Interconnectedness of the banking sector as a vulnerability to crises[☆]

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Abstract

This paper uses macro-networks to measure the interconnectedness of the banking sector, and relates it to the vulnerability to banking crises in Europe. Beyond cross-border financial linkages of the banking sector, macro-networks also account for financial linkages to the other main financial and non-financial sectors within the economy. We enrich conventional early-warning models using macro-financial vulnerabilities, by including measures of banking sector centrality as potential determinants of banking crises. Our results show that a more central position of the banking sector in the macro-network significantly increases the probability of a banking crisis. By analyzing the different types of risk exposures, our evidence shows that credit and market risk are important sources of vulnerabilities. Finally, the results show that early-warning models augmented with interconnectedness measures outperform traditional models in terms of out-of-sample predictions of recent banking crises in Europe.
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1. Introduction

The recent global financial crisis has stimulated a wave of research to better understand sources of systemic risk and potential determinants of financial crises. Two strands of literature have emerged: one stressing the identification of risks that build-up over time and another investigating the cross-sectional dimension of vulnerabilities. This paper combines the two approaches to explore whether complementing macro-financial indicators with measures of financial interconnectedness aid in explaining and predicting recent banking crises in Europe. By including measures of centrality of the banking system in the early-warning model, we are able to account for the potential shock transmissions and exposures to vulnerabilities that a banking sector could face through its domestic and cross-border interconnections. European countries seem an ideal laboratory for our empirical investigation given the central role that the banking sector plays in European economies in intermediating funds for the real economy, and as the introduction of the single currency has substantially increased the financial integration, potentially increasing cross-border spillover effects.

The early-warning literature has focused on the time-dimension of systemic risk, by identifying vulnerable states preceding financial crises using a wide range of country-level macro, financial and banking sector indicators.[4] The literature has focused on the determinants of banking crises through the analysis of univariate indicators Alessi and Detken (2011)) (i.e., signaling approach Kaminsky and Reinhart, 1998) and multivariate models (see e.g. Demirgüç-Kunt and Detragiache, 1997; Eichengreen and Rose, 1998). In general, periods prior to systemic banking crises have been shown to be explained by traditional vulnerabilities and risks that represent imbalances like lending booms and asset price misalignments. By an analysis of univariate indicators, Borio and Lowe (2002, 2004) show that banking crises tend to be preceded by strong deviations of credit and asset prices from their trend. Alessi and Detken (2011) show that best-performing indications of boom/bust cycles are given by liquidity in general and the global private credit gap in particular. Likewise, in a multivariate regression setting, vulnerabilities and risks have, overall, been shown to precede country-level crises on a large sample of developed and developing countries in Demirgüç-Kunt and Detragiache (2000) and for the US, Colombia and Mexico in Gonzalez-Hermosillo et al. (1999), as well as on a bank level in Eastern European transition economies in Männasoo and Mayes (2009). Lo Duca and Peltonen (2013) show that modern financial crises have been preceded by a range of domestic macro-financial vulnerabilities and risks, particularly credit growth, equity valuations and leverage. Their analysis also emphasizes the importance of global financial developments, such as global liquidity and asset price developments impacting a domestic vulnerability to financial crisis (for a further discussion on global liquidity see also Cerutti et al., 2014). This only provides a snapshot of the broad literature that aims to detect and proxy imbalances, risks and vulnerabilities that function as determinants of crises, with the ultimate goal of identifying vulnerable states preceding crises.

Another strand of a rapidly expanding literature analyzes the cross-sectional dimension of systemic risk. Beyond country-level vulnerabilities, the recent crisis propagated

[4] The literature acknowledges the challenges in predicting shocks that trigger crises, but rather aims at identifying states when entities are vulnerable to the occurrence of triggers. See Lang et al. (2015) for an overview of early-warning modelling framework and literature.

across markets and borders, and the banking system played a major role in this phenomenon. Adverse shocks have been exacerbated via balance sheet effects, causing insolvencies and substantial losses.[5] Recently, cross-border linkages and interdependencies of the international financial system have been modeled using network techniques. Starting with the analysis of the international trade flows as a network (Fagiolo et al., 2009, 2010), these techniques have been applied to other contexts. Kubelec and Sá (2010) and Sa (2010) represent a large dataset of bilateral cross-border exposures by asset class (FDI, portfolio equity, debt, and foreign exchange reserves) for 18 advanced and emerging market economies as a network. Minoiu and Reyes (2013) study the features of the global banking network.[6] More generally, both theoretical and empirical works show that network techniques provide useful insights with respect to financial stability. Previous literature finds that network structure matters in the generation of systemic risk (Allen et al., 2011). Network topology influences contagion (e.g., Gai and Kapadia, 2010; Georg, 2013). Network measures have been related to changes of the global banking system (Minoiu and Reyes, 2013), and economic growth and financial contagion (Kali and Reyes, 2010).

In this paper, we study the intricate web of financial linkages with the aim to detect vulnerability to banking crises. We consider the cross-border banking linkages in a network architecture to measure the extent of the direct and indirect exposures of each countrys banking sector to the international banking system. On top of that, each banking system is linked to the other institutional sectors of the economy. To include both aspects in our analysis, i.e., country-level and sector-level linkages, we build on the framework proposed by Castrén and Rancan (2014). They introduce the idea of a macro-network, a network which links the institutional sectors of the economy – financial (banks, insurance and pension fund companies and other financial intermediaries) and non-financial (non-financial corporations, general government, households, and the rest of the world). We extend their framework to 14 European countries. Then, we make use of network centrality measures to identify the position of the banking sector of each country. Combining the topics of macro-financial imbalances and networks, this paper explores whether complementing standard macro-financial vulnerabilities with networks centralities computed on the macro-network aids in explaining and predicting the occurrence of banking crises. As we control for more standard early-warning indicators, we can test whether and to what extent the computed network metrics are significant explanatory variables of pre-crisis periods and improve the predictive capabilities of standard models. Moreover, the macro-network allows us to display the patterns of asset and liability positions over time and to monitor imbalances or fragilities in the domestic and foreign portfolios.

Our paper contributes to the existing literature on financial networks by assessing the role of financial linkages, constructed over aggregate balance sheets, and provides an additional set of indicators to the early-warning literature. Few recent papers are

[5] For instance, Adrian and Shin (2010) show how balance sheets may be a conduit of shock propagation. In Caballero and Simsek (2013) fire sales of asset amplify contagion effects.

[6] A rapidly growing finance literature has focused on banking networks using data at bank-level, such as stable interbank lending (e.g., Mistrulli, 2011; Craig and von Peter, 2014), overnight interbank lending (Iori et al., 2008), and syndicated loans (e.g., Hale, 2012; Cai et al., 2011; Godlewski et al., 2012). Unlike these papers, our network is at macro level and incorporates different economic sectors of the economy.

close to our approach. Caballero (2015) investigates the level of financial integration measured in the global banking network, using detailed information on bank exposures in the syndicated loan market, as determinant of bank crisis. Chinazzi et al. (2013) relate the 2008-2009 crisis to a global banking network built with data on cross-border portfolio investment holdings. In a similar vein, Minoiu et al. (2013) show the usefulness of network measures, computed over the web of international banking exposures (the BIS bilateral locational statistics), for crisis prediction. Differently, in our analysis the banking sector is considered as one of the sectors in the broad architecture of the financial system. In this respect, our paper is related to Billio et al. (2012) who consider financial connectedness[7] between a larger set of financial institutions, like insurer corporations, brokers, and hedge funds, in addition to banking institutions, using stock returns. But they focus on individual institutions, while we consider sectors at aggregate level, additional sectors (such as non-financial corporations, general government and households), and multiple countries, and the linkages of the macro-network are constructed over balance sheets. While our representation of the financial linkages is a stylized characterization of the financial interconnectedness existing in Europe, we believe that this approach is an important step towards a comprehensive understanding of the impact of international financial integration on crises and financial performance. Moreover, this paper complements the previous literature analyzing the different dimensions of risk as the macro-network is constructed using different financial instruments (loans, deposits, securities and shares). Indeed banking institutions providing a variety of investment and financing services to other sectors are exposed to different types of vulnerability. Credit risk is due to borrowers' defaults or deterioration of credit standings. Funding and liquidity risks are linked to the availability of funds including deposits run. Price fluctuations of securities and shares exposed bank balance sheets to market risk. The macro-network including all sectors of the economy describes, to some extent, these different dimensions of risk exposures which could not fully captured by considering only a banking network.

Our findings suggest that a more central position of the banking sector in the macro-network increases the probability of a banking crisis. Our analysis also indicates that the macro-network characterizes the "position of a banking sector in a more precise way than if one considers solely the network of banking sectors. Thus, this paper shows that financial models cannot ignore the interactions of the banking sector with other sectors of the economy. In this context, among the different types of risk faced by banks, those originated from the lending and investment activities seem to predict more accurately banking crisis. Finally, our results show that early-warning models augmented with macro-networks outperform traditional models in terms of predicting recent banking crises in Europe out-of-sample. We test the robustness of the results with respect to the chosen forecast horizon, thresholds on issuing a signal and the specified preferences between issuing false alarms and missing crises. Further, the paper is complemented with a web-based interactive visualization of the macro-networks: http://vis.risklab.fi/#/macronet/ (for a further discussion of the VisRisk platform see Sarlin (2014)).

The paper is organized as follows. After discussing the underlying data, we present the techniques used for creating and evaluating the early-warning models. Then, we present

[7]Their measures are based on PCA and Granger causality. Recently other econometric approaches have been adopted to quantify financial linkages (Diebold and Yılmaz, 2014).

and discuss the early-warning models as well as the findings about macro-networks as determinants of financial crises. Before concluding, we perform an extensive robustness analysis.

2. Data

For the analysis, we need three categories of data: crisis events, macro-financial early-warning indicators and macro-networks. This section explains how the necessary data is derived. After merging all datasets, our quarterly sample covers the period 2000q1–2012q1 for 14 European countries.[8]

2.1. Crisis events

The first set of data needed are dates of systemic banking crises. The banking crisis events used in this paper are based upon the compilation initiative by Babecky et al. (2014) and the European System of Central Banks (ESCB) Heads of Research. In particular, the database includes banking crisis events for all EU countries from 1970 to 2012 on a quarterly frequency. The approach in Babecky et al. (2014) involves a compilation of banking crisis dates from a large number of influential papers, including Laeven and Valencia (2013), Kaminsky and Reinhart (1999) and Reinhart and Rogoff (2008), which have been further complemented and cross-checked by ESCB Heads of Research. Hence, it tries to align with previous literature at the same time as cross-country differences are accounted for through more qualitative assessment by a survey among country experts. A binary crisis variable takes the value 1 in case an event occurs and 0 otherwise. The used sample includes 128 quarters of systemic banking crises and 104 quarters of pre-crisis quarters.[9] Yet, in order to identify vulnerable states prior to crises, we specify the dependent variable to take the value 1 during a specified pre-crisis time window prior to the crisis events, and 0 otherwise. While the benchmark time window is 24 months, we also test performance using a number of specifications with shorter and longer horizons. Further, we define post-crisis periods to be a specific horizon (1 year) after crises and the periods that do not belong to any of the previously mentioned states as tranquil periods. This gives us three states around systemic banking crises: pre-crisis, post-crisis and tranquil periods.

