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Interconnectedness of the banking sector as a vulnerability to crises

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Abstract

This paper uses macro-network to measure the interconnectedness of the banking sector and relates it to banking crises in Europe. Beyond cross-border financial linkages of the banking sector, the macronetwork also accounts for financial linkages to the other main financial and nonfinancial sectors within the economy. We find that a more central position of the banking sector in the macronetwork significantly increases the probability of a banking crisis. By analysing the different types of risk exposures, our evidence shows that credit is an important source of vulnerability. Finally, our early-warning models augmented with interconnectedness measures outperform traditional models in terms of out-of-sample predictions.

KEYWORDS

banking crises, early-warning model, financial interconnectedness, macronetworks

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 macrofinancial 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.[1] The literature has focused on the determinants of banking crises through the analysis of univariate indicators (Kaminsky & Reinhart, 1998, i.e., signalling approach) and multivariate models (see, e.g., Demirgüç-Kunt & Detragiache, 1998, Eichengreen & Rose, 1998). In general, periods prior to systemic banking crises have been shown to be explained by traditional vulnerabilities and risks that represent imbalances such as 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 United States, Colombia, and Mexico in Gonzalez-Hermosillo (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 macrofinancial 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 analyses the cross-sectional dimension of systemic risk. Beyond country-level vulnerabilities, the recent crisis propagated 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.[2] Recently, cross-border linkages and interdependencies of the international financial system have been modelled 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.[3] 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 & Kapadia, 2010; Georg, 2013). Also, network measures have been related to changes of the global banking system (Minoiu & Reyes, 2013), as well as to economic growth and financial contagion (Kali & Reyes, 2010).

In this paper, building on these two strands of literature, 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 country's banking sector to the international banking system. On top of that, using the Euro Area Accounts (EAA), each banking system is linked to the other institutional sectors of the economy. To include both aspects in our analysis, that is, country- and sector-level linkages, we build on the framework proposed by Castrén and Rancan (2014). They introduce the idea of a macronetwork, a network representing the financial positions that links the institutional sectors of the economy, including both financial sectors (banks, insurance companies, pension funds, and other financial intermediaries) and nonfinancial sectors (nonfinancial corporations [NFC], government, households, and the rest of the world). Thus, the macronetwork provides a mapping of the balance sheet exposures and the associated financial risks in a comprehensive framework. As a large part of the financing is intermediated through banks, particularly in Europe, our focus is on the banking sector. While in studying macroeconomic fluctuations through input–output analysis, firm-level shocks seem to spread along relatively predictable patterns,[4] when looking at the banking sector, there are additional challenges. Banks' balance sheet are exposed to multiple sources of risks, and the various exposures can act as a transmission channel of shocks. With the aim 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—the macronetwork is constructed using the different financial instruments: loans, deposits, securities, and shares. There are several important differences across the financial instruments that should be noted, such as the banking sector having a dominant position in loans and deposits. Whereas 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. The instruments also capture exposures to different types of risk, such as loans to credit risk, deposits to funding and liquidity risk, and also securities and shares to market risk. To identify the position of the banking sector of each country, we make use of network centrality measures. Combining the topics of macrofinancial imbalances and networks, this paper explores whether complementing standard macrofinancial vulnerabilities with network centralities computed on the macronetwork 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 precrisis periods and improve the predictive capabilities of standard models. Moreover, the macronetwork 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 findings suggest that a more central position of the banking sector in the macronetwork increases the probability of a banking crisis. Our analysis also indicates that the macronetwork provides a more correct characterization of a banking sector's position in terms of financial linkages than if one solely considers a banking sector's cross-border exposures. Thus, this paper empirically supports the importance of considering the interactions of the banking sector with other sectors of the economy even in financial models. In this context, among the different types of risks faced by banks, those originated from the lending, that is, credit risk, and, to some extent, investment activities through market risk seem to predict more accurately banking crises. Finally, our results show that early-warning models augmented with macronetwork indicators 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.[5] Our results are confirmed also when controlling for several institutional and legal characteristics and banking sector variables that have been investigated in previous literature (Beck & Levine, 2002; Beck, Demirgüç-Kunt, & Levine, 2006; Barth, Caprio, & Levine, 2013; La Porta, Lopez-de Silanes, Shleifer, & Vishny, 1998).

Our paper contributes to the existing literature on 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 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 determinants of bank crises. Chinazzi, Fagiolo, Reyes, and Schiavo (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, Kang, Subrahmanian, and Berea (2015) 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, Getmansky, Lo, and Pelizzon (2012), who consider financial connectedness between a larger set of financial institutions, such as insurer corporations, brokers, and hedge funds, in addition to banking institutions.[6] But they focus on individual institutions, whereas we consider balance-sheet exposures for sectors at aggregate level, additional sectors, and multiple countries. Our framework is also related to some recent works using cross-holdings or input–output linkages to evaluate aggregate effects of shocks originating from firms or disaggregated sectors (Acemoglu & Akcigit et al., 2015; Acemoglu, Ozdaglar, & Tahbaz-Salehi, 2015; Cabrales, Gottardi, & Vega-Redondo, 2014; Elliott, Golub, & Jackson, 2014). This paper complements previous literature by analysing centrality using not only loans but also the other largest financial instruments and identifying the corresponding financial risks. Although our representation of the financial linkages is a stylized characterization of the financial interconnectedness existing in Europe, we believe that this approach is a step further toward a more comprehensive understanding of the banking sector as part of a system and the financial stability risks.

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 and discuss the early-warning models as well as the findings about macronetworks 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, macrofinancial early-warning indicators, and macronetworks. This section explains how the necessary data are derived. After merging all datasets, our quarterly sample covers the period 2000q1–2012q1 for 14 European countries.[7]

2.1 | Crisis events

The first set of data needed is 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 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 European System of Central Banks 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. Yet, in order to identify vulnerable states prior to crises, we specify the dependent variable to take the value 1 during a specified precrisis time window prior to the crisis events, and 0 otherwise. Although the benchmark time window is 24 months, we also test performance using a number of specifications with shorter and longer horizons. The used sample includes 128 quarters of systemic banking crises and 104 quarters of precrisis periods.[8] Further, we define postcrisis 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: precrisis, postcrisis, 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 macrofinancial 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 macronetworks as leading indicators.

We cover two types of country-specific indicators (see Table B3). First, we use country-specific indicators of banking sectors for identifying risks and imbalances in banking systems. Total assets to GDP is a measure for the size of banking sector relative to the domestic economy. Growth in noncore liabilities aims to capture rapid increase in balance sheet. Debt-to-equity and loans-to-deposits ratios capture the banking sector leverage. For risks linked to securitization and property booms, we, respectively, include the ratio of debt securities to liabilities and the ratio of mortgages to loans. The intermediation ratio, defined as the ratio of total loans to total deposits, captures differences between the domestic banking sectors in terms of their ability to convert deposits into loans. These indicators are constructed using the ECB's statistics on the Balance Sheet Items (BSI) of the Monetary, Financial Institutions and Markets. Second, we make use of country-specific macrofinancial indicators to identify macroeconomic imbalances and to control for conjunctural variation in asset prices and business cycles. The paper controls for macroeconomic imbalances by using internal and external variables from the EU Macroeconomic Imbalance Procedure, such as the international investment position, government debt, and private sector credit flow. To control for country risk, we include the long-term government bond yield. 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 macrofinancial data are sourced from Eurostat and Bloomberg.

2.3 | Macronetworks

We require a third set of data to be able to compute macronetworks. Whereas computational details are discussed in section 3.1, we focus herein on describing the two data sources necessary for computing macronetworks. First, we use the 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.[9] Those data allow us to estimate[10] the financial linkages at domestic level between the institutional sectors: 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 BSI statistics; those data provide the aggregated (or consolidated) balance sheets of the country's MFI sector and provide information on MFI counterparties at the country level to identify the MFI's cross-country exposures.

