expectation given current parameter estimates and its censoring interval. This sets the stage for the next round of iteration. At this stage, the dependent variable is no longer censored; hence, a standard SURE methodology can be applied.

Estimating the covariance matrix at the outset is also nonstandard. Because the response variable is interval censored the residuals also exhibit similar limited dependence.[16] We use the Expectation-Maximisation algorithm (Dempster *et al.*, 1977). At the outset, we estimate the model using standard interval estimation separately for each member and collect residuals. We invoke the Expectation step of the EM algorithm and obtain expected values of the residuals given that they lie in the respective intervals. Since we focus on 3 sets of five MPC members, for each monthly meeting we have to obtain conditional expectations by integrating the pdf of the 5-variate normal distribution with the given estimated covariance matrix.

Iterating the above method till convergence provides us with maximum likelihood estimates of the policy reaction function for each of the five members, under standard assumptions, specifically multivariate normality of the cross member errors. The covariance matrix of the errors is unrestricted.

Once the above model is estimated, we obtain interval censored residuals using the initial censoring scheme. These are set to their expected values, conditional on estimates of the model parameters and their own censoring interval. Similarly, policy reaction functions are estimated for other $(N-m)$ members who were in the committee in each month under study, for use as instruments. These are also placed at their conditional expected values. The stage is now set for estimating the matrix of cross member network interactions. This is achieved by two-step feasible GMM estimation, assuming that the censoring intervals are exogenous in the interaction model for the errors, and using moment conditions given in (12). We report Newey-West kernel-based arbitrary heteroskedasticity and arbitrary autocorrelation consistent (HAC) standard errors with automatic bandwidth selection (Newey and West, 1994). Tests of significance of the interaction weights are conducted using standardized test statistics based on the above standard errors.[17]

[16]For example, suppose the observed response for the j-th member in a given month t is 0.25. By our assumed censoring mechanism (27), this response is assigned to the interval $(0.20, 0.375]$. Suppose also that the linear prediction of the policy response, based on estimates of the interval regression model is $\widehat{v}_{jt} = 0.22$. Then the residual $v_{jt} - \widehat{v}_{jt}$ cannot be assigned a single numerical value, but can be assigned to the interval $(0.20 - 0.22, 0.375 - 0.22]$. In other words, the residual is interval censored: $v_{jt} - \widehat{v}_{jt} \in (-0.02, 0.155]$.

[17]Note that the idiosyncratic errors in our spatial model are heteroscedastic across the members. Further, our inference focuses of cross-section dynamics while temporal dynamics is not fully modelled here. Hence, it is important to use HAC standard errors.

The validity of the assumed moment conditions is checked using the Sargan-Hansen J-test for overidentifying restrictions (Hansen, 1982). Further, and as discussed previously, weak instruments is also potentially a problem here. Therefore, we check instrument adequacy using the Kleibergen and Paap (2006) r_k Wald test for weak instruments. For each endogenous regression estimate, we verify that the Kleibergen-Paap Wald F-statistic lies above the 5% critical value subject to a 10% maximal IV bias relative to OLS, so that the null hypothesis of weak instruments can be rejected. Stock and Yogo (2005, Table 1) report these critical values for equations with up to 3 endogenous variables. Our models (corresponding to each ow of the $\mathbf{W}$ matrix) have 4 endogenous variables. However, from Table 1 of Stock and Yogo (2005), it is clear that the critical value for 4 endogenous variables and up to 30 instruments does not exceed 11.00. All of our estimates are based on different sets of instruments that satisfy this conservative bound and do not fail the overidentifying restrictions test.

As discussed before, some estimates of the interaction weights indicate a potential violation of the spatial granularity condition discussed in Pesaran and Tosetti (2011). Further, while spatial granularity (or, weak dependence) is useful for interpretation of the estimated network structures, there is no statistical test available. We use $100,000$ Monte Carlo simulations from the estimated multivariate distribution of interaction weights to estimate the proportion of cases where the signed combination of weights in each row of the estimated $\mathbf{W}$ matrix lie within the acceptable region $(-1, 1)$ when the spatial granularity (stationarity) condition holds. This we interpret as an approximate p-value, denoted $G(p)$, for a spatial granularity test.[18] Formal tests of spatial granularity lie in the domain of future research.

