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Systemic risk rankings and network centrality in the European banking sector

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Abstract

This paper presents a methodology to calculate the Systemic Risk Ranking of financial institutions in the European banking sector using publicly available information. The model makes use of the network structure of financial institutions by including the stock return series of all listed banks in the financial system. Furthermore, a wide set of common risk factors (macroeconomic risk factors, sovereign risk, financial risk and housing price risk) is included to allow these factors to affect the banks. The model uses Bayesian Model Averaging (BMA) of Locally Weighted Regression models (LOESS), i.e. BMA-LOESS. The network structure of the financial sector is analysed by computing measures of network centrality (degree, closeness and betweenness) and it is shown that this information can be used to provide measures of the systemic importance of institutions. Using data from 2005 (2nd quarter) to 2012 (3rd quarter), this paper provides further insight into the time-varying importance of risk factors and it is shown that the model produces superior conditional out-of-sample forecasts (i.e. projections) than a classical linear Bayesian multi-factor model.

Keywords: Systemic risk, financial networks, Bayesian Model Averaging, Locally Weighted Regression, bank stock returns.

JEL:C52, C58, G15, G21

Non Technical Summary

This paper presents a methodology to calculate the Systemic Risk Ranking of financial institutions in the European banking sector using publicly available information. The proposed model measures the network structure of financial institutions (i.e. interconnectedness) by including the stock return series of all listed banks in the financial system. The measurement of the systemic risk of financial institutions has gained in importance since the recent financial crisis and frames into the context of macroprudential supervision. The goal of macroprudential supervision is to focus on the financial system as a whole, in contrast to microprudential supervision, where the main focus is the risk assessment of individual financial institutions.

To allow macroeconomic risk factors to affect the banks in the system, the model includes a set of macroeconomic variables (industrial production, inflation, interest rate, the default spread, a market index and the Vstoxx index). The model is further enhanced to allow sovereign risk to affect banks. House price risk is measured by the ECB house price index, and finally, financial sector specific risk is allowed to affect the banks in the financial system by including the EONIA – EURIBOR spread and the ITraxx Europe Financial Sector Index. The methodology developed in this paper allows to include this many variables at the same time in a model.

The technique used in the model is Bayesian Model Averaging (BMA) of Locally Weighted Regression models (LOESS), i.e. BMA-LOESS. BMA allows to identify a set of relevant risk factors out of a larger set of potentially important regressors, by considering all variable combinations which can be made out of a given set of regressors. The posterior parameter estimate is obtained as the weighted average of the parameter estimates in the different models, where the weight is given by the posterior model probability. The output of the BMA analysis is a matrix, the Interconnectedness Matrix, which indicates the probability that each bank affects another bank in the financial system. A second building block is the LOESS technique. This technique allows to condition the estimate of bank risk exposure on a certain variable. The LOESS model is transformed to a Bayesian model in order to integrate it in the BMA framework. Combining the BMA approach with LOESS regressions allows to simultaneously address issues of model uncertainty and the presence of heterogeneous effects across different realizations of a variable.

The main contribution of the BMA-LOESS model is the ability to exploit the network structure of financial institutions to calculate Systemic Risk Rankings, during different states of the economic cycle. The model allows identifying which financial institutions are most central to the financial network structure, in terms of network centrality measures such as degree, closeness and betweenness. This information is then used to provide a ranking and an assessment of the systemic risk of financial institutions. Furthermore, the parameter estimates resulting from the estimation of the model allow to track how the importance of a particular risk factor (or a block of risk factors) has evolved over time. Finally, the BMA-LOESS model is evaluated against three benchmark models and its performance is evaluated using Diebold-Mariano (1995) statistics, the PC ratio (Percentage Correctly predicted directions in bank stock prices) and RMSFE statistics (Root Mean Squared Forecast Error). It is shown that the BMA-LOESS model provides superior conditional out-of-sample forecasts than a classical linear Bayesian multi-factor model.

The questions addressed in this paper may be relevant from a policy perspective. The systemic risk rankings calculated in this paper incorporate information about the interconnectedness of financial institutions, whilst at the same time controlling for macroeconomic factors. The measures of network centrality (degree, closeness and betweenness) can be used to complement the risk assessment based on micro-prudential information.

1 Introduction

The measurement of the systemic risk of financial institutions has gained in importance since the recent financial crisis and frames into the context of macroprudential supervision. The goal of macroprudential supervision is to focus on the financial system as a whole. This paper aims to contribute to this by developing a methodology to calculate Systemic Risk Rankings for financial institutions in the European financial sector based on publicly available data.

The motivation for developing the model in this paper stems from the experience of the recent financial crisis and the lessons learnt from this. The crisis has shown us that high levels of interconnectedness between companies can be damaging for the entire economy. When the degree of codependence is high, a large individual shock to a small set of firms can have potentially vast rippling effects to all other interconnected institutions. The model in this paper makes use of the network structure of financial institutions by including the stock return series[1] of all listed banks in the system.

The model includes a wide set of other publicly available data. To allow macroeconomic risk factors to affect the banks in the system, the model includes a set of macroeconomic variables (industrial production, inflation, interest rate, the default spread, a market index and the Vstoxx index). The model is further enhanced to allow sovereign risk to affect banks. House price risk is measured by the ECB house price index, and finally, financial sector specific risk is allowed to affect the banks in the financial system by including the EONIA – EURIBOR spread and the ITraxx Europe Financial Sector Index. The methodology developed in this paper allows to include this many variables at the same time in a model.

The technique used in the model is Bayesian Model Averaging (BMA) of Locally Weighted

[1]Bank stock prices are particulary useful to study bank riskiness, because they combine market perceptions of the firm's outlook, publicly available balance sheet and income statement data and current available market data. Moreover, stock market data have a higher frequency, and hence allow a more timely assessment of risks. However, bank stock prices have some disadvantages as well, as they are polluted by too-big-to fail concerns and implicit guarantees. The too-big-to fail doctrine has been described and measured in Acharya, Aginer, and Warburton (2013) and Gandhi and Lustig (2013). On the other hand, balance sheet and income statement data are subjective to accounting discretion, such as window dressing and other earnings smoothing techniques and contain a mainly backward looking perspective on the bank's financial health. Arguably, using stock prices to infer on financial stability constraints has both good and bad sides.

Regression models (LOESS), i.e. BMA-LOESS. The BMA technique starts from 'model uncertainty', which means that a researcher is a priori uncertain about which (constellation of) risk factors affects a particular financial institution. When estimating only one model, the researcher clearly ignores the uncertainty he has about the correct model. BMA considers all variable combinations which can be made out of a given set of regressors. More specifically, if there is a list of k potential explanatory variables, 2^k different variable combinations can be made, where each model is defined through the inclusion or exclusion of (a subset of) the explanatory variables[2]. For each of the 2^k different models, the 'posterior model probability' gives insight into how likely each model is, given the model space of all variable combinations. A similar metric, labeled the 'posterior inclusion probability', expresses how likely a certain regressor affects another financial institution. These bilateral probabilities are used to construct an Interconnectedness Matrix, indicating the probability that each bank affects another bank in the financial system. By using the BMA methodology, the information from all models is combined. The posterior parameter estimate is obtained as the weighted average of the parameter estimates in the different models, where the weight is given by the posterior model probability.

LOESS models allow to condition the estimate of bank risk exposure on a certain state vector. This can for instance be the market index being on its 5th percentile, but it can also be conditioned on a recession (measured by a specific value for industrial production), or any other common factor in the model. This approach is especially useful from a financial stability perspective, since the supervisor is particularly interested in the measurement of systemic risk during times of financial market stress, during a recession, during times of money market stress, ... Combining the BMA approach with LOESS regressions allows to simultaneously address issues of model uncertainty and the presence of heterogeneous effects across different realizations of a state vector.

The model in this paper is connected to the recent strand of literature that studies the network structure of the financial sector. First, there are papers that make use of (country specific) interbank data to construct and analyse the network (for instance Karas and Schoors (2012) for

[2] The BMA approach compares all models simultaneously, as opposed to model selection criteria (such as Akaike's information criterion (Akaike (1974)), Schwarz's criterion (a Bayesian information criterion, Schwarz (1978)) or Fisher's information criteria (Wei (1992))) where only one model is retained.

Russia, Langfield, Liu, and Ota (2012) for the UK and Degryse and Nguyen (2007) for Belgium). Second, a recent strand of literature overcomes the shortcomings in the availability of bank-by-bank bilateral exposures by using publicly available data. Examples of these are Adrian and Brunnermeier (2009), Hautsch, Schaumburg, and Schienle (2011), Diebold and Yilmaz (2011), Betz, Oprica, Peltonen, and Sarlin (2012), Dungey, Luciani, and Veredas (2012) and Barigozzi and Brownlees (2013). Hautsch, Schaumburg, and Schienle (2011) provide a network description of publicly traded US financial institutions, in an approach which combines both balance sheet data of the firms, macroeconomic data and bank stock returns. Diebold and Yilmaz (2011) use high-frequency intra-day data from the Trade and Quote (TAQ) database to estimate a bivariate connectedness matrix. Betz, Oprica, Peltonen, and Sarlin (2012) incorporate the approach of Hautsch, Schaumburg, and Schienle (2011) to predict events of bank distress. Dungey, Luciani, and Veredas (2012) generate a network structure of the financial sector based on correlations in volatility shocks. Barigozzi and Brownlees (2013) propose the NETS methodology to estimate high-dimensional sparse Long Run Partial Correlation networks. Their procedure is based on a two-step LASSO (Least Absolute Shrinkage and Selection Operator). A final strand of literature uses bank balance sheet data and conducts counterfactual simulations to analyse contagion within interbank networks. Examples of these are Lu and Zhou (2011), who use link prediction algorithms to produce the missing links between agents (nodes) in a given network, and Halaj and Kok (2013), who use simulation approaches to simulate a large number of possible networks contingent on the underlying exposure data and imposed behavioural characteristics.

The main contribution of the BMA-LOESS model is the ability to exploit the network structure of financial institutions to calculate Systemic Risk Rankings, during different states of the economic cycle. The model allows identifying which financial institutions are most central to the financial network structure, in terms of network centrality measures such as degree, closeness and betweenness. This information is then used to provide a ranking and an assessment of the systemic risk of financial institutions. Furthermore, the parameter estimates resulting from the estimation of the model allow to track how the importance of a particular risk factor (or a block of risk factors) has evolved over time. Finally, the BMA-LOESS model is evaluated against three benchmark models and its performance is evaluated using Diebold-Mariano (1995) statistics, the PC ratio (Percentage Correctly predicted directions in bank stock prices) and RMSFE statistics

(Root Mean Squared Forecast Error). It is shown that the BMA-LOESS model provides superior conditional out-of-sample forecasts than a classical linear Bayesian multi-factor model.

This paper is organised as follows. Section 2 summarises the data which are used in this study. Section 3 outlines the components of the BMA-LOESS methodology, whereas Section 4 discusses the empirical results of the model and the different applications. Section 5 concludes.