2.2. Early-warning indicators

The second set of data needed are country-level indicators of risks, vulnerabilities and imbalances. We make use of standard indicators measuring macro-financial and banking-sector conditions. This paper follows a number of works in order to control for the most commonly used risk and vulnerability indicators, with the ultimate aim of testing the usefulness of macro-networks as leading indicators.

[8] Austria, Belgium, Denmark, Finland, France, Germany, Greece, Great Britain, Ireland, Italy, the Netherlands, Portugal, Spain, and Sweden.

[9] The crisis periods are as follows: Austria, 2008Q1; Belgium, 2008Q3–4; Germany, 2008Q1–4; France, 2008Q3–2012Q1; Greece, 2008Q1–2012Q1; Ireland, 2008Q3–2012Q1; Netherlands, 2008Q3–2012Q1; Portugal, 2008Q4–2012Q1; Denmark 2008Q3–4; Great Britain, 2007Q3–2012Q1; Sweden, 2008–2010.

We cover two types of country-specific indicators. First, we make use of country-specific macro-financial indicators to identify macro-economic imbalances and to control for conjunctural variation in asset prices and business cycles. The paper controls for macro-economic imbalances by using internal and external variables from the EU Macroeconomic Imbalance Procedure (MIP), such as the international investment position, government debt and its yield and private sector credit flow. Further, we capture conjunctural variation with indicators measuring asset prices, including growth rates of stock and house prices, and business cycle variables, such as growth of real GDP and CPI inflation. Most of the macro-financial data are sourced from Eurostat and Bloomberg. Second, we use country-specific indicators of banking sectors for identifying imbalances in banking systems. With the indicators, we aim at proxying for the following types of aggregate risks and imbalances in banking systems: balance-sheet booms, securitization, property booms and leverage. Indicators used in the paper are constructed using the ECBs statistics on the Balance Sheet Items (BSI) of the Monetary, Financial Institutions and Markets.

2.3. Macro-networks

We require a third set of data to be able to compute macro-networks. While computational details are discussed in Section 3.1, we focus herein on describing the two data sources necessary for computing macro-networks. First, we use the euro area accounts (EAA) data at the individual country level. The EAA provide a record of financial transactions in terms of assets and liabilities, broken down into instrument categories, for the various institutional sectors. Those data allow us to estimate[10] the financial linkages at domestic level between the institutional sectors: non-financial corporations (NFC); banks (monetary financial institutions, MFI); insurance and pension fund companies (INS); other financial intermediaries (OFI); general government (GOV); households (HH); and the rest of the world (ROW). The EAA are available on a quarterly basis for a set of European countries. Second, we use the Balance Sheet Items statistics (BSI); those data provide the aggregated (or consolidated) balance sheets of the countrys MFI sector and provide information on the identity of the MFI counterparties at the country level for the MFIs cross-country exposures.

3. Methods

This section presents the methodology for constructing the macro-networks, estimation and prediction techniques to derive early-warning signals, and evaluation techniques for assessing the usefulness of the early-warning signals.

[10]Currently, a whom-to-whom flow-of-funds statistics is available only for few countries and for selected instruments (deposits, short-term and long-term loans). Therefore, we need to estimate the sectoral flows at the domestic level using methods described in Section 3.1. We use, however, the information of the whom-to-whom flow-of-funds statistics for the available instruments to cross check the robustness of the estimated macro network (see Appendix A).

3.1. Construction of the macro-network

In this section, we describe how the macro-network is constructed. In general, a network is defined as a set of nodes and a set of linkages between them. In our context, each banking sector, as well as each institutional sector, is considered as a node indexed by i, and the total number of nodes N is 98 (7 sectors $\times$ 14 countries). A financial relation between any two sectors is a linkage w_{ij}, which is directed and weighted. Linkages are constructed in the following way: i) domestic linkages between sectors, denoted by superscript D, are estimated using the EAA data, and ii) cross-border linkages between banking sectors, denoted by superscript CB, are the actual data recorded in the BSI statistics. In detail, we obtain the domestic network W^D by using the total amount of assets and liabilities for all seven sectors of the economy, and applying the maximum entropy method for each country. The maximum entropy works as follows. Assets a and liabilities l can be interpreted as realizations of the marginal distributions $f(a)$ and $f(b)$, and the W^D as their joint distribution. The common approach is to assume that $f(a)$ and $f(b)$ are independent, which implies that bilateral linkages are given by a simple solution $w_{ij}^D = a_i l_j$. Hence, the institutional sectors maximize the dispersion of their linkages.[11] The maximum entropy is a method borrowed from the literature analyzing contagion risk in the interbank market, where the algorithm is applied at the level of individual institutions (for a review see Upper, 2011). More recent literature has proposed other methods for estimating linkages to represent incomplete and tiering structures of the interbank market (e.g., Anand et al., 2014), but here it is reasonable that each sector has at least some financial transactions with all the other sectors. Hence, we opt for the maximum entropy method which seems the most appropriate approach given the features of our context.[12]

The set of cross-border linkages W^{CB}, connecting the MFI sectors, comes from the BSI statistics which reports the whom-to-whom information (for a detailed description of the feature of this network see Castrén and Rancan, 2014). Considering both domestic linkages between sectors for all countries and the cross-border linkages between banking sectors, the resulting network of linkages, $W = W^D + W^{CB}$, is the macro-network and it is constructed in each period and for each balance sheet instrument. Figure 1 shows an example of the macro-network for securities for period Q1 2012. Nodes are identified by the abbreviation of sectors, and different colors help to identify sectors in different countries. The size of each arrow approximates the euro volume of a linkage. Although linkages are rescaled using logarithm, one can notice that there is a substantial variation across linkages connecting sectors, which capture the heterogeneous financial structure of different countries.

Overall, the macro-network provides a representation of the interconnectedness of the European financial system. In order to analyse the robustness of the estimated macro-network, we use the limited available information of the whom-to-whom flow-of-funds statistics for the available instruments (see Appendix A). The analysis performed for a country with a sufficiently good coverage of data shows that the position of the banking

[11] In our setting the diagonal matrix is not set equal zero as financial transactions may take place between institutions of the same sector.

[12] To be more precise, we use an improved algorithm of the maximum-entropy method, which takes into account additional information regarding the network structure. For further details regarding the approach, see Castrén and Rancan (2014).

sector in the example country does not change substantially when estimating the linkages instead of using the real whom-to-whom network. This supports our view that the chosen methodology seems quite reliable in this context.

3.2. Measuring banking sector centrality

For the study of banking crises, it is important to take into account the potential shock transmissions and exposures to vulnerabilities that banking sector could face through its domestic and cross-border interconnections. In order to quantify the interconnections and position of each country's banking sector relative to all other financial and non-financial sectors of the economy as well as to other cross-border banking sectors, we calculate a set of commonly used network centrality measures. In particular, we use centrality measures that provide a useful quantification of the individual position of each node relative to the network. By measuring direct linkages, In-Degree (Out-Degree) is the sum of all incoming (outgoing) linkages that each node has. Betweenness measures the extent to which a particular node lies "between" the other nodes in the network in terms of shortest weighted paths. Closeness is a measure of influence, where the most central node in the network can reach all other nodes quickly.[13] Betweenness and Closeness take into account both direct and indirect linkages. capturing the position of a node in the overall network.

We compute the above four centrality measures for four instruments available using the quarter-end balance sheet: loans, deposits, securities and shares. In order to avoid merely taking into account size effect, we use the logarithm transformation of the linkages W, and consider the weighted version of the above metrics as financial linkages differ in their volumes. Basic summary statistics are reported in Tables 1 and 11. Figure 2 depicts the evolution of the normalized centrality measures.

In general, while there is substantial cross-country heterogeneity, we find that network measures as well as various instruments for which they are computed, are highly correlated. Thus, we use a Principal Component Analysis (PCA) –a technique in which the centrality measures can be decomposed into orthogonal factors having decreasing explanatory variance– to reduce the number of potential variables to be included in the early-warning model, while still retaining most of the variance in the measures. A common procedure when using the PCA is to retain components with eigenvalues greater than one. We do so, but also show results with a larger number of principal components to assess improvements in early-warning performance. Table 14 shows the PCA results for the centrality measures across all instruments together (Panel A) and for the set of centrality measures for each individual instrument (Panel B).

3.3. Estimation and prediction

In the early-warning literature, a broad selection of different methods have been used for estimating crisis probabilities (for an extensive review and comparison see Holopainen and Sarlin, 2015). From the family of discrete-choice methods, we make use of standard logit analysis, and follow the literature by preferring pooled models (e.g., Fuertes and Kalotychou, 2007; Kumar et al., 2003; Davis and Karim, 2008). In particular, when Fuertes and Kalotychou (2006) account for time- and country-specific effects, they show

[13]See Appendix B for the mathematical definitions.

that it leads to better in-sample fit, with the cost of decreased out-of-sample performance. Further, one can also argue for pooling by the rarity of crises in individual countries, while models still strive to capture a wide variety of vulnerabilities. Thus, we do not control for country or time-fixed effects, as this would otherwise drop observations for countries or periods that do not experience a pre-crisis period. Instead of lagging explanatory variables, we define the dependent variable as a forecast horizon that includes a specified number of quarters prior to the event (8 quarters in the benchmark case). In order to account for so-called crisis and post-crisis bias (e.g., Bussire and Fratzscher, 2006; Sarlin and Peltonen, 2013), we exclude crisis and post-crisis periods from the estimation sample. As economic variables go through adjustment processes prior to reaching tranquil paths in times of crisis and recovery, these periods are not informative for identifying the path from pre-crisis regimes to crisis. Further, to control for potential correlation in the error terms (see e.g. Behn et al. (2013)), we derive robust standard errors by clustering at the level of time units. The correlation in error terms is particularly relevant in our case, as macro-network based measures tend to be correlated across countries, allowing us to better control for the global nature of the effects.