Finally, for inference on network structures, we use a LR type procedure (Newey and West, 1987; also discussed in Hall, 2004). This completes a description of our inference methods.

[18] Strictly speaking, we test for only one part of the spatial granularity condition, that the row norm of $\mathbf{W}$ is less than unity, and leave the column norm aside for the moment. Consider, for example, an estimated row of interaction weights $(-0.11, 0.40, 0.62, \mathbf{0}, -0.49)$, aggregating to a sum of absolute values of 1.62, which is much larger than 1. Based on the estimated values and covariance matrix of interaction weights, we simulate values for the above row. Based on these simulations, we report as $G(p) = 0.102$ the proportion of simulations where the signed linear combination lies within the permissible range $(-1, 1)$ under the null hypothesis of spatial granularity. In other words, since the null hypothesis has a coverage of 10.2%, we cannot reject the null at 5% and 1% confidence levels.

4.5 Results

Since our interest here lies mainly on the network structure, we present estimates only for the network interactions matrix, $\mathbf{W}$, in our model for the regression error terms (26). Estimates of the policy reaction function for the first group of members are very similar to Bhattacharjee and Holly (2009, 2010) and not discussed here. Similar to the above papers, we find evidence of substantial heterogeneity in the estimated policy rules. This indicates that monetary policy decision making within a committee is richer than that which would be inferred from an analysis of simple aggregate decisions.

Furthermore, as in Bhattacharjee and Holly (2009), the error correlations across members are large, implying therefore that there is substantial interaction between the decision making processes of MPC members. This interaction is over and above that which can be explained by the extensive set of explanatory variables included in our empirical model of individual decision making (25). We estimate the interaction weights by GMM, under the exogenous censoring interval assumption, and using selected instruments derived from residuals for other $(N - m)$ members of the committee, lagged residuals of members included in the analysis (from lag 2 backwards), and lags of regressors in the interest rate rule (25). In the spirit of dynamic panel GMM estimators (Arellano and Bond, 1991; Blundell and Bond, 1998), the instrument set is therefore different for each month under analysis, reflecting the evolving membership of the Committee. The endogenous error models for each member are estimated separately, though the entire estimation exercise can be combined together within an unified GMM setup. The estimated interaction matrix for the 3 groups are reported in Table 3.

Several important observations can be drawn from the estimates. Interactions can be understood in three ways. First, there is the degree to which a member is connected to others. We measure this by the total number of connections (positive or negative). Secondly, there is the form of the interaction. Interactions are measures of influence. An individual MPC member can influence other members but also be influenced by others. We measure the strength of the j-th member's influence on others by the sum of the squared (significant at 5% level) elements in the j-th column. We measure the strength of the influence of others on the j-th member by the sum of the squared (significant) elements in the j-th row. Finally, we measure the total interactions of the j-th member as the sum of 'influence on others' and 'influenced by others'.

Table 3: Estimated Cross Member Network Interaction Matrix

A. 33 month period September 1997 to May 2000 (Governor: George)

	George	**Clementi**	**King**	**Buiter**	**Julius**	J-stat.	$Wald$	$G(p)$
George	**0**	0.825** (0.034)	0.166** (0.046)	−0.005 (0.053)	−0.122** (0.033)	2.42 (p=0.66)	13.08	0.178
Clementi	0.951** (0.075)	**0**	−0.217+ (0.116)	0.262* (0.113)	0.185* (0.085)	3.80 (p=0.70)	12.29	0.013
King	0.291* (0.138)	−0.147 (0.149)	**0**	0.713** (0.058)	0.426** (0.129)	2.83 (p=0.83)	12.48	0.055
Buiter	−0.107 (0.235)	0.402 (0.251)	0.625** (0.110)	**0**	−0.486** (0.175)	2.52 (p=0.28)	15.36	0.102
Julius	−0.425** (0.163)	0.375* (0.190)	0.490** (0.081)	−0.228** (0.069)	**0**	1.79 (p=0.62)	20.27	0.064