3 | METHODS

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

3.1 | Construction of the macronetwork

In this section, we describe how the macronetwork 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 × 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: (a) Domestic linkages between sectors, denoted by superscript D, are estimated using the EAA data, and (b) 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 $w^D_{ij} = a_i l_j$ with the institutional sectors maximizing the dispersion of their linkages. The maximum entropy is a method borrowed from the literature analysing contagion risk in the interbank market, where the algorithm is applied at the level of individual institutions (for a review, see Upper, 2011).[11] More recent literature has proposed other methods for estimating linkages to represent incomplete and tiering structures of the interbank market (e.g., Anand, Craig, & Von Peter, 2015), but here, it is reasonable that each sector has at least some financial transactions with the other sectors and that the degree distribution is not highly skewed. Hence, we opt for the maximum entropy method that 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. 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 macronetwork, and it is constructed in each period and for each balance sheet instrument. Figure 1 shows an example of the macronetwork for securities for period Q1 2012. Nodes are identified by the abbreviation of sectors, and different colours 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. The macronetwork includes cross-border linkages between the banking sectors; in Europe, indeed banks play a crucial role as intermediaries in the cross-border flows. In contrast, the macronetwork financial linkages between the banking sector and the foreign nonbanking sectors are not directly modelled due to the absence of comprehensive data and the persistent level of segmentation in the European financial system.[13]

In order to analyse the robustness of the estimated macronetwork, we use the (limited) available information of the whom-to-whom flow-of-funds statistics for the available instruments and perform comparison tests (see Appendix A). The analysis on the network structure, linkages, and centrality measures indicates that the chosen methodology seems appropriate in this context. Overall, the macronetwork provides a representation of the interconnectedness of the European financial system.

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 a banking sector could face through its domestic and cross-border interconnections. In order to quantify the interconnections and position of each

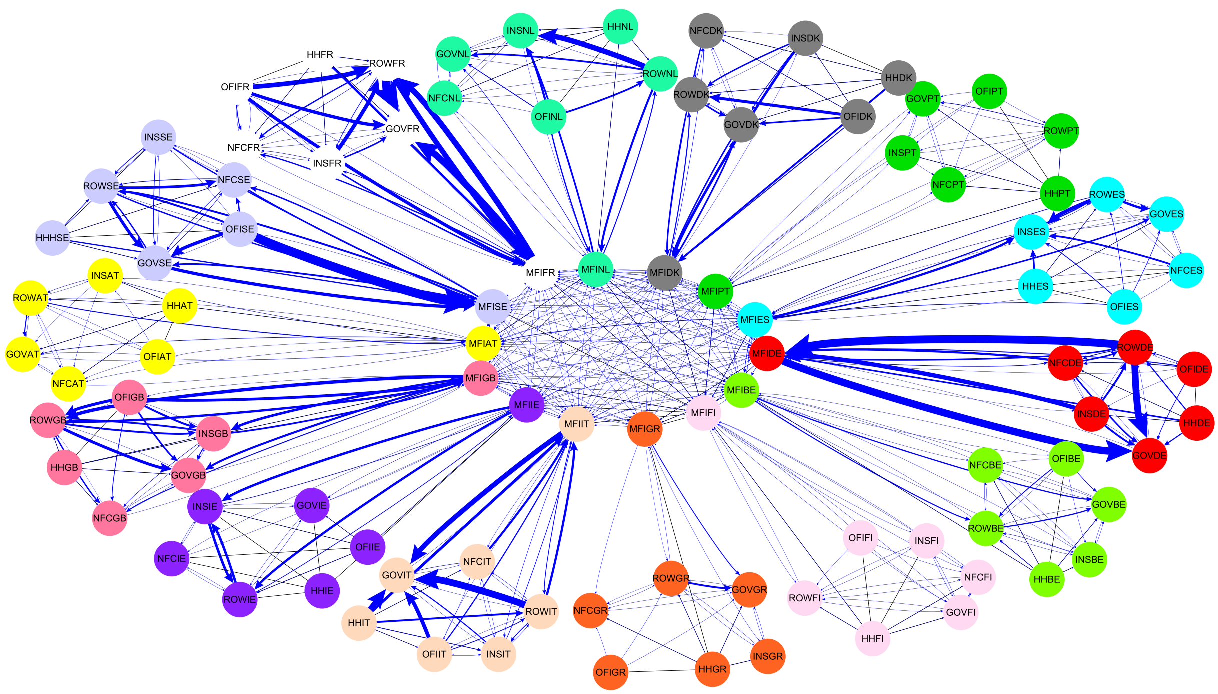


FIGURE 1 The European macronetwork. The figure illustrates the macronetwork for debt security instrument at Q1 2012q1, for fourteen European countries and sectors nonfinancial corporations (NFC), banks (monetary financial institutions [MFI]), insurance and pension fund companies (INS), other financial intermediaries (OFI), general government (GOV), households (HH), and the rest of the world (ROW). Colours refer to different countries, and the link opacity displays the size of the real/estimated transactions among sectors. The European macronetwork can be visualized also in VisRisk (http://vis.risklab.fi/\#/macronet/) [Colour figure can be viewed at wileyonlinelibrary.com]

country's banking sector relative to all other financial and nonfinancial 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.[14] 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 effects, 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 Table 1 (and Table B1). Figure 2 depicts the evolution of the centrality measures. The charts show that the network measures vary both over time (upper panel) and across countries (lower panel); however, these variations depend on the specific instrument and centrality measure. Nonetheless, we find that network measures as well as various instruments for which they are computed are highly correlated. Thus, we use 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 PCA is to retain components with eigenvalues greater than one. We do so but also consider results with a larger number of principal components to assess improvements in early-warning performance. Table B4 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

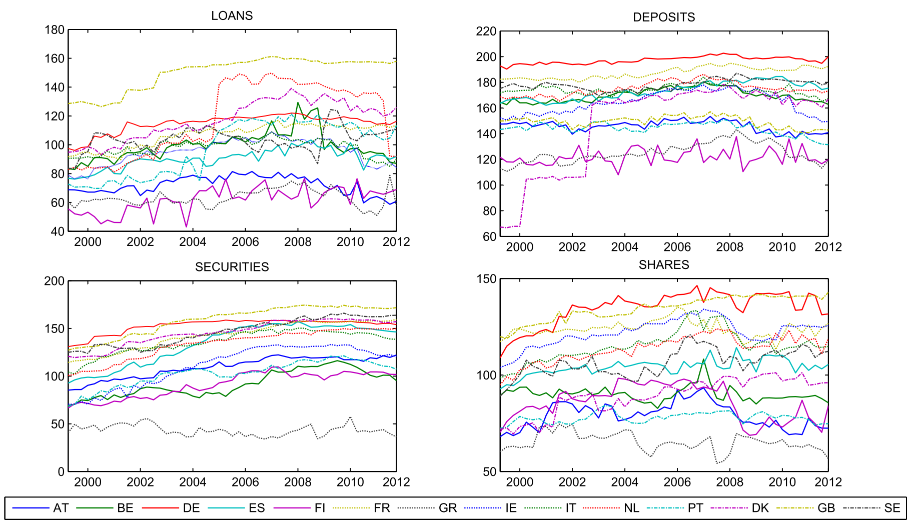
In the early-warning literature, a broad selection of different methods have been used for estimating crisis probabilities (for an extensive review and comparison, see Holopainen & Sarlin, 2015). From the family of discrete-choice methods, we make use of standard logit analysis and follow the literature by preferring pooled models (e.g., Davis & Karim, 2008; Fuertes & Kalotychou, 2007; Kumar, Moorthy, & Perraudin, 2003). In particular, when Fuertes and Kalotychou (2006) account for time- and country-specific effects, they show 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, whereas 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 crisis. 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 the so-called crisis and postcrisis bias (e.g., Bussire & Fratzscher, 2006; Sarlin & Peltonen, 2013), we exclude crisis and postcrisis 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 precrisis regimes to crisis. Further, to control for potential correlation in the

TABLE 1 Banking sector centrality measures on the macronetworks

	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)

Note. The table reports the centrality measures of the banking sectors for each country computed on the macronetworks. Centrality measures are averaged by countries and time periods. Standard deviations are in parentheses.