Rather than describing the problem from the viewpoint of time-series prediction, the focus on differentiating between vulnerable (i.e., pre-crisis) and tranquil economies forms a standard classification problem. We are aiming for a model that separates vulnerable and tranquil classes to classify (or discriminate) between them by estimating the probability of being in a vulnerable state in any given case (also denoted as crisis probability). That said, time needs to be accounted for when testing the predictive power of an early-warning model. To measure predictive performance, we divide the dataset into two samples: in-sample data and out-of-sample data. While the in-sample data are used for estimation, the out-of-sample dataset measure the predictive power of the estimated model. This is done in a recursive manner to mimic the set-up of a quasi real-time analysis by using the information set available at each quarter. We control for the indicators that would have been at hand, including the use of only data up to a quarter and accounting for publication lags, but do not account for data revisions due to lack of available public information. Another reason for the recursive exercises being quasi real-time is that they use pre-crisis events for given quarters. This simplifying assumption has to be made due to the shortness of Euro Area Accounts time series and the lack of systemic events in the years prior to the current global wave of crises. While this allows a leak of information about occurring crises slightly earlier, it provides still a comparable relative recursive performance test of the models with and without measures of interconnectedness.[14]

3.4. Evaluation of model signals

The above described problem is a classification task, yet logit analysis outputs a probability forecast for each observation rather than crisply assigning them into classes. For classification through probability forecasts, an essential part is the evaluation of the

[14] For a further discussion on quasi vis-à-vis truly real-time recursive estimations see Holopainen and Sarlin (2015). Real-time use of pre-crisis periods may distort the true relationship between indicators and vulnerable states, which could imply biased model selection, particularly variable selection. In contrast to lags on the independent variables, one should also note that the treatment of pre-crisis periods does not impact the latest available relationship in data and information set at each quarter.

results and the measures used for setting thresholds, or cut-off values, on the probabilities. An evaluation framework that accounts for imbalanced class distributions and varying misclassification costs plays a key role in this work, as crises may be described as low probability, high-impact events. In the vein of the loss-function approach proposed by Alessi and Detken (2011), the framework applied here follows an updated version in Sarlin (2013). We derive a loss function and Usefulness measure for a cost-aware decision maker with class-specific misclassification costs.

Let an ideal leading indicator be represented with a binary state variable $I_j \in \{0,1\}$, where the index $j = 1, 2, , N$ represents observations and h a forecast horizon. Hence, I_j takes the value 1 within the forecast horizon prior to a crisis, and 0 otherwise. We use logit analysis to turn multivariate data into probability forecasts of a crisis $p_j \in \{0,1\}$. For classification, the probabilities p_j need to be transformed into binary point forecasts $p_j \in \{0,1\}$ that equal one if p_j exceed a specified threshold λ and zero otherwise. The frequencies of prediction-realization combinations between P_j and I_j can be summarized into a contingency matrix consisting of: false positives (FP), true positives (TP), false negatives (FN) and true negatives (TN).

A wide range of goodness-of-fit measures can be computed from entries of a contingency matrix.[15] These do not, however, tackle imbalances in class size and class cost. We approach the problem from the viewpoint of a policymaker that is concerned of conducting two types of errors: type 1 and 2 errors. Type 1 errors represent the conditional probability $P(p_j \leq \lambda \mid I_j(h) = 1)$, and type 2 errors the conditional probability $P(p_j > \lambda \mid I_j(h) = 0)$. When estimated from data, they can be computed as the share of false negatives to all positives ($T_1 = FN/(FN + TP)$) and false positives to all negatives ($T_2 = FP/(FP + TN)$), respectively. Hence, given probabilities p_j, the aim of the decision maker is to choose a threshold that minimizes her loss. To account for imbalances in class size, the loss of a decision maker consists not only of T_1 and T_2 but also of unconditional probabilities of positives $P_1 = P(I_j(h) = 1)$ and negatives $P_2 = P(I_j(h) = 0) = 1 - P_1$. The frequency-weighted errors are then further weighted by policymakers' relative preferences between missing a crisis $\mu \in [0,1]$ and issuing a false alarm $1 - \mu$, which may either be directly specified by the policymaker or derived from a benefit/cost matrix. Finally, the loss function is as follows:

$$L(\mu) = \mu T_1 P_1 + (1 - \mu) T_2 P_2 \tag{1}$$

While this enables us to find an optimal threshold, we are still interested in the Usefulness of the model. By always signalling a crisis if $P_1 > 0.5$, or never signalling if $P_2 > 0.5$, a decision maker could achieve a loss of $\min(P_1, P_2)$. By accounting for the above specified preference parameter μ, we achieve the loss

$$U_a(\mu) = \min(\mu P_1, (1 - \mu)\, P_2) - L(\mu) \tag{2}$$

[15]Some of the commonly used simple evaluation measures are as follows. Recall positives (or TP rate) = TP/(TP+FN), Recall negatives (or TN rate) = TN/(TN+FP), Precision positives = TP/(TP+FP), Precision negatives = TN/(TN+FN), Accuracy = (TP+TN)/(TP+TN+FP+FN), FP rate = FP/(FP+TN), and FN rate = FN/(FN+TP). Receiver operating characteristics (ROC) curves and the area under the ROC curve (AUC) are also suitable for evaluating model performance. The ROC curve shows the trade-off between the benefits and costs of a certain λ. The AUC measures the probability that a randomly chosen distress event is ranked higher than a tranquil period. A coin toss has an expected AUC of 0.5, whereas a perfect ranking has an AUC equal to 1.

For an interpretable measure, we compute the amount of absolute Usefulness U_a that the model captures in relation to the Usefulness of a perfect model (i.e., available Usefulness

$$U_r(\mu) = \frac{U_a(\mu)}{\min(\mu P_1, (1-\mu)\, P_2)}, \tag{3}$$

While relative Usefulness U_r is simply a rescaled measure of U_a, the value of it is to provide a meaningful interpretation. With U_r, performance can be compared in terms of percentage points. Hence, we can focus solely on U_r when interpreting models.

4. Analysis

This section presents and discusses the early-warning models built in this paper, and particularly tests the role of macro-networks as leading indicators. We look at this from two viewpoints: i) macro-networks and its constituents as early-warning indicators, and ii) the usefulness of different instruments in early-warning exercises. The analysis is done as follows. First, we assess whether macro-network measures contain early-warning information. Second, we assess the extent to which vulnerability descends from cross-border linkages vis-à-vis sectoral exposures. Third, we consider separately different balance-sheet instruments that may convey different types of information, in order to better understand which instruments contain most vulnerabilities.

4.1. Macro-networks as early-warning indicators

In order to evaluate the performance of models, we need to specify the policymakers preferences between type I and II errors. We assume the policymaker to be more concerned with missing a crisis than giving false alarms. This coincides with reasoning when an alarm leads to an internal investigation rather than an external signal (which might be related to more complex political economy effects). Hence, our preference parameter is $\mu = 0.8$.

In Table 2, model 1 is the baseline which includes standard indicators measuring macro-financial and banking-sector conditions. By considering separately the different balance-sheet instruments, we might lose useful information exhibited by other instruments. Likewise, considering only a few of the correlated centrality measures might lead to disregarding relevant information. Thus, we perform PCA on all network measures and instruments together (PCA-MN-All). Models 2–5 confirm the usefulness of augmenting the baseline specification with network information: one principal component significantly increases performance. Adding more principal components reach a similar early-warning performance or increase it. Given that the eigenvalues and the explained variance of the third and fourth components are similar, we choose model 5 as our benchmark. In model 5, all components, with the exception of the second one, are statistically significant. However, our results are supported also by the analysis of the individual network measures, which are statistically significant in almost all cases (see Table 16). Thus, we opt for model 5 with the hope to provide a tool which is parsimonious and informative at the same time. Overall, the driving factor of the early-warning performance is network measures that quantify the position of the each banking sector with respect to all other banking sectors across Europe and non-banking sectors in the domestic economy.

4.2. Cross-border banking networks as early-warning indicators

In this section, we investigate whether MFIs cross-border linkages would be useful and sufficient to inform a policy maker. Similarly to the macro-network, we first model the set of cross-border linkages W^{CB} of MFIs as a network. Second we used the "European banking network", to derive centrality measures (Table 15 provides the summary statistics) and the corresponding PCAs.

In Table 3, Models 2–5 enrich standard early-warning indicators with the appropriate number of PCAs for each balance sheet instrument, Models 6–7 include the PCAs constructed considering all centrality measures for all instruments together. The improvements in relative Usefulness indicate that Models 2–5, which add only individual instruments, perform better than the baseline model with no network measures (Model 1). In Model 6, the relative Usefulness improves further, but does not reach same levels as the macro-network in Table 2. We interpret this as an indication of the macro-network as a more comprehensive characterization of the interconnectedness (or position) of a banking sector than if one considers solely the network of banking sectors (Chinazzi et al., 2013; Minoiu et al., 2013). By definition, it allows for more channels of vulnerability, as well as provides an explicit characterization of the closeness of the banking sector to the real economy (e.g., households and non-financial corporations) that could potentially increase the likelihood of banking distress becoming systemic. More precisely, we show that centrality measures are a better measure of vulnerability when also accounting for domestic sectoral exposures, in addition to cross-border linkages.[16]

This is an interesting finding given that data on all the existing cross-border connections between all sectors, such as linkages between households and non-financial sectors in various countries, are not available. Despite this, we show that the estimated centrality measures of the banking sector, when also accounting for sectoral exposures within the domestic economy, perform well as an indicator of risk and vulnerability. This points to the fact that the position of the banking sector is described by the composition of both international and national interconnectedness.

4.3. Early-warning properties of various instruments

Building on the previous approach, we perform PCA on the four centrality measures (In-Degree, Out-Degree, Betwenness and Closeness) used to quantify the interconnectedness of the banking sector within the macro-network. This time, we separately apply PCA to the instruments loans, deposits, securities and shares.