B. 35 month period July 2003 to May 2006 (Governor: King)

	King	**Lomax**	**Bean**	**Barker**	**Nickell**	J-stat.	$Wald$	$G(p)$
King	**0**	0.717** (0.045)	−0.159 (0.121)	0.208** (0.044)	0.243+ (0.135)	2.53 (p=0.96)	13.31	0.089
Lomax	0.796** (0.030)	**0**	−0.002 (0.044)	−0.172** (0.021)	0.189** (0.036)	2.92 (p=1.00)	18.72	0.053
Bean	−0.062 (0.071)	0.155* (0.066)	**0**	−0.087* (0.044)	0.844** (0.038)	3.12 (p=0.99)	19.17	0.081
Barker	0.350** (0.084)	−0.226** (0.069)	−0.053 (0.048)	**0**	0.588** (0.058)	2.93 (p=1.00)	21.06	0.128
Nickell	−0.002 (0.056)	0.199** (0.039)	0.619** (0.027)	0.339** (0.024)	**0**	2.90 (p=1.00)	73.16	0.060

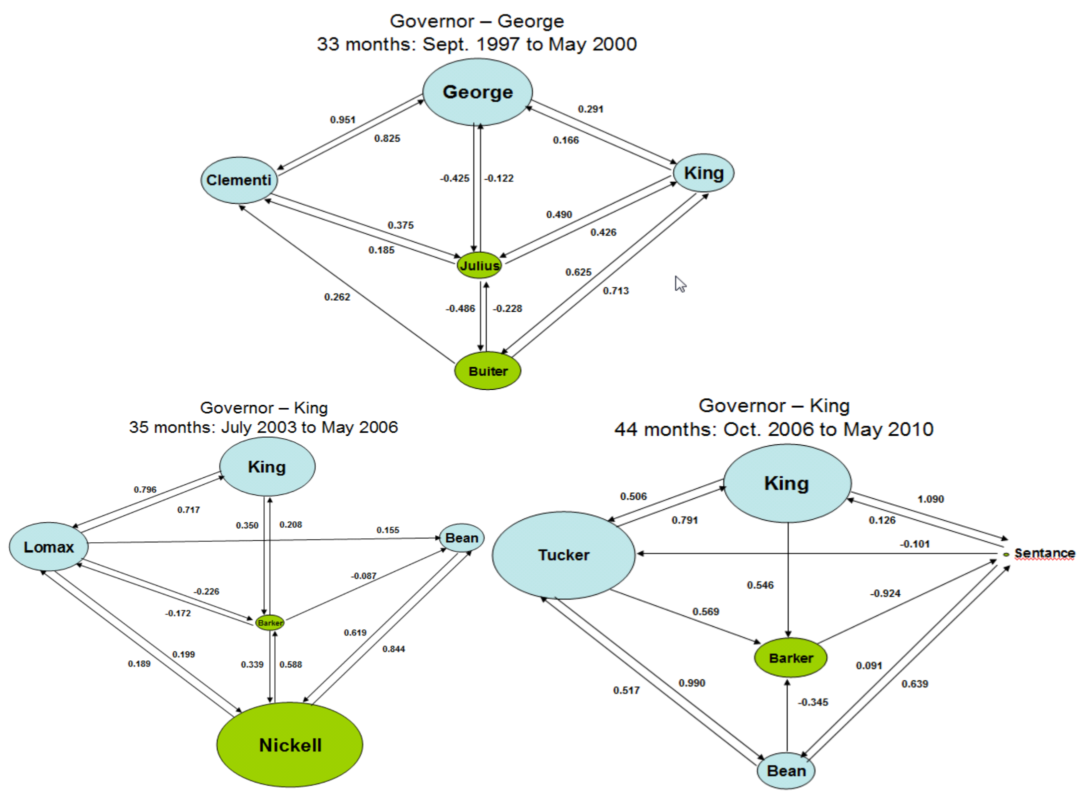
C. 44 month period October 2006 to May 2010 (Governor: King)