2 Data

< Insert Table 1 here >

The variables included in the BMA-LOESS model can broadly be divided into two categories. First, the model includes the stock returns of the banks in the system. Second, the banks in the system are exposed to common risk factors. These common risk factors can broadly be divided into 4 blocks: a macroeconomic block, a sovereign block, a housing block and a financial block[3]. The sample period ranges from the 2nd quarter of 2005 until the 3rd quarter of 2012. Table 1 contains a detailed description of the data series, source and data manipulations.

< Insert Table 2 here >

Banking Block

The sample of banks included in the sample is based on a few criteria. First, I start with the sample of banks included in the 2010/2011 stress tests of the European Banking Authority. I take log returns of the weekly stock prices of these banks. Then, I require at least 80% of liquid data points (liquid is defined as a nonzero stock return) within each quarter [4]. I further reduce the sample by excluding banks which have less than 5 years of consecutive liquid stock

[3] The current set-up does not include lags of the explanatory variables, so I measure the contemporaneous impact of each risk factor on each bank. However, this model can easily be extended with lags of (some) variables to allow for a delayed response of a risk factor. This extension is left for future research.

[4] The exception is Dexia during the second and third quarter of 2012, since this would otherwise reduce the sample period to the 1st quarter of 2012.

returns. I finally balance the sample by dropping all banks which have illiquid stock return series for at least one quarter between January 2005 and October 2012. The final result is a sample of 34 banks from 13 countries (Austria, Belgium, Germany, Denmark, Spain, France, UK, Greece, Hungary, Ireland, Italy, Portugal and Sweden). The summary statistics of the bank can be found in Table 2. The complete list of banks included in the analysis can be found in Table 3.

< Insert Table 3 here >

Macro Block

To capture the potential exposure of banks to shocks in the macroeconomic environment, 6 macro risk factors are included: inflation, Industrial Production, the 3 Month EURIBOR, a market index, the Vstoxx implied volatility index and the Itraxx index. Both the inflation rate and industrial production series are obtained from the ECB Statistical Datawarehouse. However, the frequency of these series is monthly. These two series are therefore interpolated with a cubic spline, to match the weekly frequency of the other regressors in the system. The market index is total stock market index for the EU (Datastream code TOTMKEU). It mirrors all EU stock markets, not only the financial sector. The Vstoxx volatility index captures market expectations of volatility in the Eurozone (also see, e.g., Berndt, Douglas, Duffie, Ferguson, and Schranz (2005) and Tang and Yan (2010)). This index is generally perceived as a market sentiment or investor fear indicator. Finally, the Itraxx index is included to proxy for the evolution of market-wide credit risk. The Itraxx index is constructed as the equally weighted average of the 125 most liquid CDS series in the European market. A higher iTraxx indicates a higher overall default risk in the economy. Industrial Production and inflation are included in levels, whereas the other series are included in logarithmic returns.

Sovereign Block

The recent sovereign debt crisis has indicated that bank risk and sovereign risk can become very intertwined. Studies as De Bruyckere, Gerhardt, Schepens, and Vander Vennet (2013), Alter and Schuler (2012) and Alter and Beyer (2012) therefore analyse spillovers between financial institutions and sovereigns. To allow shocks in sovereign credit risk to affect financial institutions, the 10-year government bond yield of 13 countries (Germany, Italy, France, Spain, Portugal, Greece, Ireland, Austria, Belgium, UK, Denmark, Sweden and Hungary) is included in logarithmic returns.

Financial Block

The model further includes two measures of financial sector specific risk. To measure stress in the European funding market, the spread between the 3 Month EURIBOR and the EONIA interest rate is included. Secondly, the Itraxx senior Financial index tracks the evolution of the credit risk in financial institutions in Europe. However, the Itraxx financial index is highly correlated with the Itraxx index, which is included in the macroeconomic block. Hence, the Itraxx financial index is first orthogonalized with respect to the Itraxx, and the residual series are taken instead.

Housing Block

As a measure of the evolution of house prices, the EU house price index obtained from the ECB's statistical datawarehouse is included. The quarterly house price series is interpolated with a cubic spline to a weekly frequency. The house price index is transformed to logarithmic returns.

3 Methodology

This Section explains how the different components of the BMA-LOESS model fit together. What follows first, is a presentation of the general model structure, i.e. the estimated equations of bank stock returns to the stock returns of all other banks and the common factors. In subsection 3.1, the LOESS technique is introduced, whereas subsection 3.2 explains how this model is transformed to the Bayesian version. Subsection 3.3 explains the logic of BMA and the algorithm to browse the model space. Finally, subsection 3.4 describes the different network centrality measures (degree, closeness and betweenness).

To infer on the risk exposures of each bank to the range of potential risk factors, the following equation is estimated:

$$Y = \beta . X + \varepsilon \tag{1}$$

where Y is a vector consisting of the M banks in the system

$$Y = \begin{pmatrix} y_1 \\ y_2 \\ ... \\ y_{M-1} \\ y_M \end{pmatrix} \tag{2}$$

and X is a matrix consisting of the N potential risk factors, where M is a subset of N.

$$X = \begin{pmatrix} \underbrace{x_1 \quad x_2 \quad ... \quad x_{M-1} \quad x_M}_{BankBlock} \underbrace{x_{M+1} \quad ... \quad x_{N-1} \quad x_N}_{Common\ Factors} \end{pmatrix} \tag{3}$$

More specifically, the estimated system of equations is:

$$\left\{ \begin{array}{c} y_1 = \beta_{1,2}x_2 + \beta_{1,3}x_3 + ... + \beta_{1,M}x_M + \beta_{1,M+1}x_{M+1} + ... + \beta_{1,N}x_N + \varepsilon_1 \\ y_2 = \beta_{2,1}x_1 + \beta_{2,3}x_3 + ... + \beta_{2,M}x_M + \beta_{2,M+1}x_{M+1} + ... + \beta_{2,N}x_N + \varepsilon_2 \\ y_3 = \beta_{3,1}x_1 + \beta_{3,2}x_2 + ... + \beta_{3,M}x_M + \beta_{3,M+1}x_{M+1} + ... + \beta_{3,N}x_N + \varepsilon_{31} \\ ... \\ y_M = \beta_{M,1}x_1 + \beta_{M,2}x_2 + ... + \beta_{M,M-1}x_{M-1} + \beta_{M,M+1}x_{M+1} + ... + \beta_{M,N}x_N + \varepsilon_M \end{array} \right\} \tag{4}$$

where each bank is exposed to shocks from other banks in the system, and to shocks from the common factors (macroeconomic, sovereign, financial sector specific and house price shocks).

3.1 Locally Weighted Regression (LOESS)

The core of the BMA-LOESS model is the LOESS regression, which allows to condition the estimate on the state of the economy. The LOESS regression technique has been developed by Cleveland (1979) and Cleveland and Devlin (1988) (in its non-Bayesian form). The main idea behind the LOESS technique is to condition the estimate of a variable y as a function of x on a chosen realisation of a state vector, z. As explained later on, the estimates in the paper are conditioned on industrial production being on its 25th percentile as a way to take into account the downturn in the economic activity.

To specify that the exposure of bank j to certain risk factors is conditional on a certain choice for x, equation 5 specifies the relationship between stock returns of bank j to the set of risk factors (in x_j).

$$y_{j,t} = g(x_{j,t}) + \varepsilon_{j,t} \tag{5}$$

The function $g()$ is conditional on a choice for x (x_t), for instance the economy being in a specific adverse state. I will refer to a particular choice x_t as a gridpoint. The estimate $\hat{g}(x_{j,t})$ is the coefficient estimate of the LOESS regression. The notion to focus the attention to one specific gridpoint, is implemented through two channels. First, the LOESS technique uses only a number of neighbouring observations closest to the gridpoint. The number of neighbouring observations q is determined by the fraction f, where $f = q/n$, with n the total number of observations in the sample. The choice of q determines the *proportion* of observations in the neighbourhood of x_t which is taken into account in the LOESS regression. In this paper, f is chosen and set at $1/3$, implying that one third of the observations in the neighbourhood of a specific gridpoint are taken into account[5]. The second way in which the estimate $\hat{g}(x_t)$ conditions on a specific gridpoint, is by assigning weights to the q observation vectors which are closest to x_t. To assign weights to observations, the *tricube weight function* is used:

$$W(u) = \begin{Bmatrix} (1-u^3)^3 & \text{if } 0 \leq u < 1 \\ 0 & \text{otherwise} \end{Bmatrix} \tag{6}$$

The weight function W is applied to the relative distance of the observation w.r.t. the q-th nearest observation to x_t, as follows:

$$w_t(x) = W\left(\frac{\rho(x, x_t)}{d(x)}\right)$$

where $d(x)$ is the distance between x and the qth nearest observation x and $\rho(x, x_t)$ is the Euclidian norm. Note that the x and x_t should be normalized prior to measuring the Euclidian distance.

[5] The sample period ranges from $2005Q2$ until $2012Q3$. With weekly stock returns, this implies that 127 weekly stock returns are used for each gridpoint (380/3). In the analysis over moving windows (8 quarters) (for instance subsection 4.2) , I set $f = 1$, implying that all observations in the window are used. The LOESS feature of the model then only comes from the weights assigned to neighbouring observations.

In the next subsection, the LOESS technique is modified to a Bayesian LOESS model to integrate it into the BMA framework. To the best of my knowledge, this is the first paper which develops and implements a Bayesian LOESS Regression Model.