The motivation for analysing banking sector centrality in these four financial instruments is to understand the relationship of the banking sector with different types of risks and the different role played by the banking sector, either as a direct holder or as an intermediary. There are several important differences across the financial instruments that should be noted. First, loans and deposits are instrument types for which the banking sector has traditionally a dominant position, given banks' role as takers of deposits and granters of loans vis-a-vis other institutional sectors. Second, loans and deposits are

[16] We also test that the difference is statistically significant with standard significance tests for both the Usefulness and the AUC measures. We make use of the bootstrap approach in Robin et al. (2011) that draws stratified bootstrap replicates from the data, computes the measures and the difference for each bootstrap replicate, and tests bilateral differences.

mainly bilateral direct linkages between the sectors and they are not traded in markets. In contrast, debt securities and shares are traded in financial markets and have a market price, due to which banking sectors' role can be different in these instruments. While the banking sector can hold securities and shares directly in its portfolio, it can also act as an intermediary of these instruments to other institutional sectors. Finally, there is another important difference across the financial instruments related to issuers of instruments. While deposits and loans can be received from and granted to any institutional sector, only certain institutional sectors issue securities and shares (e.g., household and government sectors do not issue shares, and the household sector does not issue debt securities). This limits the banking sector's direct risk exposures to certain sectors. As we mentioned above, different financial instruments can also be used to analyse and proxy the banking sector's exposure to different types of risk. First, loans can be seen as mainly exposing the banking sector to credit risk. Second, the main source of risk of deposits to the banking sector is funding and liquidity risk. Third, securities and shares can be seen as exposing the banking sector beyond credit and liquidity risk to market risk. One should note, however, that in systemic banking crises, increased interconnections and intertwined risks across sectors' risk categories makes this point less relevant.

Again, we retain components with eigenvalues greater than one. Thus, we consider only the first component, which explains a significant proportion of variance. As above, these components are included as independent variables in our regressions. For PCA on individual instruments, Table 14 (Panel B) shows the standard deviation and the proportion of variance explained (the coefficients for each component are omitted for brevity). In Table 4, Models 2–5 are augmented with the principal components for each balance-sheet instrument separately. The results show that by considering those variables the model performs better than the initial specification (Baseline), however with some heterogeneity across balance-sheet instruments. The PCAs of network measures computed on the macro-network for loans (Model 2) and securities (Model 4) yield more Usefulness. This points to more vulnerability descending from credit than funding and liquidity risk and to the value of accounting for market prices through securities other than shares.

Interestingly, the positive coefficients of PCAs, irrespectively of the instrument, suggest that a more central position of the banking sector in the macro-network increases the probability of a banking crisis. Indeed, the loadings of the 1-PCAs are always positive (see Table e 14). Hence, to gain further insights we estimate the model adding one by one all the centrality measures. Table 16 confirms a positive relationship in most of the regressions. Also the Usefulness always improves, yet with some heterogeneity across instruments confirming the previous results. We observe heterogeneity also across centrality measures, but there is no centrality measure which is strongly better than the others in all four cases under examination. This was an additional reason to opt for the principal component approach.

Next, Table 5 addresses concerns related to network threshold effect. To capture non-linearities we allow PCAs for each instrument to have a different impact for high and low level of interconnectedness. In one case we consider above 75 percentile, between the 75 and the 25 percentile, below the 25 percentile, in another case we split the sample just above and below the 50 percentile. In models 1, 3, 5 and 7 variables for high and intermediate level of interconnectedness are statistically significant while this is not the case for low level of interconnectedness. Evidence of non-linearity effects are confirmed also by models 2, 4, 6 and 8. These results are verified for all four instruments confirming the findings of previous works (see e.g. Acemoglu et al., 2013; Elliott et al., 2014; Battiston et al., 2012). In term of model performance, with the only exception of instrument deposit, we find that the introduction of two threshold levels in the network measures improves the relative Usefulness with respect to a single threshold level or no threshold effect (see Table 4). We also find that the non-linearity effects of interconnectedness are more pronounced when using the variables constructed over the macro-network than only the network of banking sectors. Overall these results underpin the need to account for non-linearities when studying the relationship between interconnectedness and financial stability.

5. Robustness

In this section, we test the robustness of the above presented benchmark model, as well as evaluate it in terms of predictive performance in real-time use. Robustness is tested with respect to policymakers' preferences, forecast horizons and thresholds. For measuring performance, we make use of the evaluation metrics presented in Section 3.4.

In Table 6, the models are evaluated for policymakers' preferences ranging from 0.0 to 1.0. While the model is Useful for preferences between 0.2 and 0.9, the table shows that the model yields more Usefulness to a policymaker that is more concerned about missing a crisis than giving false alarms. This confirms the findings of Sarlin (2013) and Betz et al. (2014), which is an inherent property of classification problems with imbalanced classes and costs. That is, one has to be more concerned about the rare class in order for a model to yield more Usefulness than the best guess of a policymaker.

In Tables 7 and 8, we test the robustness for forecast horizons of 12 and 36 months. Following results in Table 6, which highlight the challenge of achieving useful models on highly imbalanced classes, the difference in the results in Tables 7 and 8 derive from the impact of forecast horizons on the class-imbalance problem. In general, with a short forecast horizon, the rarity of the infrequent class even further increases, whereas a longer forecast horizon leads to a more balanced distribution of the classes. Hence, while the model with a forecast horizon of 12 months is Useful for preferences of 0.5 to 0.9, the model with a horizon of 36 months yields generally larger Usefulness for preferences ranging between 0.4 and 0.9. Once $U_r \leq 0$, as commonly with small μ values, the order of magnitude is not of importance as the method anyway be outperformed by the best guess of a policymaker.

Further, we make use of ROC curves for assessing the performance of the models over all possible thresholds. In principle, this provides an approach to evaluate the performance of the models for all values of the preference parameter, as the threshold value is impacted by the used preferences. Yet, due to the fact that the AUC measure also includes parts of the ROC curve that are less policy relevant (i.e., the threshold extremes), we only see it as a robustness check. In Figure 3, we can observe that all of the three models with forecast horizons of 12, 24 and 36 months are well above the diagonal line, which represents performance when tossing a coin. Likewise, the models with macro-netoworks (solid lines) are shown to be well-above the baseline models (dashed lines). In accordance with its highest AUC value in Tables 6, 7 and 8, Figure 3 also confirms that the largest area below the ROC curve is for a model with a forecast horizon of 36 months.

The final test takes the viewpoint of real-time analysis. We use a recursive algorithm that derives a new model at each quarter using only information available up to that point in time. This enables testing whether the use of macro-networks would have provided means for predicting the recent crisis, and whether and to what extent it performs better than the baseline model. The algorithm proceeds as follows. We estimate a model at each quarter t with all available information up to that point, evaluate the signals to set an optimal threshold, and provide an estimate of the current vulnerability of each economy with the same threshold as on in-sample data. The threshold is thus time-varying. At the end, we collect all probabilities and thresholds, as well as the signals, and evaluate how well the model has performed in out-of-sample analysis (i.e., 2005Q2 onward).

The quasi real-time analysis starts from 2005Q3, which enables to test performance with no direct prior information on the build-up phase of the recent crisis. Despite the quasi nature of the real-time tests, the recursive test increases the information set gradually over time and allows for a fair comparison of models with and without macro-network-based centrality measures. Table 9 shows model performance for the baseline model for policymakers' preferences ranging from 0.0 to 1.0. This implies that model performance is tested separately for the range of all potential preferences μ with the Usefulness measure, in addition to also reporting the AUC measure as an aggregate the range of μ. Overall, the model yields positive Usefulness, and thus indicates that recursive estimations of the model would have helped in correctly calling the recent crisis in Europe. It also confirms the above findings on better performance for policymakers more concerned about missing a crisis, which is in line with previous work on similar samples (e.g., Betz et al., 2014). Yet, the question we are interested in relates to whether macro-networks aid in out-of-sample analysis. Table 10 shows that the benchmark model that includes macro-network measures (model 5 in Table 2) outperforms the baseline model. This holds for the range of all potential preferences μ (except one) with the Usefulness measure, as well as shows much larger values for the overall AUC measure. Accordingly, macro-networks are not only shown to explain crises, but also provide means for predicting crises in a real-time manner.

6. Conclusions

The global financial crisis underlines the need for new tools to support macro-prudential and regulatory policies. The present work is an attempt toward this direction as it attempts to bridge the gap between the literature on early-warning models and financial networks by studying the role of financial interconnectedness of the banking sector on an impending banking crisis. In particular, we build a macro-network, a stylized representation of the financial interdependencies for 14 European countries, and augment an early-warning model by including measures of banking sector centrality as determinants of banking crises. This framework accounts for the complexity of different types of risk to which the banking sector is exposed.

Our results suggest that a more central position of the banking sector in the macro-network increases the probability of a banking crisis. Furthermore, our findings confirm the importance to consider the cross-border exposures and the banking network, but suggest that to understand the role of the banking sector as part of the overall financial system is even more useful. Finally, our results show that early-warning models augmented with macro-networks outperform traditional models in terms of predicting recent banking crises in Europe out-of-sample. These results highlight the importance of understanding the financial interconnectedness of the banking sector as well as augmenting traditional time series early-warning models with measures of cross-sectional interconnectedness. Important avenues for future research are to explore further the existing linkages between the banking sector and the other non-financial sectors.

Appendix A

In section 3.1, we presented the methodology for constructing the macro-networks. In this appendix, we evaluate the maximum entropy method used to estimate the domestic linkages between sectors and further discuss the relevant features of the stylized representation of the financial system.

The Euro Area Accounts (EAA) data contains year-end balance sheet information at sector level for various instruments. As mentioned in the main text, detailed information of counterparty positions vis-à-vis other sectors, i.e. bilateral data, is not available. Thus, the domestic linkages, W^D, are estimated using the maximum entropy method. Recently, some bilateral data has become available for a limited number of countries and for limited number of instruments (deposits, short-term loans and long-term loans) for the most recent time periods. The preliminary nature of this data prevents us from using this information to construct the macro-network. However, it provides means of evaluating the suitability of the maximum entropy method to estimate the domestic sectoral linkages. The comparisons are performed on i) the network structure, ii) the linkages, and iii) the centrality measures.

First, to evaluate the domestic network, we consider a country with a good coverage of bilateral data (the Netherlands) for the instruments loans, constructed as the sum of short-term and long-term loans, and deposits. Figure 4 illustrates the estimated domestic network with the maximum entropy (panel a and c) and with the real network (panel b and d). To make an accurate comparison we omit estimated linkages to and from the Rest of the Word sector (ROW) given that they are absent in the real bilateral data. As can be seen from the Figure, there are some differences in the relative sizes of linkages. In particular, when looking at the instrument loans, our estimation technique seems to under-estimate the linkages from banks (MFI) to general government (GOV) and from other financial intermediaries (OFI) to households (HH), and somewhat over-estimates the linkage from insurance and pension fund companies (INS) to households (HH). In case of deposits, the estimation technique seems to over-estimate the linkages from insurance sector (INS) to banks (MFI). But these differences are not only due to the limits of our estimation method but also to discrepancies in the two dataset. This figure shows that overall the topology of the estimated and real networks are similar for both instruments.