	King	**Bean**	**Tucker**	**Barker**	**Sentance**	J-stat.	$Wald$	$G(p)$
King	**0**	−0.043 (0.195)	0.791** (0.192)	0.268 (0.208)	0.126** (0.048)	1.87 (p=0.60)	21.46	0.528
Bean	0.022 (0.123)	**0**	0.990** (0.124)	−0.029 (0.057)	0.091** (0.025)	3.82 (p=0.80)	14.16	0.113
Tucker	0.506* (0.212)	0.517* (0.225)	**0**	−0.014 (0.062)	−0.101* (0.040)	0.002 (p=0.97)	12.95	0.143
Barker	0.546** (0.149)	−0.345* (0.175)	0.569** (0.207)	**0**	−0.076+ (0.042)	3.26 (p=0.78)	12.61	0.053
Sentance	1.090* (0.451)	0.639* (0.330)	−0.157 (0.369)	−0.924* (0.482)	**0**	3.29 (p=0.86)	12.47	0.085

** , *and +– Significant at 1%, 5% and 10% level respectively.
HAC standard errors in parentheses.

First, from the Governor George period, while most (though not all) of the significant links between members are strong (that is, they run both ways),

Figure 1: **MPC Network** (Ellipses proportional to influence)



the interaction weights matrix is far from symmetric. While Buiter affects the decisions of Clementi significantly, the opposite is not true. Asymmetry is most obvious for the strong influences running from George to King and Julius, while interactions in the opposite direction (though significant) are not as large. Second, some network weights are not significant either way. Specific examples are between George and Buiter, and between Clementi and King. This points to important constraints on information sharing within the committee. Third, some interaction weights are negative. Prominent examples are between Julius on the one hand and George and Buiter on the other. At the same time, a graphical representation of the network structure[19] (Figure 2) clearly shows that most of the interactions within these members involve Julius; in other words, she is most centrally located. Fourth, the internal members are more influential within the committee, and George (the Governor) is the most influential of all measured by the sum of the squared weights in the column for George, with Buiter and King broadly jointly second most influential, and Clementi was the least influential. Sixth, contrary to what is predicted in theoretical models of networks, neither the star network nor a cycle has emerged as the network architecture here. A star network is one in which there a central hub connected to all other points without further connections among the non-central points. A cycle network is one in which each point is only connected to two other points. This was formally tested using a LR test, which rejected the null of a star network (and a cycle network) at the 1% level of significance.

For the second period covering Governor King for 2003 to 2006, we now find that Barker and Lomax are equally central, while now an external member, Nickell is the most influential, followed by the Governor. Barker is the least influential. Moreover, there appears to be no direct link between the Governor and Bean,.who over this period was Chief Economist. As with the George era, there is considerable asymmetry and no support for a star or cycle network.

In the second period of the King era, the composition of the Committee changes again with the arrival of an internal member in the form of Tucker and an external member in the form of Sentance. Bean becomes more integrated into the Committee but he still has no direct connection with the Governor, though now there is a strong influence of Tucker on Bean. Barker no longer remains the most connected, being replaced by the two new mem-

[19] Only connections corresponding to coefficients significant at the 5% level are shown.

bers. Tucker now becomes the most influential member, closely followed by the Governor. Sentance is the least influential but the most influenced.

The above observations point to the usefulness of the methods proposed in this paper. They also point to important institutional features which may be important in developing political economy and network theories of interactions within a monetary policy committee in the first instance, and also possibly within committees in general.

Finally, the estimates are numerically, and definitely in sign, similar to estimates of spatial weights for the Governor George period reported in Bhattacharjee and Holly (2009, 2011). There, the weights were estimated using certain structural restrictions on the weights matrix, using the methodology developed in Bhattacharjee and Jensen-Butler (2011).[20] At the same time, the significance of some of the weights are different. Admittedly, such structural restrictions on the weights matrix can be quite strong and violated in empirical applications. The LR tests employed here reject the null hypothesis of symmetric interaction weights at the 1% confidence level. This observation further underscores the usefulness of the methods proposed here.