3.2 Bayesian Locally Weighted Regression

The Bayesian LOESS model is obtained by imposing the Normal-Gamma natural conjugate prior on the coefficients, together with Zellner's g-prior where $g = n$ (the number of observations). More specifically,

$$\beta|h \backsim N(\mathring{\beta}, h^{-1}\mathring{V})$$

where $\mathring{\beta}$ is a vector of zeros, and

$$\mathring{V} = g(X'X)^{-1}$$

where g is Zellner's prior, and specified as $g = n$, $\mathring{s}_j^2$ is set at 1 (which is larger than the empirical variance of the standard errors of a small subset of the models), and $\mathring{v}_j$ is set at 0.001, which is very small as compared to the sample size n, hence this implies a large uncertainty around the prior value of $\mathring{s}_j^2$.This choice of hyperparameters ensures a relatively noninformative prior on the coefficients.

$$h \backsim G(\mathring{s}^{-2}, \mathring{v})$$

With this choice of priors on the parameters, the posterior has the following form:

$$\bar{\beta} = \bar{V}(\mathring{V}^{-1}\mathring{\beta} + X'X\hat{\beta})$$

$$\bar{V} = (\mathring{V}^{-1} + X'X)^{-1}$$

where $\hat{\beta}$ corresponds to the weighted OLS estimator for β with the weighting matrix given by equation 6 above.

$$\hat{\beta} = (X'WX)^{-1}X'Wy$$

The marginal likelihood of model M_j is obtained as

$$p(y_j|M_j) = c_j \left(\frac{|\bar{V}_j|}{|\mathring{V}j|}\right)^{1/2} (\bar{v}_j\bar{s}_j^2)^{-\bar{v}_j/2}$$

where

$$c_j = \frac{\Gamma\left(\frac{\bar{v}_j}{2}\right)(\mathring{v}_j \mathring{s}_j^2)^{\mathring{v}_j/2}}{\Gamma\left(\frac{\mathring{v}_j}{2}\right)\pi^{n/2}}$$

with $\bar{v}_j = \mathring{v}_j + n$ and $\bar{s}_j^2$ implicitly defined through

$$\bar{v}_j \bar{s}_j^2 = \mathring{v}_j \mathring{s}_j^2 + v_j s_j^2 + (\hat{\beta}_j - \mathring{\beta}_j)[\mathring{V}j + (X_j' X_j)^{-1}]^{-1}(\hat{\beta}_j - \mathring{\beta}_j)$$

where $v_j = n - k_2$ and s_j^2 is the usual OLS quantity defined as:

$$s_j^2 = \frac{(y - X\hat{\beta})'(y - X\hat{\beta})}{v_j}$$

The bottomline is that this estimator is the Bayesian variant of the *weighted* OLS estimator for β where the weights W are given by the weight matrix in equation 6.

$$\hat{\beta} = (X'WX)^{-1}X'Wy$$

3.3 Bayesian model averaging

In a model with as many as 56 explanatory variables, we need a tool to infer on the importance of each of them. BMA was first developed by Leamer (1978), and has since then been used in several disciplines, ranging from statistics (Raftery, Madigan, and Hoeting (1997) and Hoeting, Madigan, Raftery, and Volinsky (1999)), to the large literature on cross-country growth regressions (Fernandez, Ley, and Steel (2001b), Brock and Durlauf (2001) and Sala-I-Martin, Doppelhofer, and Miller (2004) among others), finance (Cremers (2002), Avramov (2002) and Wright (2008)) and banking (Baele, De Bruyckere, De Jonghe, and Vander Vennet (2015)). BMA considers all variable combinations which can be made out of a given set of regressors. More specifically, if there is a list of k potential explanatory variables, 2^k different variable combinations can be made, where each model is defined through the inclusion or exclusion of (a subset of) the explanatory variables[6]. For each of the 2^k different models, the posterior model probability gives insight into how likely a specific model is, given all other models in the model space.

[6] The idea to use variable selection techniques to model drivers of stock return data, can also be found in Hautsch, Schaumburg, and Schienle (2011) and Adrian, Moench, and Shin (2010). Hautsch, Schaumburg, and

To indicate the different models estimated for each bank in the system, superscript k is added. This modifies the system of equations in (4) to

$$\left\{ \begin{array}{c} y_1 = \beta^{1,k} x^{1,k} + \varepsilon_1^k \\ y_2 = \beta^{2,k} x^{2,k} + \varepsilon_2^k \\ y_3 = \beta^{3,k} x^{3,k} + \varepsilon_3^k \\ \ldots \\ y_M = \beta^{M,k} x^{M,k} + \varepsilon_M^k \end{array} \right\} \tag{7}$$

where for instance $x^{1,k}$ indicates the regressors in model M^k for bank 1.

In the BMA methodology, the researcher has a prior belief about model k, summarized in the model prior $p(M^k)$, where every model is indicated with subscript k. The posterior probability of model k is given by

$$p(M^k|y) = \frac{p(y|M^k)p(M^k)}{\sum_{m \in M} p(y|M^m)p(M^m)} \tag{8}$$

where $p(y|M^k)$ is the marginal likelihood of model M^k, and $p(M^k)$ is the prior on model M^k.

Whereas the posterior model probability in equation 8 gives insight into how likely a specific model is, the more interesting metric expresses how likely a certain regressor should be included in the model. This is captured by the *posterior inclusion probability.* Following Leamer (1978)

Schienle (2011) propose a systemic risk beta as a measure for financial companies' contribution to systemic risk, given network interdependence between firm's tail risk exposures. In fact, the authors use the Least Absolute Shrinkage and Selection Operator (LASSO) to identify the set of relevant tail risk drivers for each financial institution. The selection technique allows to shrink the number of relevant risk drivers from a high-dimensional set of possible cross-linkages between all financial firms. Adrian, Moench, and Shin (2010) use the same idea, although in a somewhat different context. The authors investigate the predictive power of financial intermediary balance sheet aggregates for excess returns on a broad set of equity, corporate and Treasury Bond portfolios. They use the Least Angle Regression (LAR) technique (a generalization of the Least Absolute Shrinkage Selection Operator LASSO) and find that security broker-dealer leverage and the shadow bank asset growth are selected as the best predictors. However, the advantage of Bayesian Model Averaging over selection methods is that the information from all models is combined in the final estimation. Whereas variable selection approaches define a threshold up to which covariates are considered relevant, Bayesian Model averaging weights the different models according to their informativeness, i.e. the results of all models are weighted with their corresponding posterior model probability.

and Doppelhofer and Weeks (2009), it is calculated as the sum of the posterior model probabilities of the models which include the specific variable. The posterior inclusion probability of variable i for bank j is given by

$$PIP_{i,j} = \sum_{k=1}^{2^{56}} p(M^{j,k}|y_j) \cdot I(x_i \in X|y_j, M^{j,k}) \tag{9}$$

To obtain posterior estimates of risk exposure, BMA combines the information from all models. The posterior parameter estimate is obtained as the weighted average of the parameter estimates in the different models, where the weight is given by the posterior model probability.

$$E(\beta^j|y_j) = \sum_{k=1}^{2^{56}} p(M^{j,k}|y_j) \cdot E(\beta^{j,k}|y_j, M^{j,k}) \tag{10}$$

The model prior $p(M)$ used in this paper is a prior on the number of regressors. The maximum number of regressors is set to 7, whereas lambda is set to 3. The model prior follows a *poisson* distribution,

$$p(M^k) = \frac{\lambda^{l^k} e^{-\lambda}}{l^k!}$$

where l^k is the number of regressors in model M^k. Moreover, I assess the robustness of my results to the commonly used *Binomial model prior*, assuming equal prior probability for all models (but still constrained to models with a maximum dimension of 7), more specifically

$$p(M^k) = \frac{1}{2^{56}} \tag{11}$$

The correlation in posterior parameter estimates and posterior inclusion probabilities between both sets of results is always above 99%, and the minimum correlation is never below 96%.

The set of potential risk factors affecting each bank is too big to estimate every model in the model space. Given the set of 56 potential regressors, this means the model space contains 2^{56} (72057594037927900) models. Even constraining the dimension of the models to maximum 7 only reduces the model space to 268602259. Hence, some numerical technique is necessary to approximate the model space. I therefore use a stochastic search algorithm which jumps between models of the same or different dimensionality. I use a Markov Chain Monte Carlo algorithm to simulate a Markov chain consisting of different models M_k, in particular the recently proposed Subspace Carlin and Chib algorithm of Athanassios and Dellaportas (2012). The authors show that this algorithm avoids some pitfalls performs better than existing algorithms (such as the Carlin and Chib algorithm, the Metropolised Carlin and Chib, Shotgun Stochastic Search, Reversible Jump, ...).

As with any posterior simulator, it is important to verify convergence of the algorithm. I follow the suggestion of Fernandez, Ley, and Steel (2001a). Based on a reduced set of models, the posterior model probability is calculated analytically (using equation 8) and using the SCC algorithm. If the algorithm has converged, then both ways of calculating the posterior model probabilities should give the same result. Fernandez, Ley, and Steel (2001b) suggest the correlation between the analytical posterior model probabilities and the model probabilities of the algorithm to exceed 0.99. Already with 1000 burn-in draws and 15000 iterations, this result is achieved for most banks in the sample.

The posterior inclusion probabilities computed above for $i = 1, ..., M$ and $j = 1, ..., M$ form the entries of the Interconnectedness Matrix. The Interconnectedness Matrix summarizes all information regarding the probability of a connection between the banks in the system.

Interconnectedness Matrix

$$\begin{bmatrix} . & P_{1,2} & P_{1,3} & ... & P_{1,M} \\ P_{2,1} & . & P_{2,3} & ... & P_{2,M} \\ P_{3,1} & P_{3,2} & . & ... & P_{3,M} \\ ... & ... & ... & ... & ... \\ P_{M,1} & P_{M,2} & P_{M,3} & ... & . \end{bmatrix} \tag{12}$$

This Interconnectedness Matrix is similar in nature to the Connectedness Table in Diebold and Yilmaz (2011) and the Spillover Matrix in Alter and Beyer (2012). The Connectedness Table in Diebold and Yilmaz (2011) is constructed based on variance decompositions, whereas the Spillover Matrix in Alter and Beyer (2012) is constructed based on Generalized Impulse Responses. The contribution of this approach is that BMA is able to accomodate a much larger set of potential risk factors (in casu banks), such that the spillover matrix can be larger. In Alter and Beyer (2012), the size of the spillover matrix is $20x20$, allowing for spillovers between 11 countries and the banking sectors of 9 countries, whereas the dimension of the (bank specific) spillover matrix is $13x13$ in Diebold and Yilmaz (2011). Since I included stock returns of 34 financial institutions in this study, the dimension of the Interconnectedness Matrix is $34x34$ (including the common factors, the dimension of the model is $34x56$). However, the model can easily be extended with other banks (as long as (liquid) stock return data are available).

3.4 Network Centrality Measures

To study the network properties of the interbank network, three classic network centrality measures (degree centrality, closeness centrality and betweenness centrality) are calculated for each bank in the system. The network is composed of vertices (banks), which are connected to each other through edges.

Degree centrality Degree centrality equals to the number of ties a vertex has with other vertices. To classify whether a bank has a tie with another bank, a threshold is imposed on the Interconnectedness Matrix. More specifically, a bank is considered to be connected to another bank if the posterior inclusion probability is larger than 50%. Note that Interconnectedness Matrix is a *directed* matrix, hence both the indegree and the outdegree can be constructed. To be in line with other indicators of systemically important institutions, and given the goal of macroprudential policy to identify systemic risks, the focus is on the computation of the *outdegree*. The outdegree of bank j[7] is computed by summing over the columns of the Interconnectedness Matrix:

$$\text{Degree}j = \sum_{i=1}^{N} I(PIPi > 50\%)$$

where $I()$ is an indicator function equal to one if the PIP is greater than 50%, and zero otherwise. Generally, banks with a higher outdegree have a greater capacity to influence other banks.

Closeness A more sophisticated centrality measure is closeness (Freeman (1979)) which emphasizes the distance of a vertex to all others in the network. Closeness can be regarded as

[7] The terminology in terms of bank i and bank j is maintained to stress that the direction of summation is different (rows i versus columns j).

a measure of how long it will take information to spread from a given vertex to others in the network. Again, as the Interconnectedness Matrix is a directed matrix, both in- and out-closeness can be computed, but for the purpose of this analysis the focus is on the *out-closeness*.

$$\text{Closeness}_j = \sum_{i=1}^{N} \frac{1}{d(i,j)}$$

where the distance $d(i,j)$ between bank i and bank j is defined as $1 - PIP(i,j)$.