Second, we compare the estimated and the real linkages for instrument loans. In Figure 5 we plot the real linkages (x-axis) against the estimated linkages (y-axis) for each country.[17] A visual inspection of the figure shows that for most of the countries points are quite close to the 45-degree line, having the estimated and the actual linkages differences limited to few percentage points. Ireland does not perform very well due to the large role played by ROW in the estimated matrix, which affects all the other linkages.

Third, to compare the estimated and real networks more formally, we calculate centrality measures for both networks. We construct the macro-network with the real data (the resulting set of linkages are denoted by $\tilde{W}$ and calculate the centrality measures for

[17] Also for this comparison we omit estimated linkages from and to the ROW sector as they are absent in the bilateral dataset. In addition, given some inconsistency in the two dataset, we have normalized the linkages for each individual country-quarter, such that the estimated and the real linkages are expressed as percentages, w_{ij}^D/W^D and $\hat{w}_{ij}^D/\hat{W}^D$, respectively.

the MFI sectors. Then, using the real data we compute the assets and the liabilities $\tilde{a}_i$ and $\tilde{l}_i$ for each sector i. Then, we apply the maximum entropy algorithm to $\tilde{a}_i$ and $\tilde{l}_i$ to estimate the domestic network (the resulting set of linkages are denoted by $\hat{W}$ and calculate the centrality measures for the MFI sector.[18] Finally, we compare the two sets of centrality measures for the MFI sector. Table 17 shows the banking sector centrality measures in estimated and real domestic networks. By definition, values of In-Degree and Out-Degree are the same. Both values of betweenness and closeness are rather similar and within the estimated standard deviations. This means that the position of the banking sector in the example country of the Netherlands does not change substantially when estimating the linkages instead of using the real network. This supports our view that the chosen methodology seems quite reliable in this context.[19]

Still, the macro-network does not include some of the financial relations existing between the sectors. In particular, we do not model the linkages between the banking sector and the foreign non-banking sectors. This choice is motivated by the absence of data that could guide our estimation. Anecdotal evidence suggests that there is a substantial heterogeneity across countries in the sectoral composition of banks foreign assets and liabilities (i.e. Dutch MFI have substantial linkages with other OFI, while for Italian MFI, the major counterparties are other MFI). Thus, any method could have introduced a substantial bias in the macro-network or, at least, in some countries. For the same reasons, we do not model cross-border linkages for non-banking sectors. Finally, the macro-network is limited to 14 countries. Hence, in this representation, the banking sectors are not connected with other non-European countries.

Appendix B

Tables 11, 12, 14, 15, 16 here.

[18]We follow this procedure because the EAA and the real data differ in the assets and the liabilities of all sectors, i.e. $\hat{a}_{NFC} \neq \tilde{a}_{NFC}$ and $\hat{l}_{NFC} \neq \tilde{l}_{NFC}$. This fact explains, to some extent, the differences in the amount of linkages in Figure 4. As before, the ROW sector is not considered.

[19]Castrén and Rancan (2014) compare their method with the true data available for another country and they reach similar conclusions.

Table 1: Banking sector centrality measures on the macro-networks. The table reports the centrality measures of the banking sectors for each country computed on the macro-networks. Centrality measures are averaged by countries and time periods. Standard deviations in parenthesis.

	Loans	Deposits	Securities	Shares	All instruments
In-Degree	98.79	160.78	120.92	102.72	120.80
	(25.31)	(24.34)	(33.86)	(22.37)	(36.36)
Out-Degree	151.68	109.13	118.26	81.32	115.10
	(27.55)	(24.49)	(28.19)	(28.18)	(36.98)
Betweenness	383.27	369.05	990.09	1012.25	688.67
	(259.47)	(94.98)	(295.82)	(438.42)	(432.09)
Closeness	56.78	22.66	43.33	29.47	38.06
	(9.13)	(3.29)	(8.39)	(6.85)	(15.00)

Table 2: Estimates and signaling performance with macro-networks measures (all instruments and centrality measures). The table reports the estimates and predictive performance of logit models, of which Model (1) is the baseline. PCAs - MN - All refer to the PCAs computed over the centrality measures of all financial instruments for the Macro-Networks. The Usefulness measures reported have optimal thresholds given the specified preferences. Bold entries correspond to the benchmark preferences. Thresholds are shown for $\mu = 0.6, 0.7, 0.8, 0.9$ and the forecast horizon is 24 months. Standard errors are clustered at the quarter level. Statistical significance at the 0.10, 0.05, 0.01 and 0.001 levels is denoted by $\cdot, *, **, ***$ respectively.

Estimates	(1)	(2)	(3)	(4)	(5)
Intercept	-4.38***	-6.17***	-6.51***	-7.11***	-6.25***
Total assets to GDP	0.03	-0.02	-0.03	-0.04	-0.02
Non-core liabilities	12.66	25.50	25.65	33.03·	39.71
Debt to equity	0.04	0.03	0.06·	0.07*	0.03
Debt securities to liabilities	0.54	-1.91	-1.84	-2.14	-5.16·
Mortgages to loans	2.44*	5.01**	4.24**	4.67**	3.22***
Loans to deposits	-0.02	0.36	0.34	0.42	0.37
Real GDP	33.39*	38.77*	38.45*	41.09*	41.96**
Inflation	31.44	35.92	36.75·	34.18·	37.15*
Stock prices	0.21	0.39	0.46	0.37	0.73
House prices	4.56	3.91	4.17	2.70	6.13
Long-term gov. yield	-18.39	-16.90	-16.27	-11.44	-2.78
Int. investment to GDP	-0.01	-0.85**	-1.10**	-1.45***	-0.69
Government debt to GDP	0.58	1.52**	1.65**	1.84***	1.94*
Priv. credit flow to GDP	7.51***	9.74***	10.03***	8.73***	8.99***
PCA 1 - MN - All		0.32***	0.32***	0.39***	0.41***
PCA 2 - MN - All			-0.16·	-0.19*	-0.19*
PCA 3 - MN - All				0.37**	0.37**
PCA 4 - MN - All					-0.64**
AUC	0.73	0.78	0.79	0.79	0.80
$U_r(\mu)$					
μ=0.6	0.08	0.11	0.12	0.22	0.26
μ=0.7	0.12	0.21	0.24	0.33	0.36
μ=0.8	0.23	0.35	0.37	0.43	0.49
μ=0.9	0.23	0.35	0.35	0.35	0.37

Table 3: Models with cross-border banking network variables. The table reports the estimates and predictive performance of logit models. The estimates for the banking sector and macro-financial controls are not reported for brevity. Model 1 is the baseline (see Table 2). PCA - MFI -instrument refers to the PCA computed separately for each financial instrument on the centrality measures for the corresponding cross-border banking network. PCAs - MFI - All refer to the PCAs computed over all financial instruments. The Usefulness measures reported have optimal thresholds given the specified preferences. Bold entries correspond to the benchmark preferences. Thresholds are shown for $\mu = 0.6, 0.7, 0.8, 0.9$ and the forecast horizon is 24 months. Standard errors are clustered at the quarter level. Statistical significance at the 0.10, 0.05, 0.01 and 0.001 levels is denoted by $\cdot, *, **, ***$ respectively.

Estimates	(1)	(2)	(3)	(4)	(5)	(6)	(7)
PCA 1 - MFI - Loans		0.61***					
PCA 1 - MFI - Deposits			0.54***				
PCA 1 - MFI - Securities				0.41***			
PCA 1 - MFI - Shares					0.35**		
PCA 1 - MFI - All						0.34***	0.35***
PCA 2 - MFI - All						-0.35**	-0.38**
PCA 3 - MFI - All						0.10	0.10
PCA 4 - MFI - All							0.11
AUC	0.73	0.79	0.77	0.75	0.75	0.78	0.79
$U_r(\mu)$							
μ=0.6	0.08	0.11	0.11	0.09	0.09	0.15	0.17
μ=0.7	0.12	0.15	0.15	0.13	0.13	0.23	0.24
μ=0.8	0.23	0.31	0.31	0.25	0.30	0.38	0.38
μ=0.9	0.23	0.37	0.35	0.30	0.28	0.34	0.36

Table 4: Models with macro-network variables based on individual instruments. The table reports the estimates and predictive performance of logit models, of which Model (1) is the baseline. The estimates for the banking sector and macro-financial controls are not reported for brevity. PCA - MN -intrument refers to the PCA computed separately for each financial instrument on the centrality measures for the corresponding macro-network. The Usefulness measures reported have optimal thresholds given the specified preferences. Bold entries correspond to the benchmark preferences. Thresholds are shown for $\mu = 0.6, 0.7, 0.8, 0.9$ and the forecast horizon is 24 months. See Section 3.3 for further details on the measures. Standard errors are clustered at the quarter level. Statistical significance at the 0.10, 0.05, 0.01 and 0.001 levels is denoted by $\cdot, *, **, ***$ respectively.

Estimates	(1)	(2)	(3)	(4)	(5)
PCA 1 - MN - Loans		0.88***			
PCA 1 - MN - Deposits			0.39***		
PCA 1 - MN - Securities				0.54***	
PCA 1 - MN - Shares					0.38***
AUC	0.73	0.79	0.76	0.77	0.76
$U_r(\mu)$					
μ=0.6	0.08	0.17	0.09	0.10	0.11
μ=0.7	0.12	0.27	0.15	0.18	0.14
μ=0.8	0.23	0.39	0.28	0.32	0.30
μ=0.9	0.23	0.31	0.33	0.31	0.29

Table 5: Models with macro-network variables and non-linearity effects. The table reports the estimates and predictive performance of logit models, of which Model (1) is the baseline. The estimates for the banking sector and macro-financial controls are not reported for brevity. The PCA 1 refers to the first PCA computed separately for each financial instrument on the centrality measures for the corresponding macro-network. In models 1, 3, 5, and 7 PCAs are interacted with dummy variables for high (above the 75 percentile), medium (between the 75 and the 25 percentile) and low (below the 25 percentile) level of interconnectedness. In models 2, 4, 6, and 8 PCAs are interacted with dummy variables for high (above the 50 percentile) and low (below the 50 percentile) level of interconnectedness. The Usefulness measures reported have optimal thresholds given the specified preferences. Bold entries correspond to the benchmark preferences. Thresholds are shown for $\mu = 0.6, 0.7, 0.8, 0.9$ and the forecast horizon is 24 months. See Section 3.3 for further details on the measures. Standard errors are clustered at the quarter level. Statistical significance at the 0.10, 0.05, 0.01 and 0.001 levels is denoted by $\cdot, *, **, ***$ respectively.