(a) Evolution of averaged centrality measures



(b) Country trends (In-degree)

FIGURE 2 Centrality measures. In the upper panel, 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. In the lower panel, the charts depict the trends over time of In-degree for each country-instrument [Colour figure can be viewed at wileyonlinelibrary.com]

error terms, we derive robust standard errors by clustering at the level of time units.

Rather than describing the problem from the viewpoint of time-series prediction, the focus on differentiating between vulnerable (i.e., precrisis) 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. Whereas the in-sample data are used for estimation, the out-of-sample dataset measures 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 precrisis events for given quarters. This simplifying assumption has to be made due to the shortness of EAA time series and the lack of systemic events in the years prior to the current global wave of crises. Although 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.[15]

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 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 1 if p_j exceed a specified threshold λ and 0 otherwise. The frequencies of prediction–realization combinations between P_j and I_j can be summarized into a contingency matrix consisting of false positives (FPs), true positives (TPs), false negatives (FNs), and true negatives (TNs).

A wide range of goodness-of-fit measures can be computed from entries of a contingency matrix.[16] 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: Types 1 and 2 errors. Type 1 errors represent the conditional probability $P(p_j \leq \lambda | I_j(h) = 1)$, and Type 2 errors the conditional probability $P(p_j > \lambda | I_j(h) = 0)$. 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 ($T_2 = FP/(FP + TN)$). 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:

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

Although 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 relative usefulness:

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

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:

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

Although 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 mainly 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 macronetworks as leading indicators. We look at this from two viewpoints: (a) macronetworks and its constituents as early-warning indicators and (b) the usefulness of different instruments in early-warning exercises. The analysis is done as follows. First, we assess whether macronetwork 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 | Macronetworks as early-warning indicators

In order to evaluate the performance of models, we need to specify the policymakers preferences between Types 1 and 2 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 benchmark preference parameter is $\mu = 0.8$.

In Table 2, Model 1 is the baseline that includes standard indicators measuring macrofinancial 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 increases early-warning performance. 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 are statistically significant. However, our results are supported also by the analysis of the individual network

TABLE 2 Estimates and signalling performance with macronetwork measures (all instruments and centrality measures)

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
$U_r(\mu)$					
$\mu = 0.6$	0.08	0.11	0.12	0.22	0.26
$\mu = 0.7$	0.12	0.21	0.24	0.33	0.36
$\mu = 0.8$	**0.23**	**0.35**	**0.37**	**0.43**	**0.49**
$\mu = 0.9$	0.23	0.35	0.35	0.35	0.37

Note. 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 macronetworks. 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 time level.

*Statistical significance at 0.10 level.

**Statistical significance at 0.05 level.

***Statistical significance at 0.01 level.

****Statistical significance at 0.001 level.

measures, which are always positive and statistically significant in almost all cases (see Table B6). Thus, we opt for Model 5 with the hope to provide a tool that is parsimonious and informative at the same time. To illustrate model output, Figure B1a shows estimated probabilities and the optimal threshold for Ireland, for whom the model starts signalling in early 2005. 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 nonbanking 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 policymaker. Similarly to the macronetwork, we first model the set of cross-border linkages W^{CB} of MFIs as a network. Second, we used a cross-border network to derive centrality measures (Table B5 provides 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 macronetwork in Table 2. We interpret this as an indication of the macronetwork 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 & Reyes, 2013). By definition, it allows for more channels of vulnerability and provides an explicit characterization of the closeness of the banking sector to the real economy (e.g., households and NFC) that could potentially increase the likelihood of banking distress becoming systemic. More precisely, we show that centrality measures are better indicators of vulnerability when also accounting for domestic sectoral exposures, in addition to cross-border linkages.[17]

This is an interesting finding, given that data on all the existing cross-border connections between all sectors, such as linkages between households and nonfinancial sectors in various countries, are not available. Despite this, we show that the estimated centrality measures of

TABLE 3 Models with cross-border banking network variables

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
$U_r(\mu)$							
$\mu = 0.6$	0.08	0.11	0.11	0.09	0.09	0.15	0.17
$\mu = 0.7$	0.12	0.15	0.15	0.13	0.13	0.23	0.24
$\mathbf{\mu = 0.8}$	**0.23**	**0.31**	**0.31**	**0.25**	**0.30**	**0.38**	**0.38**
$\mu = 0.9$	0.23	0.37	0.35	0.30	0.28	0.34	0.36

Note. The table reports the estimates and predictive performance of logit models. All models include the banking sector and macro-financial controls (coefficients not reported). 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.

*Statistical significance at 0.10 level.

**Statistical significance at 0.05 level.

***Statistical significance at 0.01 level.

****Statistical significance at 0.001 level.

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, betweenness, and closeness) used to quantify the interconnectedness of the banking sector within the macronetwork. This time, to exploit the granularity of the data, we separately apply PCA to the instruments loans, deposits, securities, and shares. As mentioned earlier, the motivation for analysing banking sector centrality in these four financial instruments is to understand how exposures built up and the relationship of the banking sector with different types of risks. Indeed, the banking sector plays different role 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 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. Whereas 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. Although deposits and loans can be received from and granted to most institutional sectors, 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 make this point less observable.

TABLE 4 Models with macronetwork variables based on individual instruments

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
$U_r(\mu)$					
$\mu = 0.6$	0.08	0.17	0.09	0.10	0.11
$\mu = 0.7$	0.12	0.27	0.15	0.18	0.14
$\boldsymbol{\mu = 0.8}$	**0.23**	**0.39**	**0.28**	**0.32**	**0.30**
$\mu = 0.9$	0.23	0.31	0.33	0.31	0.29

Note. The table reports the estimates and predictive performance of logit models, of which Model 1 is the baseline. All models include the banking sector and macrofinancial controls (coefficients not reported). PCA - MN - instrument refers to the PCA computed separately for each financial instrument on the centrality measures for the corresponding macronetwork. The instruments considered are loans, deposits, securities, and share. 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 time level.
*Statistical significance at 0.10 level.
**Statistical significance at 0.05 level.
***Statistical significance at 0.01 level.
****Statistical significance at 0.001 level.

Again, using PCA for the four groups of financial instruments, 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 B4 (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 macronetwork for loans (Model 2) and securities (Model 4) yield slightly more usefulness than for deposits (Model 3) and shares (Model 5). This points to more vulnerability descending from credit risk rather than from funding and liquidity risk or market risk.

Interestingly, the positive coefficients of PCAs, irrespectively of the instrument, suggest that a more central position of the banking sector in the macronetwork increases the probability of a banking crisis. Indeed, the loadings of the first principals are always positive (see Table B4).

TABLE 5 Models with macronetwork variables and non-linearity effects

	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·	
(PCA 1)*Above p50		0.99***		0.36*		0.56***		0.39***
(PCA 1)*Below p50		0.68**		0.50·		0.41		0.33
AUC	0.82	0.79	0.78	0.76	0.82	0.77	0.81	0.76
$U_r(\mu)$								
$\mu = 0.6$	0.26	0.20	0.12	0.09	0.20	0.10	0.19	0.11
$\mu = 0.7$	0.36	0.28	0.21	0.15	0.30	0.18	0.27	0.14
$\boldsymbol{\mu = 0.8}$	**0.45**	**0.38**	**0.34**	**0.28**	**0.41**	**0.32**	**0.39**	**0.30**
$\mu = 0.9$	0.38	0.31	0.28	0.31	0.41	0.32	0.40	0.30

Note. The table reports the estimates and predictive performance of logit models, of which Model 1 is the baseline. All models include the banking sector and macrofinancial controls (coefficients not reported). The PCA 1 refers to the first PCA computed separately for each financial instrument on the centrality measures for the corresponding macronetwork. 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 time level.