Betweenness centrality. Betweenness centrality is based on the number of shortest paths passing through a vertex. Vertices with a high betweenness play the role of connecting different banks. In financial networks, vertices with high betweenness are typically the brokers and connectors who bring others together. Being between means a vertex has the ability to control the flow of knowledge between most others. As in the case of the degree centrality, the threshold on the posterior inclusion probability is 50% to consider a link between bank i and bank j.

4 Empirical Results

This Section describes the empirical results of the BMA-LOESS model. First, bank specific measures of network centrality (degree, closeness and betweenness) are calculated in Subsection 4.1 and this information is used to calculate the systemic risk ranking of financial institutions. Subsection 4.2 provides insight in to the time varying importance of risk factors by running the BMA-LOESS model on rolling windows of 8 quarters. Finally, the power of the model is illustrated in Subsection 4.3, where the out-of-sample conditional forecast properties of the BMA-LOESS model are evaluated against three benchmark models. The different models are compared using Diebold-Mariano statistics (Diebold and Mariano (1995)), the PC ratio (Percentage Correct) and RMSFE (Root Mean Squared Forecast Error) statistics. This illustrates the power of the BMA-LOESS model to project future evolutions of bank stock prices.

4.1 Systemic Risk Rankings

In this Subsection, the empirical results of the network centrality measures is analysed, and it is shown how this information is used to calculate the systemic risk rankings of financial institutions on the basis of this information. Figure 1 visualizes the financial network structure centered at two values of Industrial Production. The figure on the left hand side takes the lowest value of Industrial Production in the sample (the value at the end of April 2009) as the gridpoint in the BMA-LOESS estimation, whereas the figure at the right hand side takes the maximum (in sample) value of industrial production (end of May 2010) as a gridpoint. The graph only visualizes connections between banks when the PIP is larger than 50 percent. The probability of the connection (the PIP) is connected to the darkness of the lines. All banks in the graph get equal size (the red circle). The location of the banks on the graph is an approximation of their geographical location in Europe. However, it is hard to draw strong conclusions about the interconnectedness of the system from this graph. Therefore, the network centrality measures discussed in Section 3.4 are computed over moving windows.

< **Insert Figure 1 here** >

Figure 2 summarizes how the degree, closeness and betweenness vary over moving windows of 8 quarters. Panel A shows that the average degree (the average number of connections a bank has in the system) reached a maximum of 3.7 in the last quarter of 2010. The estimation window for the value ranges from $2008Q1$ until $2010Q4$, which is exactly the period with the highest market tensions within the financial system. Panel B of Figure 2 confirms that the closeness was also at its highest value during that quarter. This means that information was spreading very fast between banks during this period. The graph shows that there is a spike in the network centrality in the third quarter of 2011 for all three measures. The LTRO program launched by the ECB in the fourth quarter could be a possible explanation for the decline afterwards. Moreover, the three graphs show the decline in network centrality from then until the end of the sample period. The network centrality measures indicate that the stress between banks in the system has declined over time. Indeed, credit risk in the financial sector has become more bank specific, and the sovereign debt problems of certain European countries have dominated the news more than before.

< **Insert Figure 2 here** >

To get insight into how these network centrality measures relate to certain values of the common factors, the BMA-LOESS model is estimated conditional on specific values of the 5 common factors: Industrial Production, the Vstoxx implied volatility index, the total market index (TOTMKEU), the Itraxx and the Spread. Figure 3 shows the values of the three network centrality measures (degree, closeness and betweenness, in Panel A to C) for 5 values of the common factors. The 5 values are the values at equally spaced intervals between the minimum and the maximum (in the levels) of the common factor. The observed patterns are not always monotonous, but some patterns can be observed. At low levels of Industrial Production, the average number of connections a bank has with other banks is slightly higher. This means that some banks seem to affect other banks more in periods of extreme negative growth. In line with intuition, the degree and the closeness of the system are higher when the Itraxx is higher. For the betweenness, this relationship is not there. This can be explained by the fact that information may also be spreading rapidly over the financial system in times of low credit risk. Exactly the opposite pattern can be found for the stock market index. At high values of the stock market index, the degree and closeness are lower. The Vstoxx does not seem to be meaningfully related to the degree and betweenness, although the closeness of the system is higher for extreme volatility as compared to extremely low volatility in the market. Finally, in line with intuition, the interconnectedness of the financial system is higher when the spread is higher. This relationship holds for all three measures of network centrality, although the middle gridpoints are not always linearly related to the outer ones.

< Insert Figure 3 here >

Finally, the bank specific network centrality measures are extremely useful because they can be used to compute systemic risk rankings of financial institutions. As such, the focus is on the cross sectional dimension, i.e. the identification of institutions which are most central to the network. Figure 4 shows the average rankings based on degree, closeness and betweenness. The averages are taken over the rolling windows of 8 quarters. As can be noticed from these rankings, each metric produces a different ranking of firms, which is in line with the different meaning and content of these measures. However, the correlation between the ranking is relatively high[8], which is not surprising as the measures are computed from the same model estimates. These rankings provide interesting information for the supervisors who wants to take into account the interconnectedness of the financial system and can be used to complement the micro-prudential risk assessment of the financial institution.

< Insert Table 4 here >

4.2 Time varying importance of blocks

This subsection illustrates how the importance of certain risk factors has changed over time. The BMA-LOESS model is estimated over rolling windows of 8 quarters (2 years), rolling forward every quarter. The sample period starts in the second quarter of 2005, so the first estimate is obtained for the first quarter of 2007. Presenting the results of all 56 regressors would be infeasible, and therefore the results are summarized per block. Figure 4 shows the maximum posterior inclusion probability of the regressors in each block. Already in the third quarter of 2007, the PIP of the bank sector jumps to 65%, indicating the stress in the bank sector. The underlying results indicate that this maximum is due to Dexia. Figure 5 shows the median and the interquartile range of the PIPs in the banking block. This graph indicates that the median (and also the mean) hide considerable cross sectional heterogeneity.

< Insert Figure 4 here >

< Insert Figure 5 here >

In general, the importance of shocks to house prices in Europe is relatively low (below 5%). Macroeconomic risk factors have in general a PIP of below 30%. Figure 6 shows time evolution in the PIPs of the factors in the macroeconomic block. Credit risk (measured using the Itraxx index) and inflation become a more important driver of bank stock returns towards 2011 and

[8] The correlation between the degree and closeness is as high as 96%, the degree-betweenness correlation is 92% and the closeness-betweenness correlation is 89%.

2012. Within the set of macroeconomic risk factors, the market index has the largest effect on bank stock returns over the observed sample period. Figure 7 shows the PIPs of the GIIPS countries' sovereign bond yields. The maximum of 39% is due to the sovereign debt problems in Ireland. Note that the importance of the risk factors is averaged over the banks, meaning that the sovereign debt problems of Ireland had the largest effect on the bank stock prices in the sample[9]. The importance of financial sector specific risks (as shown in Figure 8) is in general also low (below 10%), except for the last quarter of 2009, where the maximum importance was 20%, due to the increase in financial sector specific credit risk (Itraxx financial series).

< **Insert Figure 6 here** >

< **Insert Figure 7 here** >

< **Insert Figure 8 here** >

4.3 Out-of-sample conditional forecast accuracy

The BMA-LOESS model is evaluated in terms of producing accurate out-of-sample conditional forecasts, i.e. projections. The term *projection* is used throughout the paper to refer to the estimate produced by a model, conditional on a path for a(n) (set of) explanatory variable(s). To assess the ability of the model to correctly project future bank stock prices, I assume for every equation in (4) the realized path. In other words, I assume that history is realized to assess how well a hypothetical scenario would project the future stock price evolution. The performance of the model is evaluated for periods of one to eight quarters ahead.

The BMA-LOESS model is compared to three benchmark models. In the first benchmark model, the LOESS feature of the model is relaxed, whereas the model averaging feature is preserved. This model is labeled the BMA-BAYES model, and it implies a model averaging technique over a classical linear Bayesian model (i.e. the Bayesian variation of the OLS model). The second benchmark model relaxes the model averaging feature of the model, but keeps the Bayesian LOESS feature. This model is labeled Bayesian LOESS and is the locally weighted

[9] The fact that this sample contains more banks of certain countries might affect the conclusions.

regression model (explained in section 3.2). In the third benchmark model, both the model averaging and the LOESS feature of the model are relaxed. Hence, this is the classical linear Bayesian regression model (in frequentist economics, this would be the OLS model), as suggested above. Decomposing the BMA-LOESS model into its subcomponents allows to verify where the main advantages stem from in terms of projection accuracy. Summarizing,the BMA-LOESS model is compared with the:

1. BMA-BAYES model (LOESS feature is relaxed)
2. Bayesian LOESS model (BMA feature is relaxed)
3. BAYES model (both BMA and LOESS features are relaxed)

To assess the difference in projection accuracy, these models are evaluated against three criteria: first, the Diebold and Mariano (1995) test statistic (DM) for the equality of forecast accuracy of two forecasts under general assumptions. The DM test statistic is calculated on the base of the loss differential which is defined as the difference of the squared forecast errors[10]. Secondly, the PC ratio (Percentage Correct) calculates the proportion of correct signals. Label with H the number of correct positive signals, F the number of false positive signals, Z the number of correct negative signals and M the number of false negative signals, then the proportion of correct signals can be calculated as

$$PC(\%) = \frac{H + Z}{H + F + Z + M} \tag{13}$$

The last criterion is the RMSFE statistic (Root Mean Squared Forecast Error), which expresses the magnitude of all forecast (projection) errors into one metric. By evaluating the BMA-LOESS model against these three statistics, it is clarified which features improve the conditional out-of-sample performance of the model. The statistical features of conditional forecasting are compared over projection horizons ranging from one to 8 quarters ahead.

Table 5 shows the DM statistic computed for projection horizons ranging from 1 to 8 quarters ahead. The DM statistic is to be evaluated against the critical values of the standard normal

[10] The model does not include lags of the explanatory variables. However, inspection of the Durbin Watson statistics over the rolling windows suggests that for some banks, during some quarters, there is still autocorrelation left in the residuals. From an econometric point of view, this implies that the coefficient estimates are biased and consistent, but not efficient. Including lags of the explanatory variables could improve the efficiency, and could potentially even further improve the projection accuracy. This is left for future research.

distribution (1.285 at the 10% confidence level and 1.645 at the 5% confidence level). The DM statistic is computed as the difference between the squared forecast errors of the benchmark versus the alternative model. Hence, a superior performance of the benchmark BMA-LOESS model is identified by a significantly negative DM statistic.