5 Conclusions

In this paper we proposed estimation and inference on interaction weights in social networks and committees. Our method is based on GMM, and based on moment conditions motivated by the literature on dynamic panel data models. We place special emphasis on interval censored regression. Both the above aspects of the addressed problem are hard. First, estimation in censored regression models is difficult except under very strong assumptions. While assumptions may be untenable in some applications, we also point out alternative sets of assumptions and alternative ways to proceed in such cases. Second, estimation of interaction weights is also difficult and, as shown in Bhattacharjee and Jensen-Butler (2011), a partially identified problem. Existing estimation methods in Bhattacharjee and Jensen-Butler (2011) and Pesaran and Tosetti (2011) placed strong restrictions, on the structure of

[20]Specifically, Bhattacharjee and Holly (2009) assumed that: (a) the sum of squares for each row was unity (row standardisation), (b) idiosyncratic error variances for the equations corresponding to the 3 internal members were equal (partial homoscedasticity), and (c) interactions between the internal members were symmetric (partial symmetry). Bhattacharjee and Holly (2011) assumed a symmetric interaction weights matrix.

the weights matrix and the determinants of spatial dependence respectively, which we do not. At the same time, we make assumptions on moment conditions, and largely for simplicity, also on the nature of endogeneity and the distribution of the error terms. Which of these approaches contributes to more credible inferences is a question which is partly application-specific, and partly to be addressed through simulations.

An important advantage of the proposed methods is that they are simple to implement, and as our application to interactions within a monetary policy committee shows, they also contribute to very useful inferences. Specifically, our empirical study of voting behaviour within the Bank of England's MPC provides good support for the above method as well as our theoretical model, and uncovers new evidence on the process of monetary policy decision making. In particular, we provide more extensive evidence on the strength and nature of cross-member interactions and provide valuable insights into the process of decision making within the MPC. The evidence of strong interactions found here requires further examination within the context of an appropriate theory on incentives and strategic behaviour within a monetary policy committee. The emerging theoretical literature in this area may provide interesting new insights on this aspect.

Our empirical application also contributes towards understanding the process of network formation in a committee setting. The emerging and very active theoretical literature provides additional insights into the stability of different network architectures under assumptions on information sharing and bargaining. Empirical insights using our proposed methods can help in understanding these issues more fully.

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5.1 A model of a MPC

A standard way of understanding how a committee comes to a decision is that each member reacts independently to a 'signal' coming from the economy and makes an appropriate decision in the light of this signal and the particular preferences/expertise of the member. A voting method then generates a decision that is implemented. In practice there is also various forms of cross committee dependence. Before a decision is made there is a shared discussion of the state of the world as seen by each of the members. In this section we model the possible interactions between members of a committee as one in which interaction occurs in the form of deliberation. Views are exchanged about the interpretation of signals and an individual member may decide to revise his view depending upon how much weight he places on his own and the views of others.

This process can be cast as a simple signal extraction problem within a highly stylised framework. Let the j-th MPC member formulate an (unbiased) estimate of, say, the output gap, y_t^j. We adopt this notation here since we wish to consider situations where $j = 1, \ldots, m$ members could be a subset of a committee of N members. Then the underlying model for the j-th member is:

$$y_t^j = \beta_j.x_t^j + \omega_t^j \text{ with } \omega_t^j \backsim N(0, \sigma^2_{\omega^j}) \text{ and } E\left(y_t^j\right) = \beta_j.x_t^j = y_t, \text{ for } j = 1, \ldots, m. \tag{28}$$

The internal process of deliberation between the members of the Committee reveals to everyone individual views of the output gap brought to the meeting[21]. The j-th member then optimally combines his estimate with the

[21] Austin-Smith and Banks (1996) point out that we need each committee member to be open in revealing his estimate of the output gap and sincere in casting a vote for an interest rate decision that corresponds to the infomation available. Although we consider only the one period problem here, in a multi-period context we assume that reputational considerations are sufficiently powerful to ensure fair play.

estimates of the others, attaching a weight to each. This weight depends on the j-th member's (subjective) evaluation of the usefulness of the forecasts of others. For example the j-th member's view of the (unbiased) estimate of the output gap of the k-th member is:

$$y_t^{jk} = y_t + \omega_t^{jk} \text{ with } \omega_t^{jk} \backsim N(0, \sigma_{jk}^2), \text{ for } j = 1, \ldots, m. \tag{29}$$

A diffuse prior, σ_{jk}^2, in the Bayesian sense, suggests little confidence in the forecast of the k-th member's estimate relative to the estimate of the j-th member himself and the estimates of the rest of the committee. The updated (and optimal in the mean squared error sense) estimate of the output gap for the j-th member is then a weighted average (with the weights summing to one) of the m members.