*Statistical significance at 0.10 level.

*Statistical significance at 0.05 level.

**Statistical significance at 0.01 level.

****Statistical significance at 0.001 level.

Hence, to gain further insights, we estimate the model adding one by one all the centrality measures. Table B6 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 that is strongly better than the others in all four cases under examination. This was an additional reason to opt for the PCA approach.

Next, Table 5 addresses concerns related to network threshold effects. 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 the 75th percentile, between the 75th and the 25th percentile, and 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, whereas 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 & Ozdaglar et al., 2015; Battiston, Gatti, Gallegati, Greenwald, & Stiglitz, 2012; Elliott et al., 2014). In terms of model performance, 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 macronetwork than only the network of banking sectors. Overall these results suggest the importance to monitor the dynamic of the system and the need to account for non-linearities when studying the relationship between interconnectedness and financial stability.

5 | ROBUSTNESS

5.1 | Different modelling parameters

In this section, we test the robustness of the above presented benchmark model and 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.[18]

In Table 6, the models are evaluated for policymakers' preferences ranging from 0.0 to 1.0. Whereas the model is useful for preferences between 0.2 and 0.9, the table shows that the model yields more usefulness to a poli-

TABLE 6 Model performance over policymakers' preferences for the benchmark model

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

Note. 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 $\mu = 0.0, 0.1, \ldots, 1.0$. 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 sections 3.3 and 3.4 for further details on the measures.

TABLE 7 Model performance over policymakers' preferences with a forecast horizon of 12 months

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	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

Note. 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 $\mu = 0.0, 0.1, \ldots, 1.0$. 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 sections 3.3 and 3.4 for further details on the measures.

cymaker that is more concerned about missing a crisis than giving false alarms. This confirms the findings of Sarlin (2013) and Betz, Opric, Peltonen, and Sarlin (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, whereas 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.

TABLE 8 Model performance over policymakers' preferences with a forecast horizon of 36 months

						Positive		Negative							
Preferences	λ	**TP**	**FP**	**TN**	**FN**	**Precision**	**Recall**	**Precision**	**Recall**	**Accuracy**	**FP rate**	**FN rate**	$U_a(\mu)$	$U_r(\mu)(\%)$	**AUC**
$\mu = 0.0$	0.99	7	0	514	137	1.00	0.05	0.79	1.00	0.79	0	0.95	0	—	0.82
$\mu = 0.1$	0.99	7	0	514	137	1.00	0.05	0.79	1.00	0.79	0	0.95	0	5	0.82
$\mu = 0.2$	0.99	7	0	514	137	1.00	0.05	0.79	1.00	0.79	0	0.95	0	5	0.82
$\mu = 0.3$	0.99	7	0	514	137	1.00	0.05	0.79	1.00	0.79	0	0.95	0	5	0.82
$\mu = 0.4$	0.88	53	26	488	91	0.67	0.37	0.84	0.95	0.82	0.05	0.63	0	10	0.82
$\mu = 0.5$	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
$\mu = 0.6$	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
$\mu = 0.7$	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
$\boldsymbol{\mu = 0.8}$	**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**
$\mu = 0.9$	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
$\mu = 1.0$	0	144	514	0	0	0.22	1.00	—	0	0.22	1.00	0.00	0	—	0.82

Note. 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 sections 3.3 and 3.4 for further details on the measures.

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 macronetworks (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.

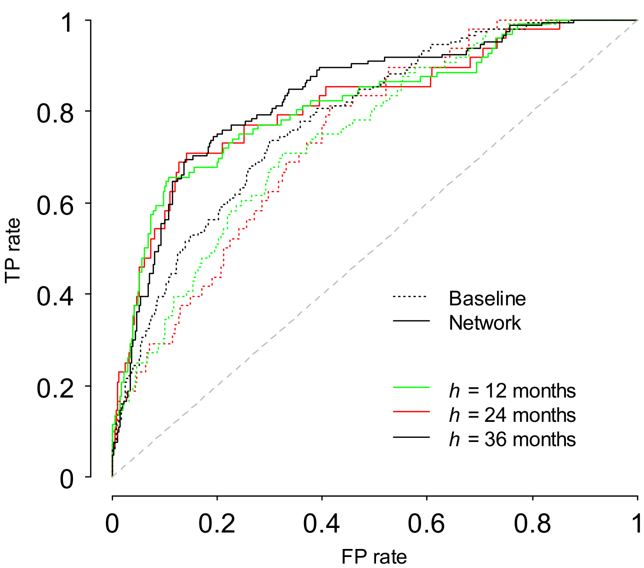


FIGURE 3 ROC curves for models with forecast horizons of 12, 24, and 36 months [Colour figure can be viewed at wileyonlinelibrary.com]

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 macronetworks 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).[19]

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 quasinature 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 macronetwork-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

TABLE 9 Real-time predictions with the baseline model, including no network measures

						Positive		Negative							
Preferences	λ	**TP**	**FP**	**TN**	**FN**	**Precision**	**Recall**	**Precision**	**Recall**	**Accuracy**	**FP rate**	**FN rate**	$U_a(\mu)$	$U_r(\mu)(\%)$	**AUC**
$\mu = 0.0$	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
$\mu = 0.1$	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
$\mu = 0.2$	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
$\mu = 0.3$	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
$\mu = 0.4$	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
$\mu = 0.5$	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
$\mu = 0.6$	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
$\mu = 0.7$	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
$\mu = \mathbf{0.8}$	**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**
$\mu = 0.9$	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
$\mu = 1.0$	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

Note. 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 sections 3.3 and 3.4 for further details on the measures.

TABLE 10 Real-time predictions with the benchmark model, including network measures

						Positive		Negative							
Preferences	λ	**TP**	**FP**	**TN**	**FN**	**Precision**	**Recall**	**Precision**	**Recall**	**Accuracy**	**FP rate**	**FN rate**	$U_a(\mu)$	$U_r(\mu)(\%)$	**AUC**
$\mu = 0.0$	1.00	19	0	366	77	1.00	0.20	0.83	1.00	0.83	0.00	0.80	0.00	—	0.8
$\mu = 0.1$	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
$\mu = 0.2$	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
$\mu = 0.3$	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
$\mu = 0.4$	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
$\mu = 0.5$	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
$\mu = 0.6$	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
$\mu = 0.7$	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
$\mu = \mathbf{0.8}$	**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**
$\mu = 0.9$	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
$\mu = 1.0$	0.00	96	366	0	0	0.21	1.00	—	0.00	0.21	1.00	0.00	0.00	—	0.8

Note. 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 sections 3.3 and 3.4 for further details on the measures.

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 macronetworks aid in out-of-sample analysis. Table 10 shows that the benchmark model that includes macronetwork 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 and shows much larger values for the overall AUC measure. Finally, to illustrate model output in recursive analysis, Figure B1b shows estimated probabilities and optimal thresholds for Ireland. The model starts signalling in mid-2006, which is a few quarters later than the in-sample analysis, but still clearly early enough for macroprudential policy. Accordingly, macronetworks are not only shown to explain crises but also provide means for predicting crises in a quasi real-time manner.

5.2 | Legal and institutional setup

The macronetwork measures may capture other aspects of the overall financial market and, more generally, the quality of institutions. To investigate this, we include a variety of additional country variables conducting a number of robustness tests to control for the institutional and legal set up (Table 11), and the banking sector characteristics (Table 12).