< **Insert Table 5 here** >

The comparison of the BMA-LOESS model with the BMA-BAYES model illustrates no statistically significant difference between both models up to forecasts of 5 quarters ahead. From 6 quarters ahead onwards, the BMA-LOESS model outperforms the BMA-BAYES model. The second benchmark model relaxes the model averaging feature, but keeps the LOESS feature of the model. The comparison of the BMA-LOESS model with the Bayesian LOESS model shows that the BMA feature improves the (conditional) forecast performance at all horizons. The final column displays the DM statistics computed from the comparison the BMA-lOESS model and the Bayesian linear regression model (BAYES). Here again, it is shown that the BMA-LOESS model is superior at all forecast horizons. The decomposition of the BMA-LOESS model into its subcomponents illustrates that the BMA feature improves its performance for conditional forecasts at all horizons, whereas it is only for forecasts of 6 quarters ahead or more that the LOESS feature proves superior.

Table 6 depicts the percentage of correctly predicted (projected) directions in banks' equity price returns, i.e. the PC ratio, at different projection horizons. The second column reports the PC ratio of the BMA-LOESS model, column 3 to 6 report the PC ratio for the BMA-BAYES, the LOESS and the BAYES model. For the reader's convenience, the highest PC ratio at every forecast horizon is indicated in bold.

< **Insert Table 6 here** >

It can be seen from the table that the BMA-LOESS model is superior to the LOESS and the BAYES model at all horizons. This conclusion is in line with the results from the Diebold-Mariano (1995) statistic, which illustrated that the BMA feature improves the out-of-sample conditional forecast performance. Comparing the BMA-LOESS model with the BMA-BAYES model, it proves to be again at longer forecast horizons that the BMA-LOESS model beats the BMA-BAYES model. For projections of 4, 6, 7 and 8 quarters ahead, the BMA-LOESS model is superior, although it seems that the main improvement if forecast performance stems from the BMA feature. Furthermore, it is interesting to see that the LOESS feature of the model only improves the forecast performance in combination with the BMA feature: when comparing the PC ratios in column 4 and 5 of the table, we find that the Bayesian linear model performs better at all horizons, although the PC ratio is hardly higher than 50%, the threshold of a useless model.

< Insert Figure 9 here >

Figure 9 shows the time varying ratio PC for projection horizons from one to eight quarters ahead. Note that the PC ratios of projections of two to eight quarters ahead do not reach the end of the sample period, as these data are necessary to assess the projection accuracy. The PC ratio is compared to the 50% threshold. The results in Figure 9 show that the PC ratio exceeds the threshold in most periods. The only exception is for projections of one quarter ahead in the third quarter of 2008 and the fourth quarter of 2010. The estimations of the third quarter of 2008 contain the fall of Lehman Brothers, and the fourth quarter 2010 results contain the intensification of the sovereign debt crisis. Both events had large knock-on effects in and outside of the financial sector.

< Insert Table 7 here >

Finally, the Rout Mean Squared Forecast Error (RMSFE) statistic is computed, as illustrated in Table 7. The sequence of the models in the columns is identical to the table with the PC ratio above, and for convenience, the lowest RMSFE statistic is indicated in bold for every projection horizon. The conclusion from the table are very much in line with the conclusions from the Diebold-Mariano test and the PC ratio. The main improvement in terms of forecast performance stems from the BMA feature, which improves the projection accuracy at all horizons. The LOESS feature of the model improves only for projections further ahead.

5 Conclusion

This paper presents a methodology to calculate the Systemic Risk Ranking of financial institutions in the European banking sector using publicly available information. The proposed model measures the network structure of financial institutions (i.e. the interconnectedness) by including the stock return series of all listed banks in the financial system. The measurement of the systemic risk of financial institutions has gained in importance since the recent financial crisis and frames into the context of macroprudential supervision. The goal of macroprudential supervision is to focus on the financial system as a whole, in contrast to microprudential supervision, where the main focus is the risk assessment of individual financial institutions.

To allow macroeconomic risk factors to affect the banks in the system, the BMA-LOESS model includes a set of macroeconomic variables (industrial production, inflation, interest rate, the default spread, a market index and the Vstoxx index). The model is further enhanced to allow sovereign risk to affect banks. House price risk is measured by the EU ECB house price index, and finally, financial sector specific risk is allowed to affect the banks in the financial system by including the EONIA – EURIBOR spread and the ITraxx Europe Financial Sector Index. The methodology developed in this paper (the BMA-LOESS model) allows to include this many variables at the same time in a model.

The technique used in the model is Bayesian Model Averaging (BMA) of Locally Weighted Regression models (LOESS), i.e. BMA-LOESS. BMA allows to identify a set of relevant risk factors out of a larger set of potentially important regressors. The model space includes all variable combinations that can be made out of a given set of regressors, and the information from all models is combined. The posterior parameter estimate is obtained as the weighted average of the parameter estimates in the different models, where the weight is given by the posterior model probability. The output of the BMA analysis is a matrix, the Interconnectedness Matrix, which indicates the probability that each bank affects another bank in the financial system. A second building block is the LOESS technique. This technique allows to condition the estimate of bank risk exposure on a certain state vector. The LOESS model is transformed to a Bayesian model in order to integrate it in the BMA framework. Combining the BMA approach with LOESS regressions allows to simultaneously address issues of model uncertainty and the presence of heterogeneous effects across different realizations of a state vector.

The main contribution of the BMA-LOESS model is the ability to exploit the network structure of financial institutions to calculate Systemic Risk Rankings, during different states of the economic cycle. The model allows identifying which financial institutions are most central to the financial network structure, in terms of network centrality measures such as degree, closeness and betweenness. This information is then used to provide a ranking and an assessment of the systemic risk of financial institutions. Furthermore, the parameter estimates resulting from the estimation of the model allow to track how the importance of a particular risk factor (or a block of risk factors) has evolved over time. Finally, the BMA-LOESS model is evaluated against three benchmark models and its performance is evaluated using Diebold-Mariano (1995) statistics, the PC ratio (Percentage Correctly predicted directions in bank stock prices) and RMSFE statistics (Root Mean Squared Forecast Error). It is shown that the BMA-LOESS model provides superior conditional out-of-sample forecasts than a classical linear Bayesian multi-factor model.

The questions addressed in this paper may be relevant from a policy perspective. The systemic risk rankings calculated in this paper incorporate information about the interconnectedness of financial institutions, whilst at the same time controlling for macroeconomic factors. The measures of network centrality (degree, closeness and betweenness) can be used to complement the risk assessment based on micro-prudential information.

The approach in this paper offers interesting possibilities for future research. The Bayesian nature of this set-up offers interesting opportunities to incorporate other sources of information. Hartmann, de Bandt, and Peydro-Alcalde (2009) stress that financial systemic risk is characterized by both a cross-sectional and a time series dimension. This idea is also exploited in Schwaab, Lucas, and Koopman (2010). In the specification of the prior on the parameters, this paper uses relatively uninformative priors. Hence, it could be interesting to see whether the incorporation of balance sheet based characteristics of banks would allow to further improve the projection performance, by centering the parameter prior around the posterior estimate of similar banks (in terms of balance sheet characteristics). The same idea could be used along the time series dimension of the data, incorporating information from the previous time window into the new parameter prior.

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6 Tables & Figures

Table 1: Summary table of the regressors in the model

This table summarizes the different regressors in the model. The regressors are grouped into different blocks: a banking block, a macoreconomic block, a sovereign block, a house price price block and a financial block. The table indicates the source of the data, the data transformation(s) and the frequency of the series. Series with a frequency lower than weekly are transformed to a weekly frequency using a cubic spline interpolation.

			Source	**Data Transformation**	**Frequency**
BANKING BLOCK					
	Bank stock prices	34 stock listed banks in the EBA stress test sample of 2010	Bloomberg	log returns	weekly
MACRO BLOCK					
1	Industrial production	Euro area 17 (fixed composition) - Industrial Production Index, Annual rate of change	ECB SDW	cubic spline + level	monthly
2	HICP inflation	Euro area (changing composition) - HICP - Overall index, Annual rate of change	ECB SDW	cubic spline + level	monthly
3	ST interest rate	3 month EURIBOR rate	ECB SDW	log returns	weekly
4	Default spread	iTraxx Europe Benchmark Index	DS	log returns	weekly
5	Market index	total EU market index (mnemonic TOTMKEU)	DS	log returns	weekly
6	VSTOXX	option implied volatility index (mnemonic VSTOXXI)	DS	log returns	weekly
SOVEREIGN BLOCK					
1	Sovereign bond yield (10 year maturity)	10 year government bond yield	Bloomberg	log returns	weekly
HOUSING					
1	Real estate	The EU ECB house price index	ECB	cubic spline +log returns	quarterly
FINANCIAL BLOCK					
1	Stress in interbank market	Spread between the 3 month eonia index swap and the 3 month euribor	Bloomberg	level	weekly
2	Bank specific credit risk	iTraxx Europe Financial Sector Index, orthogonalized w.r.t. the iTraxx Europe Financial Sector Index	Bloomberg	logreturns	weekly

Table 2: Summary statistics

This table contains the summary statistics (mean, standard deviation, minimum, maximum, skewness and kurtosis) of the regressors in the model. The frequency of all regressors is weekly, and the time period ranges from the second quarter of 2005 until the third quarter of 2012.

	MEAN	ST.DEV.	MIN	MAX	SKEW.	KURT.
BANKING BLOCK						
Banks	-0.0044	0.0766	-1.4887	0.7286	-0.6212	11.6337
MACRO BLOCK						
Inflation	2.1117	0.9691	-0.6000	4.0303	-0.7146	3.5826
IP	0.2573	7.2780	-21.2900	9.7865	-1.4103	4.2146
EURIBOR (3m)	-0.0060	0.0282	-0.1735	0.0692	-1.6869	8.2686
VSTOXX	0.0016	0.1220	-0.3654	0.6774	0.6969	6.1511
TOTMKEU	-0.0001	0.0369	-0.2543	0.1211	-1.3795	10.2072
Itraxx	0.0033	0.0860	-0.2870	0.4868	0.6154	6.9414
FINANCIAL BLOCK						
Spread	0.4052	0.3584	-0.0080	1.8640	1.4221	5.5571
Itraxx (fin)	0.0000	0.0589	-0.2395	0.4835	1.4736	16.7982
SOVEREIGN BLOCK						
DE	-0.0022	0.0433	-0.1775	0.1806	-0.1218	5.8889
IT	-0.0011	0.0326	-0.1246	0.1283	-0.2933	5.2887
FR	0.0010	0.0297	-0.1930	0.0966	-1.1099	10.1016
ES	0.0016	0.0359	-0.1972	0.1150	-0.9929	8.5740
PT	0.0023	0.0445	-0.3013	0.2013	-0.5447	11.1475
GR	0.0045	0.0616	-0.6984	0.3286	-4.5444	58.0086
IE	0.0013	0.0415	-0.2457	0.3066	1.3913	21.4691
AT	-0.0013	0.0354	-0.1659	0.1682	0.1857	8.3290
BE	-0.0007	0.0353	-0.2320	0.2034	-0.2437	11.2843
UK	-0.0025	0.0370	-0.1676	0.1543	0.0030	5.8136
DK	-0.0025	0.0462	-0.2574	0.2242	-0.3365	11.9814
SE	-0.0020	0.0428	-0.1999	0.1929	-0.1709	6.8492
HU	0.0003	0.0397	-0.1202	0.2578	1.2142	9.4775
HOUSE PRICE BLOCK						
House price	0.0003	0.0008	-0.0014	0.0017	-0.3194	2.3591

Table 3: List of banks included in the sample

This table lists the 34 banks included in the banking block, along with the home country of the bank. The selection is based on the 91 banks included in the 2010 stress test, further reducing this sample by only considering stock listed banks, and applying stringent liquidity criteria.