	Loans		Deposits		Securities		Shares	
Estimates	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(PCA 1)*Above p75	1.10***		0.38**		0.64***		0.60***	
(PCA 1)*Between p25 and p75	2.66***		2.69***		3.31***		3.54***	
(PCA 1)*Below p75	0.21		0.38		-0.10		-0.45$^{\cdot}$	
(PCA 1)*Above p50		0.99***		0.36*		0.56***		0.39***
(PCA 1)*Below p50		0.68**		0.50$^{\cdot}$		0.41		0.33
AUC	0.82	0.79	0.78	0.76	0.82	0.77	0.81	0.76
$U_r(\mu)$								
μ=0.6	0.26	0.20	0.12	0.09	0.20	0.10	0.19	0.11
μ=0.7	0.36	0.28	0.21	0.15	0.30	0.18	0.27	0.14
μ=0.8	0.45	0.38	0.34	0.28	0.41	0.32	0.39	0.30
μ=0.9	0.38	0.31	0.28	0.31	0.41	0.32	0.40	0.30

Table 6: Model performance over policymakers' preferences for the benchmark model. The table reports results of a logit model with optimal thresholds w.r.t. Usefulness with specific preferences and a forecast horizon of 24 months. Bold entries correspond to the benchmark preferences. Thresholds λ are calculated for $\mu = 0.0, 0.1, ..., 1.0$. The table also reports in columns the following measures to assess the overall performance of the models: TP = True positives, FP = False positives, TN= True negatives, FN = False negatives, Precision positives = TP/(TP+FP), Recall positives = TP/(TP+FN), Precision negatives = TN/(TN+FN), Recall negatives = TN/(TN+FP), Accuracy = (TP+TN)/(TP+TN+FP+FN), absolute and relative usefulness U_a and U_r (see formulae 1-3), and AUC = area under the ROC curve (TP rate to FP rate). See Section 3.3 for further details on the measures.

Preferences	λ	TP	FP	TN	FN	Positive Precision	Positive Recall	Negative Precision	Negative Recall	Accuracy	FP rate	FN rate	$U_a(\mu)$	$U_r(\mu)(\%)$	AUC
μ=0.0	0.99	7	0	562	89	1.00	0.07	0.86	1.00	0.86	0	0.93	0	-	0.80
μ=0.1	0.99	7	0	562	89	1.00	0.07	0.86	1.00	0.86	0	0.93	0	0.07	0.80
μ=0.2	0.99	7	0	560	89	1.00	0.07	0.86	1.00	0.86	0	0.93	0	0.07	0.80
μ=0.3	0.98	12	2	560	84	0.86	0.12	0.87	1.00	0.87	0	0.88	0	0.08	0.80
μ=0.4	0.98	12	2	560	84	0.86	0.12	0.87	1.00	0.87	0	0.88	0.01	0.09	0.80
μ=0.5	0.88	46	33	531	50	0.58	0.48	0.91	0.94	0.87	0.06	0.52	0.01	0.14	0.80
μ=0.6	0.86	52	41	513	44	0.56	0.54	0.92	0.93	0.87	0.07	0.46	0.02	0.26	0.80
μ=0.7	0.80	64	68	513	32	0.48	0.67	0.94	0.88	0.85	0.12	0.33	0.04	0.36	0.80
μ=0.8	**0.80**	**64**	**68**	**497**	**32**	**0.48**	**0.67**	**0.94**	**0.88**	**0.85**	**0.12**	**0.33**	**0.05**	**0.49**	**0.80**
μ=0.9	0.80	64	68	475	32	0.48	0.67	0.94	0.88	0.85	0.12	0.33	0.03	0.37	0.80
μ=1.0	0	96	562	0	0	0.15	1.00	-	0	0.15	1	0	0	-	0.80

Table 7: Model performance over policymakers' preferences with a forecast horizon of 12 months. The table reports results of a logit model with optimal thresholds w.r.t. Usefulness with specific preferences. Bold entries correspond to the benchmark preferences. Thresholds λ are calculated for $\mu = 0.0, 0.1, ..., 1.0$. The table also reports in columns the following measures to assess the overall performance of the models: TP = True positives, FP = False positives, TN= True negatives, FN = False negatives, Precision positives = TP/(TP+FP), Recall positives = TP/(TP+FN), Precision negatives = TN/(TN+FN), Recall negatives = TN/(TN+FP), Accuracy = (TP+TN)/(TP+TN+FP+FN), absolute and relative usefulness U_a and U_r (see formulae 1-3), and AUC = area under the ROC curve (TP rate to FP rate). See Section 3.3 for further details on the measures.

Preferences	λ	TP	FP	TN	FN	Positive		Negative		Accuracy	FP rate	FN rate	$U_a(\mu)$	$U_r(\mu)(\%)$	AUC
						Precision	Recall	Precision	Recall						
μ=0.0	1.00	0	0	610	48	-	0	0.93	1.00	0.93	0	1.00	0	-	0.79
μ=0.1	1.00	0	0	610	48	-	0	0.93	1.00	0.93	0	1.00	0	0	0.79
μ=0.2	1.00	0	0	610	48	-	0	0.93	1.00	0.93	0	1.00	0	0	0.79
μ=0.3	1.00	0	0	610	48	-	0	0.93	1.00	0.93	0	1.00	0	0	0.79
μ=0.4	1.00	0	0	610	48	-	0	0.93	1.00	0.93	0	1.00	0	0	0.79
μ=0.5	0.98	8	6	604	40	0.57	0.17	0.94	0.99	0.93	0.01	0.83	0	4	0.79
μ=0.6	0.98	8	6	604	40	0.57	0.17	0.94	0.99	0.93	0.01	0.83	0	8	0.79
μ=0.7	0.90	24	42	568	24	0.36	0.50	0.96	0.93	0.90	0.07	0.50	0.01	13	0.79
μ=0.8	**0.90**	**24**	**42**	**568**	**24**	**0.36**	**0.50**	**0.96**	**0.93**	**0.90**	**0.07**	**0.50**	**0.02**	**28**	**0.79**
μ=0.9	0.83	32	80	530	16	0.29	0.67	0.97	0.87	0.85	0.13	0.33	0.03	48	0.79
μ=1.0	0	48	610	0	0	0.07	1.00	-	0	0.07	1.00	0	0	-	0.79

Table 8: Model performance over policymakers' preferences with a forecast horizon of 36 months. The table reports results of a logit model with optimal thresholds w.r.t. Usefulness with specific preferences. Bold entries correspond to the benchmark preferences. Thresholds λ are calculated for $\mu = 0.6, 0.7, 0.8, 0.9$. The table also reports in columns the following measures to assess the overall performance of the models: TP = True positives, FP = False positives, TN= True negatives, FN = False negatives, Precision positives = TP/(TP+FP), Recall positives = TP/(TP+FN), Precision negatives = TN/(TN+FN), Recall negatives = TN/(TN+FP), Accuracy = (TP+TN)/(TP+TN+FP+FN), absolute and relative usefulness U_a and U_r (see formulae 1-3), and AUC = area under the ROC curve (TP rate to FP rate). See Section 3.3 for further details on the measures.

Preferences	λ	TP	FP	TN	FN	Positive		Negative		Accuracy	FP rate	FN rate	$U_a(\mu)$	$U_r(\mu)(\%)$	AUC
						Precision	Recall	Precision	Recall						
μ=0.0	0.99	7	0	514	137	1.00	0.05	0.79	1.00	0.79	0	0.95	0	-	0.82
μ=0.1	0.99	7	0	514	137	1.00	0.05	0.79	1.00	0.79	0	0.95	0	5	0.82
μ=0.2	0.99	7	0	514	137	1.00	0.05	0.79	1.00	0.79	0	0.95	0	5	0.82
μ=0.3	0.99	7	0	514	137	1.00	0.05	0.79	1.00	0.79	0	0.95	0	5	0.82
μ=0.4	0.88	53	26	488	91	0.67	0.37	0.84	0.95	0.82	0.05	0.63	0	10	0.82
μ=0.5	0.78	87	58	456	57	0.60	0.60	0.89	0.89	0.83	0.11	0.40	0.02	20	0.82
μ=0.6	0.77	90	62	452	54	0.59	0.62	0.89	0.88	0.82	0.12	0.38	0.04	34	0.82
μ=0.7	0.73	99	79	435	45	0.56	0.69	0.91	0.85	0.81	0.15	0.31	0.07	45	0.82
μ=0.8	**0.70**	**104**	**94**	**420**	**40**	**0.53**	**0.72**	**0.91**	**0.82**	**0.80**	**0.18**	**0.28**	**0.08**	**51**	**0.82**
μ=0.9	0.44	130	239	275	14	0.35	0.90	0.95	0.54	0.62	0.46	0.10	0.02	29	0.82
μ=1.0	0	144	514	0	0	0.22	1.00	-	0	0.22	1.00	0.00	0	-	0.82

Table 9: Real-time predictions with the baseline model, including no network measures. The table reports results of real-time analysis with the baseline logit model (including no network measures), for which thresholds are optimized recursively w.r.t. Usefulness with different preferences and a forecast horizon of 24 months. Bold entries correspond to the benchmark preferences. Thresholds λ are calculated for $\mu = 0.6, 0.7, 0.8, 0.9$. The table also reports in columns the following measures to assess the overall performance of the models: TP = True positives, FP = False positives, TN= True negatives, FN = False negatives, Precision positives = TP/(TP+FP), Recall positives = TP/(TP+FN), Precision negatives = TN/(TN+FN), Recall negatives = TN/(TN+FP), Accuracy = (TP+TN)/(TP+TN+FP+FN), absolute and relative usefulness U_a and U_r (see formulae 1-3), and AUC = area under the ROC curve (TP rate to FP rate). See Section 3.3 for further details on the measures.