Following previous works (see, eg, Beck, De Jonghe, & Schepens, 2013) to control for financial market developments, we consider indicators of both the stock market and the bond market, which may affect the macronetwork structure (see Table B7 for the detailed definitions). In Table 11, Column 1 presents again the results of the benchmark model (as in Table 2, Column 5). In Columns 2–4, we control for stock and bond markets development. In Column 2, we include the stock market turnover, the ratio of stocks traded to stocks listed. For the bond market, we consider the bond market size defined as the private domestic debt securities issued by financial institutions and corporation plus public domestic debt securities issued by government over GDP (Column 3), and the outstanding private debt over GDP (Column 4). These indicators show positive coefficients, but only stock market turnover is highly statistically significant. Importantly, in all specifications, the coefficients of the macronetwork variables do not vary much, and, in most of the cases, they are statistically significant. Beck et al. (2006) find that the probability of suffering a systemic banking crisis has a negative relationship with the degree of economic freedom in the economy. In Column 5, we control for the economic freedom indicator, available from the Heritage Foundation, based on several economic and financial factors.[20] The coefficient is positive but not statistically significant; however, when including in our model financial freedom—that is, easiness and effectiveness in the accessability to financing opportunities for people and business and independence from government and interference in the banking sector—the coefficient is negative and statistically significant. Previous papers (see, eg, Beck & Levine, 2002; Porta et al., 1998) show that legal origin and the quality of legal enforcement affect cross-country differences in financial development. In Column 6, we add as control a dummy variable that takes value 1 if a country has

TABLE 11 Models with macronetwork measures and institutional and legal variables

	Benchmark		Financial markets		Ec. freedom		Legal system	
Estimates	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
PCA 1 - MN - All	0.41***	0.34***	0.41***	0.41***	0.42***	0.32***	0.40***	0.42***
PCA 2 - MN - All	−0.19*	−0.15·	−0.20*	−0.20*	−0.16*	−0.70***	−0.20·	−0.07
PCA 3 - MN - All	0.37**	0.26·	0.37**	0.37**	0.36*	0.26·	0.39**	0.37**
PCA 4 - MN - All	−0.64**	−0.63**	−0.65**	−0.66**	−0.66**	−0.07	−0.65**	−0.75***
Stock market turnover		0.01·						
Bond market size			0.01					
Outstanding private debt				0.01				
Economic freedom					−0.01			
Civil law						4.36**		
Rule of law							−0.09	
Creditors rights								0.22·
AUC	0.80	0.81	0.80	0.80	0.80	0.81	0.80	0.81
$U_r(\mu)$								
$\mu = 0.6$	0.26	0.22	0.26	0.26	0.24	0.27	0.27	0.20
$\mu = 0.7$	0.36	0.35	0.36	0.46	0.36	0.38	0.38	0.36
$\mu = 0.8$	**0.49**	**0.47**	**0.49**	**0.49**	**0.47**	**0.49**	**0.49**	**0.48**
$\mu = 0.9$	0.37	0.39	0.37	0.37	0.36	0.37	0.37	0.37

Note. The table reports the estimates and predictive performance of logit models, of which Model 1 is the benchmark (Table 2, Column 5). All models include the banking sector and macrofinancial controls (coefficients not reported). 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 time level.

*Statistical significance at 0.10 level.

*Statistical significance at 0.05 level.

**Statistical significance at 0.01 level.

****Statistical significance at 0.001 level.

TABLE 12 Models with macronetwork measures and additional banking sector variables

Estimates	Benchmark (1)	Concentration (2)	Risk (3)	(4)	Regulation (5)	(6)
PCA 1 - MN - All	0.41***	0.36***	0.40***	0.41***	0.55***	0.49***
PCA 2 - MN - All	−0.19*	−0.17˙	−0.20*	−0.20*	−0.18˙	−0.36***
PCA 3 - MN - All	0.37**	0.35*	0.36*	0.37*	0.36**	0.40**
PCA 4 - MN - All	−0.64**	−0.93**	−0.63**	−0.55*	−0.37	−0.67*
Concentration		−0.02**				
Z score			0.01			
Activity restrictions				0.13		
Capital stringency					−0.37***	
Multiple supervisors						
Strength external audit						1.28***
AUC	0.80	0.80	0.80	0.80	0.81	0.84
$U_r(\mu)$						
$\mu = 0.6$	0.26	0.24	0.24	0.29	0.21	0.29
$\mu = 0.7$	0.36	0.35	0.35	0.39	0.30	0.33
$\mu = \mathbf{0.8}$	**0.49**	**0.45**	**0.46**	**0.45**	**0.45**	**0.44**
$\mu = 0.9$	0.37	0.45	0.35	0.37	0.43	0.40

Note. The table reports the estimates and predictive performance of logit models, of which Model 1 is the benchmark (Table 2, Column 5). All models include the banking sector and macrofinancial controls (coefficients not reported). Concentration is PCAs - MN - All refer to the PCAs computed over the centrality measures of all financial instruments for the macronetworks. 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 time level.

*Statistical significance at 0.10 level.

**Statistical significance at 0.05 level.

***Statistical significance at 0.01 level.

****Statistical significance at 0.001 level.

civil law origin. Consistent with the fact that common law countries afford the best legal protections to shareholders, we find that the civil law dummy has a positive sign. Also rule of law, a measure of quality of enforcement, in Specification 7 shows a negative coefficient yet not statistically significant. Finally, in Column 8, we control for creditors rights an indicator concerning the bankruptcy and reorganization laws. Again, in these specifications, the coefficients of the macronet variables are still statistically significant.[21]

Next, in Table 12, we conduct a series of test related more specifically to the banking sector. Column 1 presents again the results of the benchmark model (Table 2, Column 5). In Column 2, we control for concentration defined as the share of assets of the three largest banks in total banking system assets. Consistent with Beck et al. (2006), our results confirm that banking crises are less likely in economies with more concentrated banking systems. We then control for banking system fragility using a measure of the distance from default, the *Z* score (Roy, 1952), defined as the return on assets plus the capital asset ratio divided by the standard deviation of asset return. Finally, we control for regulation and supervision aspects. In Column 4, we add an indicator of regulatory restrictions on the activities of banks, such as securities market activities, insurance activities, real estate activities, and the ownership of nonfinancial firms (Barth et al., 2013). Controlling for this index is important as restrictions placed on this type of diversification could affect significantly the role of both the banking sector and other financial intermediaries in the macronetwork. The positive coefficient of the activity restriction index might suggest that restrictions on activities might not prevent from banking crises occurrence; however, it is not statistically significant. In Column 5, we consider capital stringency, a higher values of this indicator implies a more stringent capital regulation. As expected, the coefficient has a negative value, whereas the multiple supervisors index does not have a statistically significant effect. In all models, the coefficients of the macronet variables are still statistically significant.

Overall, our results are robust to control for several institutional and legal characteristics as well as banking sector variables. This suggests that our findings are not driven by some omitted variables, rather the macronetwork indicators provide additional information on top of the determinants considered in the previous literature. A related issue is whether and to which extent financial linkages and network architecture are affected by the institutional setup. We let this question for future research because, as discussed in sections 2.3 and 3.1, only partial information about financial linkages are available.