Nr	**Country**	**Bank Name**
1	AT	Erste Bank Group (EBG)
2	BE	DEXIA
3	BE	KBC BANK
4	DE	DEUTSCHE BANK AG
5	DE	COMMERZBANK AG
6	DK	DANSKE BANK
7	DK	Jyske Bank
8	DK	Sydbank
9	ES	BANCO SANTANDER S.A.
10	ES	BANCO BILBAO VIZCAYA ARGENTARIA S.A. (BBVA)
11	ES	BANCO POPULAR ESPAÑOL, S.A.
12	ES	BANCO DE SABADELL, S.A.
13	FR	BNP PARIBAS
14	FR	CREDIT AGRICOLE
15	FR	SOCIETE GENERALE
16	GB	ROYAL BANK OF SCOTLAND GROUP plc
17	GB	HSBC HOLDINGS plc
18	GB	BARCLAYS plc
19	GB	LLOYDS BANKING GROUP plc
20	GR	EFG EUROBANK ERGASIAS S.A.
21	GR	ALPHA BANK
22	GR	PIRAEUS BANK GROUP
23	HU	OTP BANK NYRT.
24	IE	ALLIED IRISH BANKS PLC
25	IE	BANK OF IRELAND
26	IE	IRISH LIFE AND PERMANENT
27	IT	INTESA SANPAOLO S.p.A
28	IT	UNICREDIT S.p.A
29	IT	BANCA MONTE DEI PASCHI DI SIENA S.p.A
30	IT	UNIONE DI BANCHE ITALIANE SCPA (UBI BANCA)
31	PT	Banco BPI, SA
32	SE	Nordea Bank AB (publ)
33	SE	Skandinaviska Enskilda Banken AB (publ) (SEB)
34	SE	Swedbank AB (publ)

Table 4: Rankings of Banks based on Degree, Closeness and Betweenness

This table shows the average ranking of financial institutions across time for the network centrality measures Degree, Closeness and Betweenness, based on the BMA-LOESS model. The sample period ranges from 2005Q2 to 2012Q3 and the estimation windows are 8 quarters.

Nr	Degree		Closeness		Betweenness	
1	DEUTSCHE BANK A	7.61	DEUTSCHE BANK A	0.0419	DEUTSCHE BANK A	58.67
2	DEXIA	6.74	DEXIA	0.0415	DEXIA	56
3	BNP PARIBAS	4.74	Nordea Bank AB	0.0364	OTP BANK NYRT.	49.96
4	Nordea Bank AB	4.43	BNP PARIBAS	0.0362	Nordea Bank AB	47.06
5	Erste Bank Grou	4.22	OTP BANK NYRT.	0.0351	BANK OF IRELAND	46.16
6	BANCO DE SABADE	4.17	BANCO DE SABADE	0.0351	BNP PARIBAS	42.36
7	OTP BANK NYRT.	3.91	CREDIT AGRICOLE	0.0349	BANCO DE SABADE	36.52
8	CREDIT AGRICOLE	3.78	Erste Bank Grou	0.0346	KBC BANK	35.53
9	HSBC HOLDINGS p	3.61	HSBC HOLDINGS p	0.0342	DANSKE BANK	34.95
10	UNICREDIT S.p.A	3.09	BANCA MONTE DEI	0.0341	PIRAEUS BANK GR	34.38
11	ROYAL BANK OF S	2.87	UNICREDIT S.p.A	0.034	Erste Bank Grou	33.37
12	BANK OF IRELAND	2.83	KBC BANK	0.0338	UNICREDIT S.p.A	31.92
13	BANCA MONTE DEI	2.78	PIRAEUS BANK GR	0.0337	CREDIT AGRICOLE	25.78
14	Jyske Bank	2.74	BANK OF IRELAND	0.0333	HSBC HOLDINGS p	24.71
15	PIRAEUS BANK GR	2.39	ROYAL BANK OF S	0.0332	Jyske Bank	24.33
16	DANSKE BANK	2.13	Sydbank	0.033	COMMERZBANK AG	23.73
17	SOCIETE GENERAL	2.09	COMMERZBANK AG	0.0328	ROYAL BANK OF S	23.61
18	KBC BANK	2	Jyske Bank	0.0328	Banco BPI, SA	22.19
19	COMMERZBANK AG	1.96	DANSKE BANK	0.0328	BANCA MONTE DEI	21.17
20	Sydbank	1.83	SOCIETE GENERAL	0.0327	SOCIETE GENERAL	19.94
21	BARCLAYS plc	1.83	BARCLAYS plc	0.0323	BARCLAYS plc	18.15
22	ALPHA BANK	1.17	ALPHA BANK	0.032	ALLIED IRISH BA	17.73
23	Banco BPI, SA	0.91	ALLIED IRISH BA	0.0316	UNIONE DI BANCH	14.77
24	EFG EUROBANK ER	0.87	EFG EUROBANK ER	0.0315	Sydbank	14.36
25	ALLIED IRISH BA	0.87	Skandinaviska E	0.0314	ALPHA BANK	10.19
26	UNIONE DI BANCH	0.78	BANCO SANTANDER	0.0314	LLOYDS BANKING	7.06
27	BANCO SANTANDER	0.65	UNIONE DI BANCH	0.0314	EFG EUROBANK ER	6.96
28	INTESA SANPAOLO	0.61	Swedbank AB (pu	0.0314	BANCO SANTANDER	6.81
29	LLOYDS BANKING	0.57	INTESA SANPAOLO	0.0314	Swedbank AB (pu	6.54
30	Swedbank AB (pu	0.43	Banco BPI, SA	0.0313	INTESA SANPAOLO	5.96
31	IRISH LIFE AND	0.35	LLOYDS BANKING	0.0312	IRISH LIFE AND	5.09
32	Skandinaviska E	0.35	IRISH LIFE AND	0.0307	BANCO BILBAO VI	0.5
33	BANCO BILBAO VI	0.13	BANCO BILBAO VI	0.0306	BANCO POPULAR E	0.19
34	BANCO POPULAR E	0.04	BANCO POPULAR E	0.0306	Skandinaviska E	0

Table 5: Diebold-Mariano (2005) statistic

This table shows the Diebold-Mariano (1995) statistics (DM) calculated from comparing the forecast (projection) errors of the BMA-LOESS model with the BMA - BAYES model (second column), the LOESS model (third column) and the BAYES model (fourth column). The DM statistics are computed for horizons of 1 to 8 quarters ahead. Significant (at the 10 percent confidence level) DM statistics are indicated in bold.

	BMA-LOESS versus		
# quarters ahead	BMA - BAYES	LOESS	BAYES
1	1.26	**-2.11**	**-1.78**
2	1.65	**-1.94**	**-1.71**
3	1.32	**-1.56**	**-2.35**
4	-1.07	**-1.60**	**-2.70**
5	-1.06	**-1.85**	**-2.80**
6	**-1.46**	**-2.09**	**-3.10**
7	**-1.50**	**-2.99**	**-3.29**
8	**-1.78**	**-2.94**	**-2.91**

Table 6: PC ratio

This table shows the PC (Percentage Correct) ratio of the BMA - LOESS model (second column), the BMA - BAYES model (third column), the LOESS model (fourth column) and the BAYES model (fifth column). The PC ratios are computed for horizons of 1 to 8 quarters ahead. The higest PC ratio at each horizon is indicated in bold.

# quarters ahead	BMA-LOESS	BMA - BAYES	LOESS	BAYES
1	71.37%	**71.96%**	47.45%	51.76%
2	76.86%	**77.84%**	46.27%	55.10%
3	84.12%	**85.88%**	48.63%	54.90%
4	**87.84%**	84.51%	50.00%	53.53%
5	83.73%	**85.88%**	50.98%	51.76%
6	**87.45%**	86.08%	50.59%	54.90%
7	**88.24%**	87.45%	50.39%	52.55%
8	**89.80%**	88.43%	51.18%	52.16%

Table 7: Root Mean Squared Forecast Error (RMSFE) statistic

This table shows the Root Mean Squared Forecast Error (RMSFE) statistic of the BMA - LOESS model (second column), the BMA - BAYES model (third column), the LOESS model (fourth column) and the BAYES model (fifth column). The RMSFE statistics are computed for horizons of 1 to 8 quarters ahead. The lowest RMSFE statistic at each horizon is indicated in bold.

# quarters ahead	BMA-LOESS	BMA - BAYES	LOESS	BAYES
1	0.2338	**0.2271**	26.5250	4.8142
2	0.3595	**0.3573**	50.1851	9.3801
3	0.4800	**0.4779**	69.2134	13.4072
4	**0.5875**	0.5981	82.7698	16.9998
5	**0.7137**	0.7227	91.1135	19.7346
6	**0.8237**	0.8241	95.9598	21.7910
7	0.9306	**0.9282**	98.9049	23.2936
8	**0.9879**	0.9898	105.4749	24.2541

Figure 1: Visualisation of the Financial Network for two gridpoints of industrial production

This Figure visualizes the financial network structure centered around two values of industrial production. The figure on the left hand side takes the lowest value of industrial production in the sample (the value at the end of April 2009) as the gridpoint in the LOESS estimation, whereas the figure at the right hand side takes the maximum (in sample) value of industrial production (end of May 2010) as a gridpoint. The graph only visualizes connections between banks when the PIP is larger than 50 percent. The probability of the connection (the PIP) is connected to the darkness of the lines. All banks in the graph get equal size (the red circle). The location of the banks on the graph is an approximation of their geographical location in Europe.