$$y_t^j = \mathbf{w}_j' \mathbf{y}_t, \text{ for } j = 1, \ldots, m. \tag{30}$$

where $\mathbf{y}_t$ is a $m \times 1$ vector of estimates of y and $\mathbf{w}_j$ is a $m \times 1$ vector of weights (that sum to one) given by[22]:

$$\mathbf{w}^j = \mathbf{e}' \mathbf{S}_j^{-1} / \mathbf{e}' \mathbf{S}_j^{-1} \mathbf{e}, \text{ for } j = 1, \ldots, m.$$

Here, $\mathbf{e}$ is a $m \times 1$ unit vector and $\mathbf{S}_j$ is defined as the matrix:

$$\mathbf{S}_j = \begin{bmatrix} \sigma_{j11}^2 & \sigma_{j12} & \ldots & \sigma_{j1m} \\ \sigma_{j21} & \sigma_{j22}^2 & \ldots & \sigma_{j2m} \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{jm1} & \sigma_{jm2} & \ldots & \sigma_{jmm}^2 \end{bmatrix}, \text{ for } j = 1, \ldots, m.$$

The weights that members attach to the estimate of the output gap can in principle be negative if there is a sufficiently large negative covariance, or larger than one if there is a large positive covariance. Deliberation then implies a revised $1 \times m$ vector of estimates of the output gap: $\mathbf{y}_t^r = (y_t^1, y_t^2, \ldots y_t^m)'$. This vector in turn maps into an interest decision through:

$$i_{jt} = \pi_{t|t} + \frac{1}{\alpha_j \beta_{2j}} (\pi_{t+1|t} - \pi^*) + \frac{\beta_1}{\beta_{2j}} y_{t|t}^j + \varsigma_{jt} \quad \text{for } j = 1, \ldots, m, \tag{31}$$

[22] This is the standard formula for the optimal combination of linear signals and was first introduced into economics by Bates and Granger (1969) as a way of combining forecasts.

where π^* is the inflation target, $\pi_{t+1|t}$ the forecast of inflation at time period $t+1$ based on information available in period t, and likewise for $\pi_{t|t}$ and $y^j_{t|t}$, and the subscript $t|t$ indicates that current realisations of the output gap and inflation may well be imperfectly observed, and need to be forecasted.[23] Therefore, the $1 \times m$ vector, $\mathbf{i}_t$ of decisions about the setting of the interest rate is a linear mapping from $\mathbf{y}^r_t$ to $\mathbf{i}_t$. The actual interest setting is then the median of $\mathbf{i}_t$, $median(\mathbf{i}_t)$.

It is important to note that we assume a single revision to the estimate of the output gap as a result of deliberation.[24] Then the weighting matrix, obtained by stacking the row matrices of optimal weights, is:

$$\Gamma = \begin{bmatrix} w_{11} & w_{12} & \dots & w_{1m} \\ w_{21} & w_{22} & \dots & w_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ w_{m1} & w_{m2} & \dots & w_{mm} \end{bmatrix} \tag{32}$$

and if $\mathbf{y}^k_t$ is a $m \times 1$ vector of estimates of y with which each member of the Committee enters the meeting, then after deliberation we have

$$\mathbf{y}^{k+1}_t = \Gamma \mathbf{y}^k_t \tag{33}$$

where $\mathbf{y}^{k+1}_t$ is a $1 \times m$ vector of revised estimates of the output gap after deliberation[25].

[23]The derivation of the above inflation 'feed forward' rule (22) is based on Svensson (1997), where the policymaker only targets inflation, and the central bank can (in expectation) use the current interest rate to hit the target for inflation two periods hence; for further details, see Bhattacharjee and Holly (2009, 2010).

[24]If the revised estimate of the output gap after the initial stage of deliberation is made subject to further revision through a recursive process of sharing new information and deliberation, iteratively a stage would be reached when no further changes would be made to the estimate of the j-th member. In this case under reasonable assumptions this will converge to a position in which all members have the same belief about the output gap. We feel that there are often constraints in the degree of information sharing in committees that our assumption of one step revision captures better.

[25]In principle some of the diagonal elements of W could be zero. This would mean that a Committee member attached no credence to his own opinions. Given that the selection of members is made from a group of internal and expernal experts it would be unlikely to happen.