6 | CONCLUSIONS

The global financial crisis underlines the need for novel tools to support macroprudential and regulatory policies. The present work is an attempt 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 macronetwork, 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 macronetwork increases the probability of a banking crisis. This overall result is also supported in our analysis of banking sector centrality using various financial instruments (loans, deposits, securities, and shares), which is motivated by understanding the different roles (direct exposure or intermediary role) and the different types of risks (credit, funding and liquidity, and market risks) that the banking sector may face. In this context, risks originated from the lending activities, that is, credit risk, and to some extent investment activities through market risk, seem to predict more accurately banking crisis. Furthermore, our findings confirm the importance to consider the cross-border exposures but suggest that assessing the role of the banking sector as part of the overall financial and nonfinancial system is even more useful. Finally, our results show that early-warning models augmented with macronetworks 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 early-warning models for cyclical developments with measures of cross-sectional interconnectedness. Our paper is relevant also for policy makers, as improvements in early-warning models are crucial for designing appropriate and timing policy actions. Future work could widen the scope of the analysis investigating what financial structure may contain spillover effects and adverse economic impact of a banking crisis. Important avenues for future research are to explore further the existing linkages between the banking sector and the other nonfinancial sectors.

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ENDNOTES

[1] 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, Peltonen, and Sarlin (2015) for an overview of the early-warning literature and a modelling framework.

[2] 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 assets amplify contagion effects.

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

[4] Acemoglu & Akcigit et al. (2015) show that supply-side shocks propagate mainly downstream, whereas demand shocks propagate mainly upstream.

[5] Further, the paper is complemented with a web-based interactive visualization of the macronetworks: http://vis.risklab.fi/#/macronet/ (for a further discussion of the VisRisk platform see Sarlin, 2014).

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

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

[8] 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.

[9] The data were accessed in January 2014 through the ECB web site. The data available at that time were compiled according to the methodological framework of the European System of Accounts 1995 (ESA95), which differ from the methodological framework applied more recently, ESA2010, in the definition of sectors and instruments.

[10] Currently, whom-to-whom flow-of-funds statistics are 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 macronetwork (see Appendix B).

11 One difference with the methodology applied to estimate interbank exposures at bank level is that 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. We add two constraints to the standard maximum entropy method: (a) the realized data on the links between the banking (MFI) sector and all other sectors is used from the BSI statistics, and (b) the intrasector transactions within the ROW sector are set equal to zero. See Castrén and Rancan (2014) for further details and an evaluation of this approach.

13 Data that could provide some information are often only partial, limited in the time series, and inconsistent with the EAA. Nonetheless, all cross-border exposures, besides those between banking sectors, are somehow incorporated in our framework with the linkages to/from the sector "rest of the world sector" without specifying the counterparty sector-country.

14 See Table B2 for the mathematical definitions.

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

16 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.

17 We also test that the difference is statistically significant with standard significance tests for both the usefulness and the AUC measures. In the vein of Holopainen and Sarlin (2015), 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.

18 In addition to the below tests, which mainly focus on different modelling parameters, we have also tested robustness to controlling for size effects in the macronetwork. All of the main results are confirmed when scaling the linkages with the logarithm of GDP.

19 In addition to recursive estimations, we have also tested so-called leave-on-country-out validation and found that the models perform well. This is no surprise due to the similar patterns experienced by European countries prior to this crisis. For brevity, these tables have not been included but are available upon request.

20 The score is based on the following indicators: property rights, judicial effectiveness, government integrity, tax burden, government spending, fiscal health, business freedom, labour freedom, monetary freedom, trade freedom, investment freedom, and financial freedom.

21 Robustness tests have been conducted also for the models with macronetwork variables based on individual instruments (Table 4). Results are confirmed but not reported for brevity.

22 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^D_{ij}/W^D and $\hat{w}^D_{ij}/\hat{W}^D$, respectively.

23 We follow this procedure because the EAA and the real data differ in the assets and the liabilities of all sectors, that is, $\hat{a}_{NFC} \neq \tilde{a}_{NFC}$ and $\hat{l}_{NFC} \neq \tilde{l}_{NFC}$. This fact explains, to some extent, the differences in the amount of linkages in Figure A1. As before, the ROW sector is not considered.

24 For example, banks' sovereign bond holdings have been published by the European Banking Authority in the context of bank stress tests, and we know that this has been an important channel of cross-border contagion. However the limited availability of information prevents us from using them.

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REFERENCES

Acemoglu, D., Akcigit, U., Kerr, W., et al. (2015). Networks and the macroeconomy: An empirical exploration.

Acemoglu, D., Ozdaglar, A., & Tahbaz-Salehi, A. (2015). Systemic risk and stability in financial networks. *American Economic Review*, *105*(2), 564–608.

Adrian, T., & Shin, H. S. (2010). Liquidity and leverage. *Journal of financial intermediation*, *19*(3), 418–437.

Alessi, L., & Detken, C. (2011). Quasi real time early warning indicators for costly asset price boom/bust cycles: A role for global liquidity. *European Journal of Political Economy*, *27*(3), 520–533.

Allen, F., Beck, T., Carletti, E., Lane, P. L., Schoenmaker, D., & Wagner, W. (2011). Cross-Border Banking in Europe: Implications for Financial Stability and Macroeconomic Policies. (*CEPR Report*).

Anand, K., Craig, B., & Von Peter, G. (2015). Filling in the blanks: Network structure and interbank contagion. *Quantitative Finance*, *15*(4), 625–636.

Babecky, J., Havranek, T., Mateju, J., Rusnak, M., Smidkova, K., & Vasicek, B. (2014). Banking, debt, and currency crises: Early warning indicators for developed countries. *Journal of Financial Stability*, *15*, 1–17.

Barth, J. R., Caprio, G. Jr., & Levine, R. (2013). Bank regulation and supervision in 180 countries from 1999 to 2011. *Journal of Financial Economic Policy*, *5*(2), 111–219.

Battiston, S., Gatti, D. D., Gallegati, M., Greenwald, B., & Stiglitz, J. E. (2012). Credit chains and bankruptcy propagation in production networks. *Journal of Economic Dynamics and Control*, *31*(6), 2061–2084.

Beck, T., De Jonghe, O., & Schepens, G. (2013). Bank competition and stability: Cross-country heterogeneity. *Journal of Financial Intermediation*, *22*(2), 218–244.

Beck, T., Demirgüç-Kunt, A., & Levine, R. (2006). Bank concentration, competition, and crises: First results. *Journal of Banking & Finance*, *30*(5), 1581–1603.

Beck, T., & Levine, R. (2002). Industry growth and capital allocation: Does having a market-or bank-based system matter? *Journal of Financial Economics*, *64*(2), 147–180.

Betz, F., Opric, S., Peltonen, T. A., & Sarlin, P. (2014). Predicting distress in european banks. *Journal of Banking & Finance*, *45*, 225–241.

Billio, M., Getmansky, M., Lo, A. W., & Pelizzon, L. (2012). Econometric measures of connectedness and systemic risk in the finance and insurance sectors. *Journal of Financial Economics*, *104*(3), 535–559.

Borio, C. E., & Lowe, P. W. (2002). Asset prices, financial and monetary stability: Exploring the nexus.

Borio, C. E., & Lowe, P. W. (2004). Securing sustainable price stability: Should credit come back from the wilderness?

Bussire, M., & Fratzscher, M. (2006). Towards a new early warning system of financial crises. *Journal of International Money and Finance*, *25*(6), 953–973.

Caballero, J. (2015). Banking crises and financial integration: Insights from networks science. *Journal of International Financial Markets, Institutions and Money*, *34*, 127–146.

Caballero, R. J., & Simsek, A. (2013). Fire sales in a model of complexity. *The Journal of Finance*, *68*(6), 2549–2587.

Cabrales, A., Gottardi, P., & Vega-Redondo, F. (2014). Risk-sharing and contagion in networks.

Cai, J., Saunders, A., & Steffen, S. (2011). Syndication, interconnectedness, and systemic risk.

Castrén, O., & Rancan, M. (2014). Macro-networks: An application to euro area financial accounts. *Journal of Banking & Finance*, *46*, 43–58.

Cerutti, E., Claessens, S., & Ratnovski, L. (2014). Global liquidity and drivers of cross-border bank flows. (*IMF Working Paper WP/14/69*).