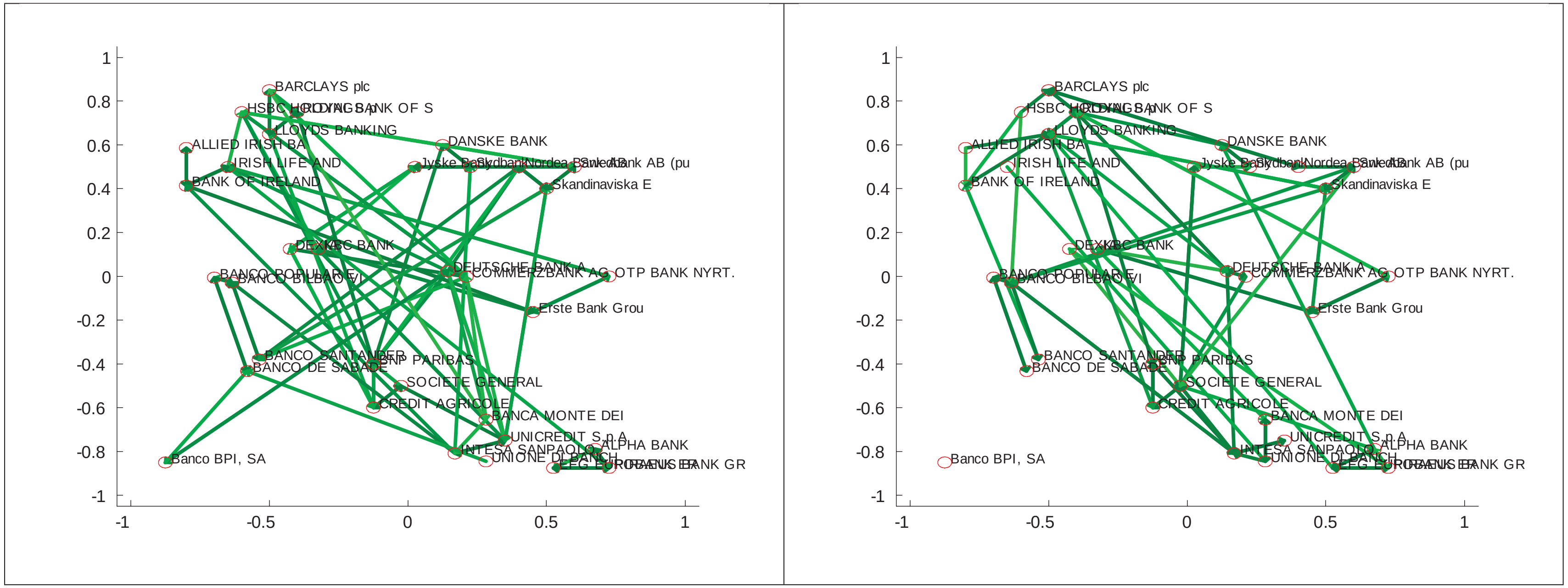
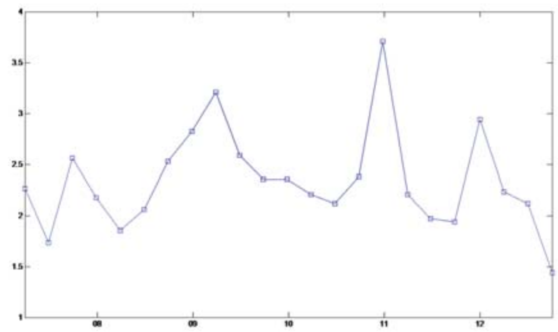


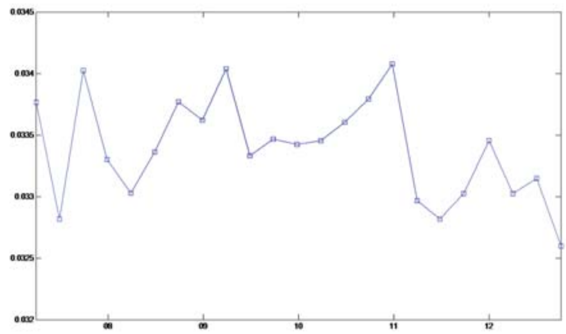
Figure 2: Network Centrality Measures over time

This graph shows how the three measures of network centrality (degree, closeness and betweenness) have evolved over time. I use 8 quarter rolling windows for the estimations.

Panel A: Degree



Panel B: Closeness



Panel C: Betweenness

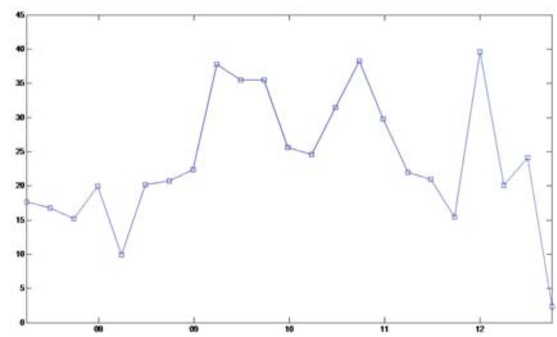
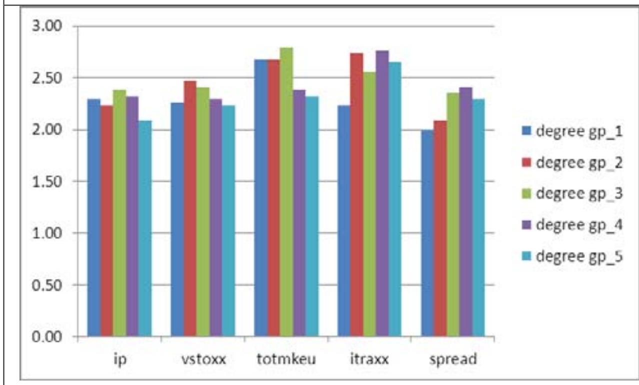


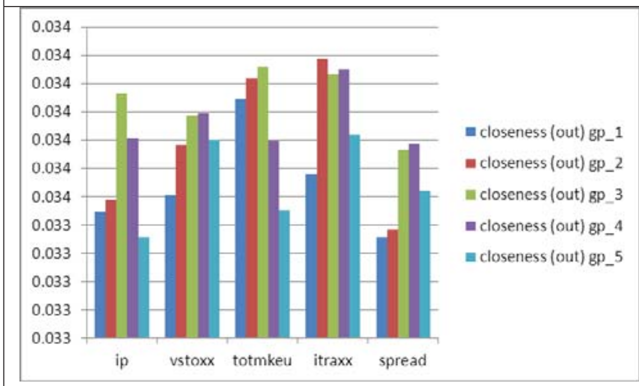
Figure 3: Network Centrality Measured over different values of the common factors

This graph shows how the degree, closeness and betweenness vary for different values of industrial production, market volatility (Vstoxx), the stock market index (TOTMKEU), the Itraxx and the Spread. The gridpoints range from 1 to 5 (1 is the lowest value, 5 is the highest value in sample).

Panel A: Degree



Panel B: Closeness (out)



Panel C: Betweenness

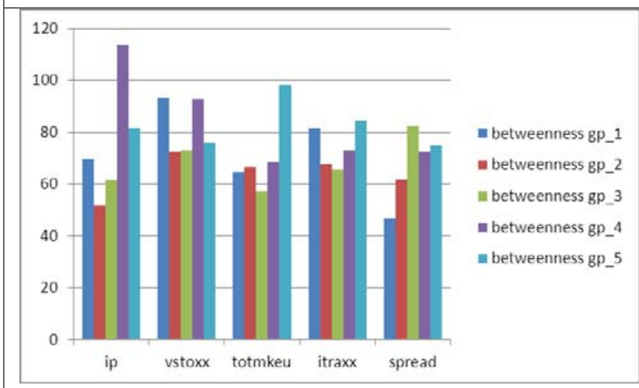


Figure 4: Maximum PIP per block over rolling windows of 8 quarters

This Figure shows for each quarter the maximum PIP in each block. The length of one window is 8 quarters. The sample period starts in the second quarter of 2005, so the first estimate is obtained for the first quarter of 2007.

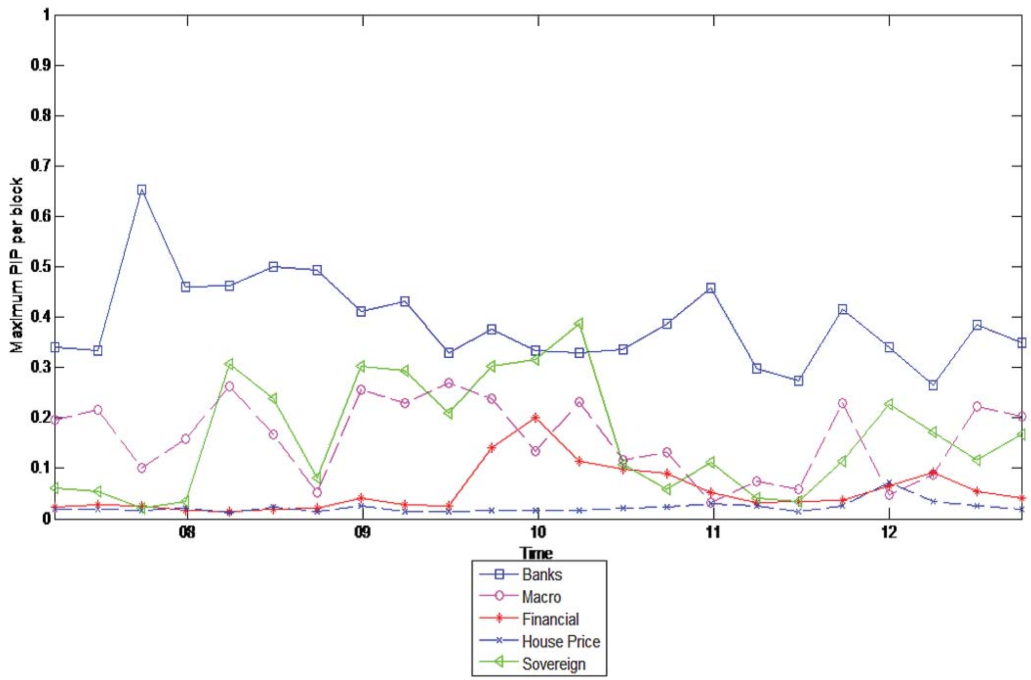


Figure 5: Interquartile Range of PIP in the Banking Block

This Figure shows for each quarter the Interquartile Range of PIP in the Banking Block. The length of one window is 8 quarters. The sample period starts in the second quarter of 2005, so the first estimate is obtained for the first quarter of 2007.

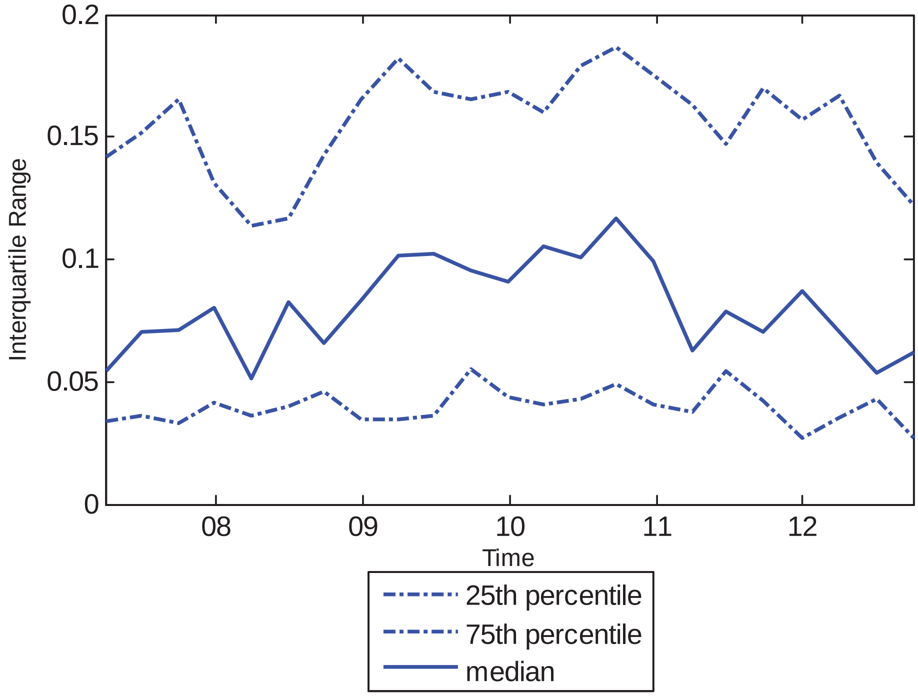


Figure 6: PIP of macroeconomic risk factors

This Figure shows for each quarter the PIP of the components of the macroeconomic block. The length of one window is 8 quarters. The sample period starts in the second quarter of 2005, so the first estimate is obtained for the first quarter of 2007.