Preferences	λ	TP	FP	TN	FN	Positive Precision	Positive Recall	Negative Precision	Negative Recall	Accuracy	FP rate	FN rate	$U_a(\mu)$	$U_r(\mu)$(%)	AUC
μ=0.0	1.00	3	93	1	0.03	1.00	0.75	0.80	0.80	0.00	0.97	0.12	0.00	-	0.74
μ=0.1	1.00	3	93	1	0.03	1.00	0.75	0.80	0.80	0.00	0.97	0.12	0.00	-6	0.74
μ=0.2	0.99	3	93	1	0.03	1.00	0.75	0.80	0.80	0.00	0.97	0.12	0.00	-1	0.74
μ=0.3	0.99	4	92	2	0.04	0.99	0.67	0.80	0.80	0.01	0.96	0.13	0.00	-1	0.74
μ=0.4	0.99	7	89	2	0.07	0.99	0.78	0.80	0.80	0.01	0.93	0.20	0.00	4	0.74
μ=0.5	0.98	13	83	5	0.14	0.99	0.72	0.81	0.81	0.01	0.86	0.26	0.01	8	0.74
μ=0.6	0.98	26	70	24	0.27	0.93	0.52	0.83	0.80	0.07	0.73	0.27	0.01	10	0.74
μ=0.7	0.92	51	45	41	0.53	0.89	0.55	0.88	0.81	0.11	0.47	0.43	0.05	35	0.74
μ=0.8	**0.72**	**76**	**20**	**102**	**0.79**	**0.72**	**0.43**	**0.93**	**0.74**	**0.28**	**0.21**	**0.43**	**0.08**	**50**	**0.74**
μ=0.9	0.35	86	10	159	0.90	0.57	0.35	0.95	0.63	0.43	0.10	0.38	0.03	32	0.74
μ=1.0	0.00	96	0	365	1.00	0.00	0.21	1.00	0.21	1.00	0.00	0.02	0.00	-	0.74

Table 10: Real-time predictions with the benchmark model, including network measures. The table reports results of real-time analysis with the baseline logit model including network measures, for which thresholds are optimized recursively w.r.t. Usefulness with different preferences and a forecast horizon of 24 months. Bold entries correspond to the benchmark preferences. Thresholds λ are calculated for $\mu = 0.6, 0.7, 0.8, 0.9$. The table also reports in columns the following measures to assess the overall performance of the models: TP = True positives, FP = False positives, TN= True negatives, FN = False negatives, Precision positives = TP/(TP+FP), Recall positives = TP/(TP+FN), Precision negatives = TN/(TN+FN), Recall negatives = TN/(TN+FP), Accuracy = (TP+TN)/(TP+TN+FP+FN), absolute and relative usefulness U_a and U_r (see formulae 1-3), and AUC = area under the ROC curve (TP rate to FP rate). See Section 3.3 for further details on the measures.

Preferences	λ	TP	FP	TN	FN	Positive Precision	Positive Recall	Negative Precision	Negative Recall	Accuracy	FP rate	FN rate	$U_a(\mu)$	$U_r(\mu)$(%)	AUC
μ=0.0	1.00	19	0	366	77	1.00	0.20	0.83	1.00	0.83	0.00	0.80	0.00	-	0.8
μ=0.1	1.00	20	1	365	76	0.95	0.21	0.83	1.00	0.83	0.00	0.79	0.00	11	0.8
μ=0.2	0.99	29	9	357	67	0.76	0.30	0.84	0.98	0.84	0.02	0.70	0.00	-7	0.8
μ=0.3	0.98	36	10	356	60	0.78	0.38	0.86	0.97	0.85	0.03	0.62	0.01	13	0.8
μ=0.4	0.98	44	15	351	52	0.75	0.46	0.87	0.96	0.85	0.04	0.54	0.02	22	0.8
μ=0.5	0.88	45	25	341	51	0.64	0.47	0.87	0.93	0.84	0.07	0.53	0.02	21	0.8
μ=0.6	0.85	51	57	309	45	0.47	0.53	0.87	0.84	0.78	0.16	0.47	0.02	14	0.8
μ=0.7	0.85	63	60	306	33	0.51	0.66	0.90	0.84	0.80	0.16	0.34	0.06	39	0.8
μ=0.8	**0.81**	**71**	**80**	**286**	**25**	**0.47**	**0.74**	**0.92**	**0.78**	**0.77**	**0.22**	**0.26**	**0.08**	**51**	**0.8**
μ=0.9	0.81	93	110	256	3	0.46	0.97	0.99	0.70	0.76	0.30	0.03	0.05	63	0.8
μ=1.0	0.00	96	366	0	0	0.21	1.00	-	0.00	0.21	1.00	0.00	0.00	-	0.8

Table 11: Banking sector centrality measures on the macro-networks. The table reports the centrality measures of the banking sectors for each country computed on the macro-networks. Centrality measures are averaged by instruments and time periods.

	In-Degree	Out-Degree	Betweenness	Closeness
Austria	110.32	98.15	548.46	35.29
Belgium	127.42	108.92	566.04	36.61
Germany	156.56	148.66	1287.25	44.93
Denmark	129.36	115.96	555.95	38.74
Spain	85.65	81.30	572.55	31.66
Finland	156.08	138.56	900.16	42.17
France	79.57	74.48	552.00	29.41
Great Britain	121.87	116.81	613.74	38.66
Greece	128.68	121.60	629.89	40.11
Ireland	131.64	125.72	654.13	40.24
Italy	107.38	95.99	634.68	34.13
Netherland	117.11	112.64	660.50	36.67
Portugal	116.28	158.46	778.49	46.59
Spain	123.33	114.11	710.90	36.52

Table 12: Measures of network statistics. The table shows the network measures we use in our empirical exercises. In-Degree (Out-Degree) is the sum of all incoming (outgoing) links that each node has with other nodes, betweenness measures the number of geodesic paths g that pass through a node and closeness quantifies how close a vertex is to all other vertices in the graph. Measures are weighted by the amounts of linkages.

Degree	$C_D(i) = \sum_{j}^{N} w_{ij}^{\alpha}$
Betweenness	$C_B(i) = \frac{g_{ij}^{w\alpha}(i)}{g_{ij}^{w\alpha}}$
Closeness	$C_C(i) = \sum_{j}^{N} [\min(\frac{1}{(w_{ih})^{\alpha}} + ... + \frac{1}{(w_{hj})^{\alpha}})]$

Table 13: Indicators, definitions, and data sources.

Indicators	Definition	Source
Total assets to GDP	Total Assets / GDP	ECB MFI statistics
Non-core liabilities	Growth rate of (Total Liabilities - Capital and Reserves - Deposits)	ECB MFI statistics
Debt to equity	(Total Liabilities - Capital and Reserves) / Capital and Reserves	ECB MFI statistics
Debt securities to liabilities	Debt securities to Liabilities	ECB MFI statistics
Mortgages to loans	Mortgages to Total Loans	ECB MFI statistics
Loans to deposits	Total Loans / Deposits	ECB MFI statistics
Real GDP	Growth rate of real GDP	Eurostat
Inflation	Growth rate of the HICP index	Eurostat
Stock prices	Growth rate of the stock price index	Bloomberg
House prices	Growth rate of the house price index	ECB
Long-term government bond yield	10-year government bond yield	Bloomberg
International investment position to GDP	Net International Investment Position as a % of GDP	Eurostat / Alert Mechanism Report
Government debt to GDP	General government debt as % of GDP	Eurostat / Alert Mechanism Report
Private sector credit flow to GDP	Private sector credit flow as % of GDP	Eurostat / Alert Mechanism Report

Table 14: Centrality Measures for the banking sectors on the macro-networks: Principal Component Analysis. The table reports the loadings of the PCAs, the standard deviation and the proportion of explained variance for each balance sheet instrument of the macro-networks. Panel A shows the results based on the PCA performed over all instruments together. Panel B shows the results based on the PCA performed separately over each instrument.

	1-Component	2-Component	3-Component	4-Component
PANEL A: All instruments				
In-Degree$_{LOANS}$	0.21	-0.44	0.21	-0.03
Out-Degree$_{LOANS}$	0.30	0.13	0.15	0.02
Betweenness$_{LOANS}$	0.15	-0.43	-0.11	-0.54
Closeness$_{LOANS}$	0.25	0.29	0.06	-0.01
In-Degree$_{DEPOSITS}$	0.26	0.09	0.19	-0.12
Out-Degree$_{DEPOSITS}$	0.26	-0.23	0.02	0.47
Betweenness$_{DEPOSITS}$	0.16	-0.28	-0.57	-0.00
Closeness$_{DEPOSITS}$	0.26	-0.18	-0.01	0.55
In-Degree$_{SECURITIES}$	0.23	-0.28	0.24	-0.30
Out-Degree$_{SECURITIES}$	0.27	0.15	0.08	-0.05
Betweenness$_{SECURITIES}$	0.23	0.20	-0.48	-0.06
Closeness$_{SECURITIES}$	0.25	0.24	0.04	-0.08
In-Degree$_{SHARES}$	0.26	-0.16	0.09	0.15
Out-Degree$_{SHARES}$	0.27	0.13	0.07	-0.06
Betweenness$_{SHARES}$	0.24	0.12	-0.46	-0.05
Closeness$_{SHARES}$	0.27	0.23	0.13	-0.11
St. Dev.	3.07	1.45	1.08	0.90
Proportion of Variance Explained	0.59	0.13	0.07	0.05
PANEL B:Individual instruments				
LOANS				
In-Degree	0.50	-0.44	0.65	-0.32
Out-Degree	0.55	0.38	0.18	0.70
Betweenness	0.43	-0.58	-0.66	0.15
Closeness	0.49	0.54	-0.30	-0.60
St. Dev.	1.57	1.08	0.51	0.27
Proportion of Variance Explained	0.62	0.29	0.06	0.01
DEPOSITS				
In-Degree	0.42	0.68	0.59	-0.00
Out-Degree	0.57	0.00	-0.40	0.71
Betweenness	0.41	-0.72	0.54	-0.01
Closeness	0.56	0.01	-0.42	-0.70
St. Dev.	1.65	0.84	0.71	0.18
Proportion of Variance Explained	0.68	0.17	0.12	0.01
SECURITIES				
In-Degree	0.39	-0.85	0.31	0.14
Out-Degree	0.57	0.01	-0.35	-0.73
Betweenness	0.45	0.48	0.74	0.01
Closeness	0.55	0.19	-0.47	0.65
St. Dev.	1.67	0.84	0.66	0.22
Proportion of Variance Explained	0.69	0.17	0.11	0.01
SHARES				
In-Degree	0.44	-0.73	-0.51	-0.02
Out-Degree	0.53	0.39	-0.13	0.72
Betweenness	0.48	-0.28	0.82	-0.04
Closeness	0.52	0.47	-0.18	-0.68
St. Dev.	1.71	0.75	0.63	0.29
Proportion of Variance Explained	0.73	0.14	0.09	0.02

Table 15: Banking sector centrality measures on the cross-border banking network: summary statistics. The table reports the centrality measures of the banking sectors for each country computed on the cross-border banking network. Centrality measures are averaged by countries and time periods. Standard deviations in parenthesis.