Chinazzi, M., Fagiolo, G., Reyes, J. A., & Schiavo, S. (2013). Post-mortem examination of the international financial network. *Journal of Economic Dynamics and Control*, *37*(8), 1692–1713.

Craig, B., & von Peter, G. (2014). Interbank tiering and money center banks. *Journal of Financial Intermediation*, *23*(3), 322–347.

Čihák, M. Demirgüč-Kunt, A. Feyen, E., & Levine, R. (2013). Financial development in 205 economies, 1960 to 2010 (No. w18946). National Bureau of Economic Research.

Davis, E. P., & Karim, D. (2008). Comparing early warning systems for banking crises. *Journal of Financial stability*, *4*(2), 89–120.

Demirgüç-Kunt, A., & Detragiache, E. (1998). The determinants of banking crises in developing and developed countries. *Staff Papers*, *45*(1), 81–109.

Demirgüç-Kunt, A., & Detragiache, E. (2000). Monitoring banking sector fragility: A multivariate logit approach. *The World Bank Economic Review*, *14*(2), 287–307.

Diebold, F. X., & Yılmaz, K. (2014). On the network topology of variance decompositions: Measuring the connectedness of financial firms. *Journal of Econometrics*, *182*(1), 119–134.

Eichengreen, B., & Rose, A. K. (1998). Staying a oat when the wind shifts: External factors and emerging-market banking crises. (*Tech. rep.*): National bureau of economic research.

Elliott, M., Golub, B., & Jackson, M. O. (2014). Financial networks and contagion. *American Economic Review*, *104*(10), 3115–3153.

Fagiolo, G., Reyes, J., & Schiavo, S. (2009). World-trade web: Topological properties, dynamics, and evolution. *Physical Review E*, *79*(3), 036115.

Fagiolo, G., Reyes, J., & Schiavo, S. (2010). The evolution of the world trade web: A weighted-network analysis. *Journal of Evolutionary Economics*, *20*(4), 479–514.

Fuertes, A.-M., & Kalotychou, E. (2006). Early warning systems for sovereign debt crises: The role of heterogeneity. *Computational Statistics & Data Analysis*, *51*(2), 1420–1441.

Fuertes, A.-M., & Kalotychou, E. (2007). Optimal design of early warning systems for sovereign debt crises. *International Journal of Forecasting*, *23*(1), 85–100.

Gai, P., & Kapadia, S. (2010). Contagion in financial networks. In *Proceedings of the Royal Society A: Mathematical, Physical and Engineering Science,* The Royal Society. pp. rspa20090410.

Georg, C.-P. (2013). The effect of the interbank network structure on contagion and common shocks. *Journal of Banking & Finance*, *37*(7), 2216–2228.

Godlewski, C. J., Sanditov, B., & Burger-Helmchen, T. (2012). Bank lending networks, experience, reputation, and borrowing costs: Empirical evidence from the french syndicated lending market. *Journal of Business Finance & Accounting*, *39*(1-2), 113–140.

Gonzalez-Hermosillo, B. (1999). Determinants of ex-ante banking system distress: A macro-micro empirical exploration of some recent episodes. International Monetary Fund.

Hale, G. (2012). Bank relationships, business cycles, and financial crises. *Journal of International Economics*, *88*(2), 312–325. fNBERg Global.

Holopainen, M., & Sarlin, P. (2015). Toward Robust Early-Warning Models: A Horse Race, Ensembles and Model Uncertainty. (*Bank of Finland Discussion Paper 06/2015*).

Iori, G., De Masi, G., Precup, O. V., Gabbi, G., & Caldarelli, G. (2008). A network analysis of the italian overnight money market. *Journal of Economic Dynamics and Control*, *32*(1), 259–278.

Kali, R., & Reyes, J. (2010). Financial contagion on the international trade network. *Economic Inquiry*, *48*(4), 1072–1101.

Kaminsky, G. L., & Reinhart, C. M. (1998). Financial crises in asia and latin america: Then and now. *American Economic Review*, *88*, 444–448.

Kaminsky, G. L., & Reinhart, C. M. (1999). The twin crises: The causes of banking and balance-of-payments problems. *American Economic Review*, *89*(3), 473–500.

Kubelec, C., & Sá, F. (2010). The geographical composition of national external balance sheets: 1980-2005.

Kumar, M., Moorthy, U., & Perraudin, W. (2003). Predicting emerging market currency crashes. *Journal of Empirical Finance*, *10*(4), 427–454.

Laeven, L., & Valencia, F. (2013). Systemic banking crises database. *IMF Economic Review*, *61*(2), 225–270.

Lang, J. H., Peltonen, T., & Sarlin, P. (2015). A framework for early warning modelling. ECB WP forthcoming.

La Porta, R. L., Lopez-de Silanes, F., Shleifer, A., & Vishny, R. W. (1998). Law and finance. *Journal of Political Economy*, *106*(6), 1113–1155.

Lo Duca, M., & Peltonen, T. A. (2013). Assessing systemic risks and predicting systemic events. *Journal of Banking & Finance*, *37*(7), 2183–2195.

Männasoo, K., & Mayes, D. G. (2009). Explaining bank distress in eastern european transition economies. *Journal of Banking & Finance*, *33*(2), 244–253.

Minoiu, C., Kang, C., Subrahmanian, VS, & Berea, A. (2015). Does financial connectedness predict crises? *Quantitative Finance*, *15*(4), 607–624.

Minoiu, C., & Reyes, J. A. (2013). A network analysis of global banking: 1978–2010. *Journal of Financial Stability*, *9*(2), 168–184.

Mistrulli, P. E. (2011). Assessing financial contagion in the interbank market: Maximum entropy versus observed interbank lending patterns. *Journal of Banking & Finance*, *35*(5), 1114–1127.

Reinhart, C. M., & Rogoff, K. S. (2008). Banking crises: An equal opportunity menace. (*Tech. rep.*): National Bureau of Economic Research.

Robin, X., Turck, N., Hainard, A., Tiberti, N., Lisacek, F., Sanchez, J.-C., & Muller, M. (2011). pROC: An open-source package for r and s+ to analyze and compare roc curves. *BMC Bioinformatics*, *12*(1), 77.

Sa, F. G. (2010). Evidence on financial globalization and crisis: Geographic/bilateral external balance sheets. (*Tech. rep.*): Faculty of Economics, University of Cambridge.

Sarlin, P. (2013). On policymakers loss functions and the evaluation of early warning systems. *Economics Letters*, *119*(1), 1–7.

Sarlin, P (2014). Macroprudential oversight, risk communication and visualization. (*LSE SP Working Paper No. 4.*)

Sarlin, P., & Peltonen, T. (2013). Mapping the state of financial stability. *Journal of International Financial Markets, Institutions & Money*, *26*, 46–76.

Upper, C. (2011). Simulation methods to assess the danger of contagion in interbank markets. *Journal of Financial Stability*, *7*(3), 111–125.