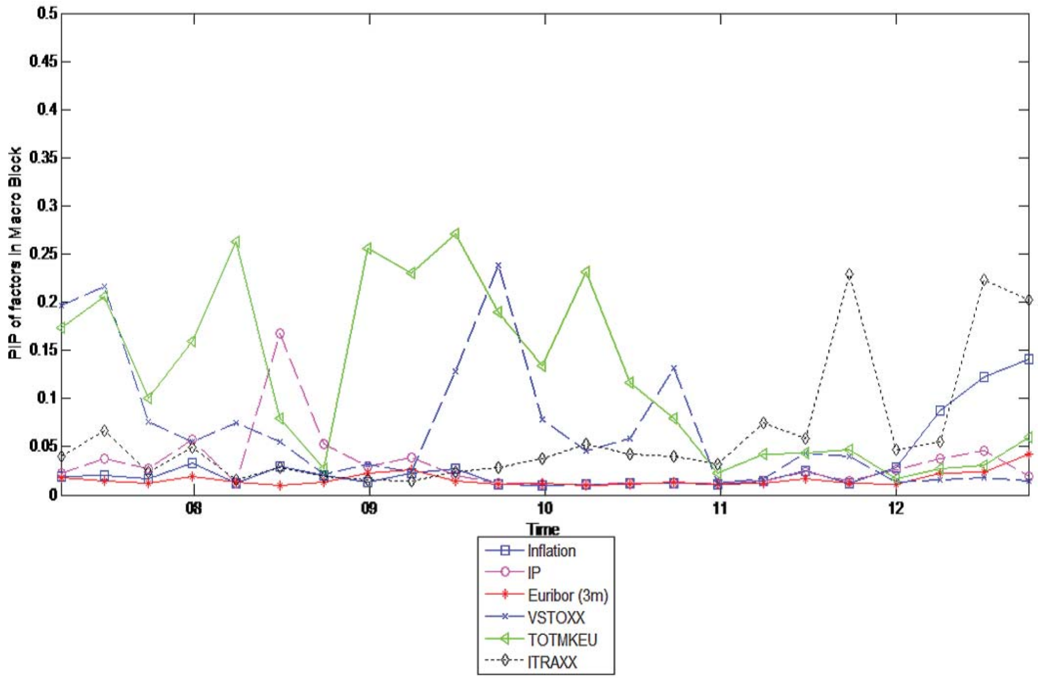


Figure 7: PIP of GIIPS countries sovereign bond yields

This Figure shows for each quarter the PIP of the components of the GIIPS countries sovereign bond yields. The length of one window is 8 quarters. The sample period starts in the second quarter of 2005, so the first estimate is obtained for the first quarter of 2007.

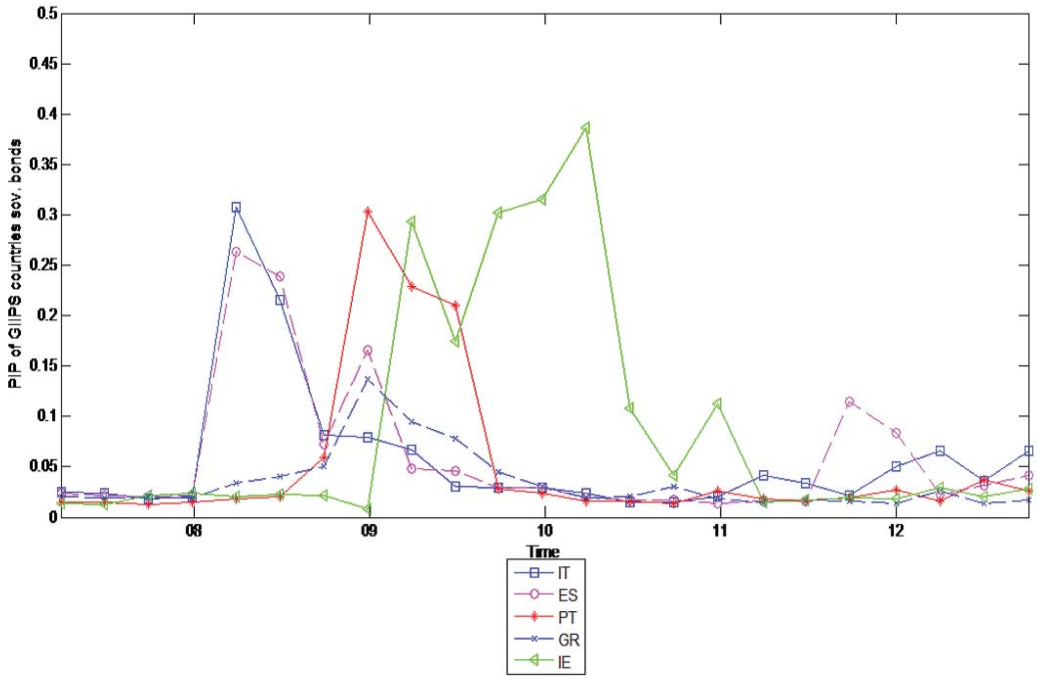


Figure 8: PIP of financial risk factors

This Figure shows for each quarter the PIP of the components of the financial block. The length of one window is 8 quarters. The sample period starts in the second quarter of 2005, so the first estimate is obtained for the first quarter of 2007.

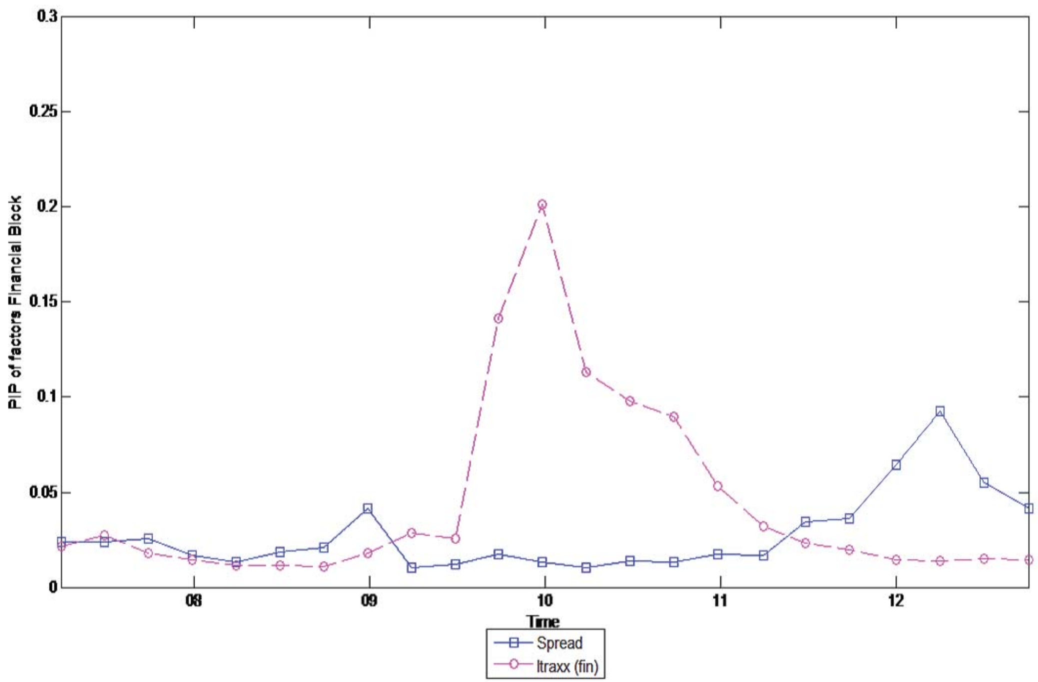
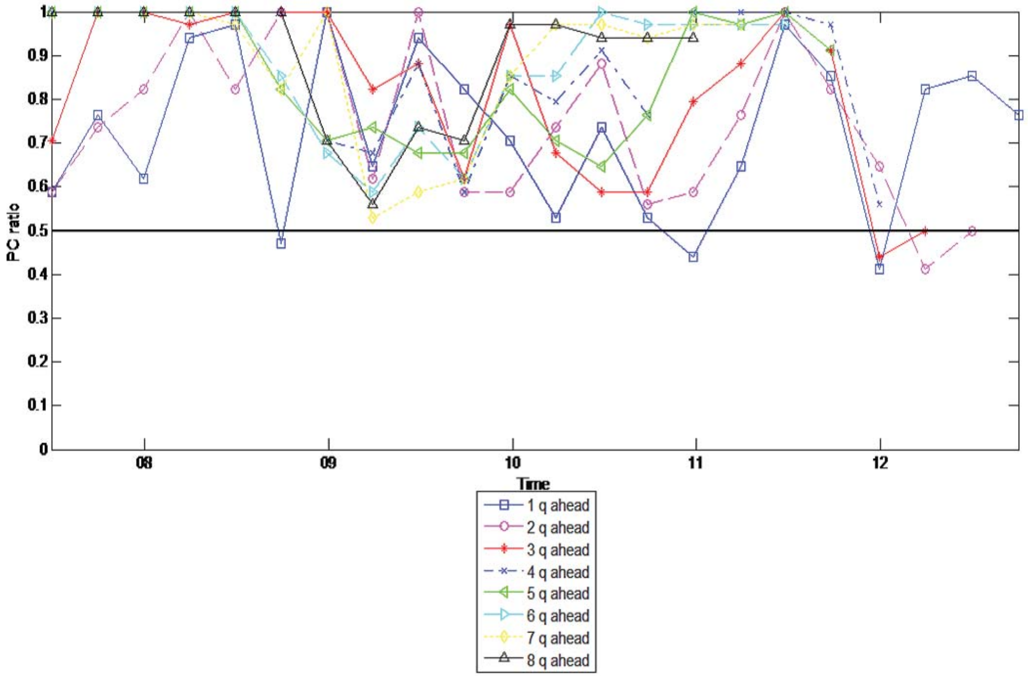


Figure 9: PC ratio

This Figure shows the PC ratio of the BMA-LOESS model on rolling windows of 8 quarters. The horizontal black line is the benchmark of a PC ratio of 50 percent.



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The Fellowship programme is named after Baron Alexandre Lamfalussy, the first President of the European Monetary Institute. Mr Lamfalussy was one of the leading central bankers of his time and one of the main supporters of a single capital market within the European Union.
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