	Loans	Deposits	Securities	Shares	All instruments
In-Degree	90.74	94.03	73.54	47.86	76.54
	(23.94)	(19.70)	(24.81)	(25.17)	(23.41))
Out-Degree	90.74	94.03	73.54	47.86	76.54
	(19.92)	(21.20)	(23.83)	(20.16)	(21.28)
Betweenness	1.80	1.54	2.62	6.23	3.05
	(5.05)	(3.62)	(6.87)	(11.66)	(6.81)
Closeness	12.75	12.89	12.56	11.71	12.48
	(2.25)	(2.36)	(2.60)	(2.54)	(2.44)

Table 16: Individual centrality measures in early-warning models. The table reports the estimates and predictive performance of logit models, but the estimates for the banking sector and macro-financial controls are not reported for brevity. The Usefulness measures reported have optimal thresholds given the specified preferences. Bold entries correspond to the benchmark preferences. Thresholds are shown for $\mu = 0.6, 0.7, 0.8, 0.9$ and the forecast horizon is 24 months. Centrality measures are computed for each balance sheet instrument (loans, deposits, securities, and shares). See Section 3.3 and 4.1 for further details on the measures. Standard errors are clustered at the quarter level. Statistical significance at the 0.10, 0.05, 0.01 and 0.001 levels is denoted by $\cdot, *, **, ***$ respectively.

	Loans				Deposits				Securities				Shares			
Estimates	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
In-Degree	0.031***				0.034***				0.022***				0.021*			
Out-Degree		0.043***				0.039***				0.039***				0.023***		
Betweenness			2.702e-03***				3.944e-04				1.044e-03***				4.798e-04*	
Closeness				0.065***				0.147**				0.127***				0.120***
AUC	0.77	0.77	0.77	0.78	0.76	0.78	0.73	0.75	0.75	0.78	0.74	0.76	0.75	0.76	0.73	0.76
$U_r(\mu)$																
μ=0.6	0.17	0.09	0.18	0.09	0.11	0.14	0.09	0.08	0.09	0.11	0.09	0.09	0.09	0.10	0.09	0.13
μ=0.7	0.24	0.18	0.29	0.12	0.18	0.20	0.11	0.14	0.15	0.17	0.11	0.13	0.15	0.17	0.12	0.18
μ=0.8	0.34	0.36	0.38	0.29	0.32	0.33	0.24	0.26	0.31	0.30	0.28	0.27	0.31	0.29	0.22	0.30
μ=0.9	0.28	0.31	0.30	0.25	0.30	0.35	0.24	0.25	0.27	0.35	0.24	0.33	0.27	0.28	0.24	0.28

Table 17: Estimated network vs Real Network, instrument loans. The table reports the centrality measures of the banking sectors computed on the macro-network for instrument loans. In one case the domestic network of country x is estimated, in the other case the true domestic network is considered. Centrality measures are averaged over time periods. Standard deviations in parenthesis.

	In-Degree	Out-Degree	Betweenness	Closeness
Estimated $\widehat{W}$	121.51	152.76	495.88	54.95
	(3.46)	(9.37)	(44.99)	(4.25)
Real $\widetilde{W}$	121.51	152.76	512.23	57.27
	(3.46)	(9.37)	(45.06)	(4.31)

Figure 1: The European macro-network visualized in VisRisk (http://vis.risklab.fi/#/macronet/). The figure illustrates the macro-network for debt security instrument at Q1 2012q1, for fourteen European countries and sectors non-financial corporations (NFC), banks (monetary financial institutions, MFI), insurance and pension fund companies (INS), other financial intermediaries (OFI), general government (GOV), households (HH), and the rest of the world (ROW). We use VisRisk's force-directed layouting algorithms for positioning nodes. Colors refer to different countries and the link opacity displays the size of the real/estimated transactions among sectors.

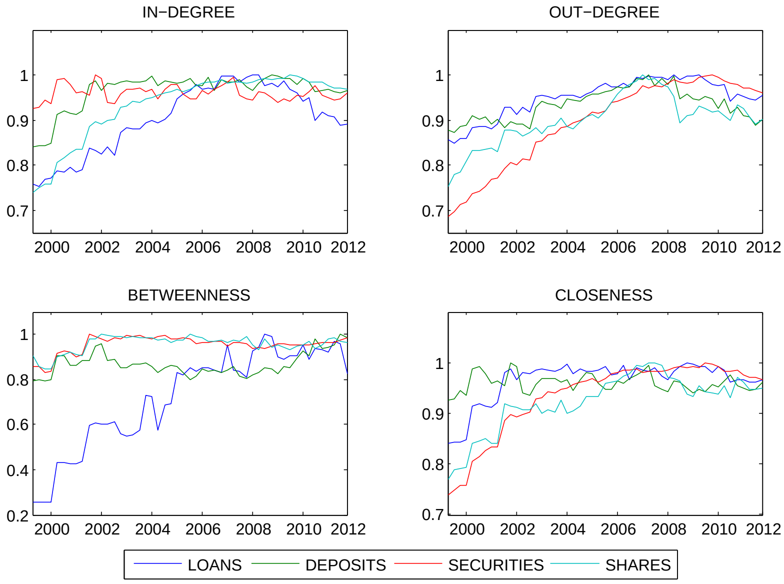


Figure 2: Evolution of normalized centrality measures across instruments. The charts depict the trends of the centrality measures of MFIs (in-degree, out-degree, betweenness and closeness) in the macro-networks. All measures are averaged across MFIs for each instrument-year and normalized.

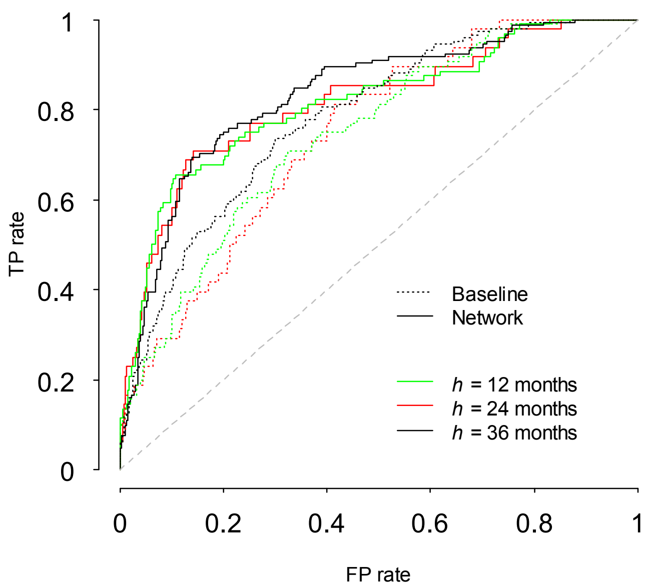
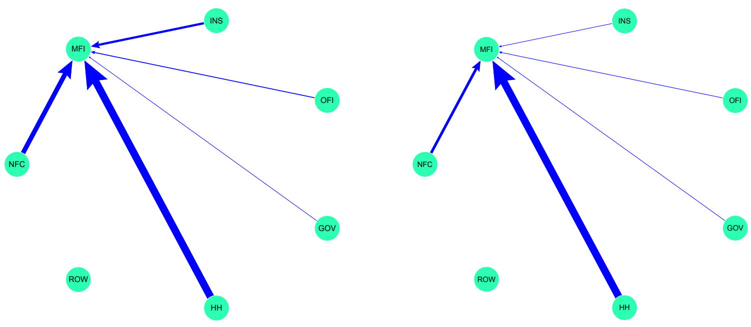


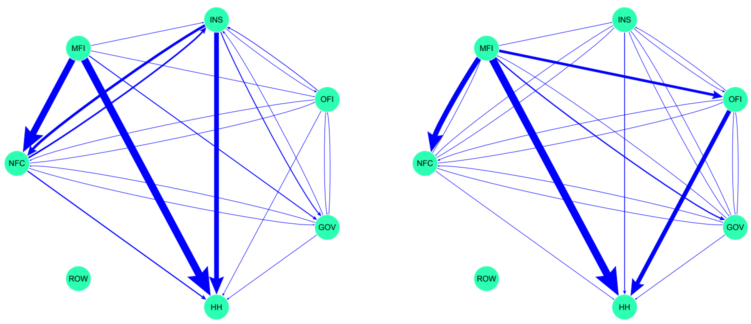
Figure 3: ROC curves for models with forecast horizons of 12, 24 and 36 months.

Deposits



(a) Estimated network (b) Real network

Loans



(c) Estimated network (d) Real network

Figure 4: Estimated domestic network vs Real domestic network. The figures illustrate the domestic network of the Netherlands for loan (upper panel) and deposit instrument (lower panel) at Q1 2012. Panel (a) and (c) display the estimated network with the maximum entropy method, while panel (b) and (d) shows the real network based on the bilateral data. The size of arrow shows different weights, i.e. the volume of transactions between the sectors.

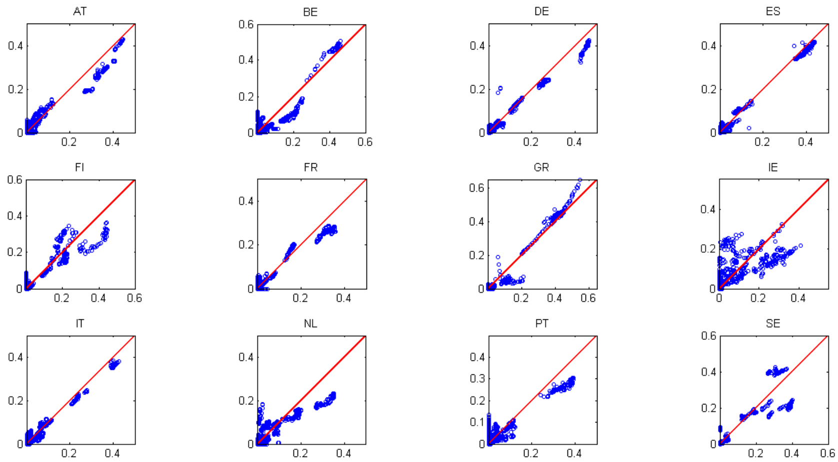


Figure 5: Estimated vs actual linkages. We plot real linkages (x-axis) against the estimated linkages (y-axis), expressed in percentages (w_{ij}^D/W^D and $\hat{w}_{ij}^D/\hat{W}^D$), for each quarter. The subplots refers to different countries.

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