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APPENDIX A

In section 3.1, we presented the methodology for constructing the macronetworks. 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 contain 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, that is, bilateral data, is not available. Thus, the domestic linkages, W^D, are estimated using the maximum entropy method. Recently, some bilateral data have 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

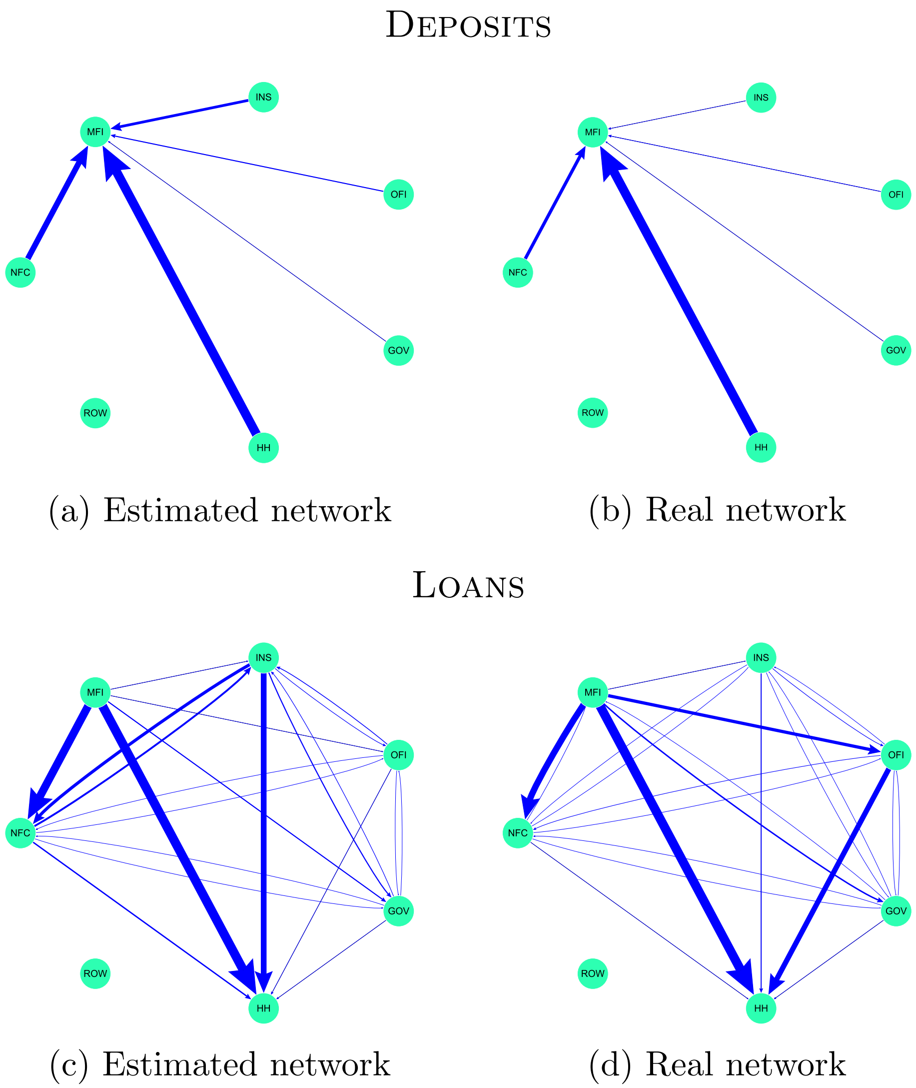


FIGURE A1 Estimated domestic network versus real domestic network. The figures illustrate the domestic network of the Netherlands for loan (upper panel) and deposit instrument (lower panel) at Q1 2012. Panels (a) and (c) display the estimated network with the maximum entropy method, whereas panels (b) and (d) show the real network based on the bilateral data. The size of arrow shows different weights, that is, the volume of transactions between the sectors [Colour figure can be viewed at wileyonlinelibrary.com]

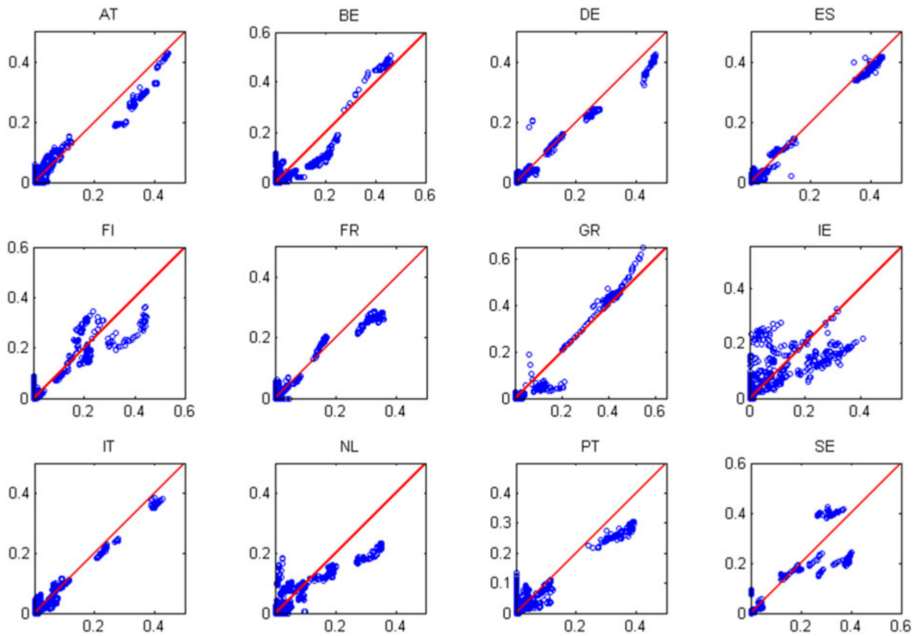


FIGURE A2 Estimated versus actual linkages. We plot real linkages (x-axis) against the estimated linkages (y-axis), expressed in percentages (w_{ij}^D/W^D and $\hat{w}_{ij}^D/\hat{W}^D$), for each quarter. The subplots refers to different countries [Colour figure can be viewed at wileyonlinelibrary.com]

information to construct the macronetwork. However, it provides means of evaluating the suitability of the maximum entropy method to estimate the domestic sectoral linkages. The comparisons are performed on (a) the network structure, (b) the linkages, and (c) 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- and long-term loans, and deposits. Figure A1 illustrates the estimated domestic network with the maximum entropy (panels a and c) and with the real network (panels 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 underestimate the linkages from banks (MFI) to general government (GOV) and from other financial intermediaries (OFI) to households (HH) and somewhat overestimates the linkage from INS to households (HH). In case of deposits, the estimation technique seems to overestimate 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 A2, we plot the real linkages (x-axis) against the estimated linkages (y-axis) for each country.[22] A visual inspection of the figure shows that for most of the countries points are quite close to the 45° 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 macronetwork with the real data (the resulting set of linkages is denoted by $\tilde{W}$) and calculate the centrality measures for 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.[23] Finally, we compare the two sets of centrality measures for the MFI sector. Table B8 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.

Overall, these results supports our view that the chosen methodology seems quite reliable in this context. Still, the macronetwork 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 nonbanking sectors, such as the exposures of the banking sector to foreign government sectors. This choice is motivated by the absence of data that could guide our estimation.[24] 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, whereas for Italian MFI, the major counterparties are other MFI). Thus, any method could have introduced a substantial bias in the macronetwork or, at least, in some countries. For the same reasons, we do not model cross-border linkages for nonbanking sectors. Finally, the macronetwork is limited to 14 countries. Hence, in this representation, the banking sectors are not connected with other non-European countries.

APPENDIX B

TABLE B1 Banking sector centrality measures on the macronetworks

	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

Note. The table reports the centrality measures of the banking sectors for each country computed on the macronetworks. Centrality measures are averaged by instruments and time periods.

TABLE B2 Measures of network statistics

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	$C_C(i) = \sum_j^N \left[\min\left(\frac{1}{(w_{ih})^{\alpha}} + \ldots + \frac{1}{(w_{hj})^{\alpha}}\right)\right]$

Note. 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.

TABLE B3 Indicators, definitions, and data sources

Indicator	Definition	Source
Banking variables:		
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
Macroeconomic variables:		
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 B4 Centrality Measures for the banking sectors on the macronetworks: Principal component analysis

	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

Note. The table reports the loadings of the PCAs, the standard deviation and the proportion of explained variance for each balance sheet instrument of the macronetworks. Panel A shows the results based on the PCA performed over all instruments together (and centrality measures). Panel B shows the results based on the PCA performed separately over each instrument.

TABLE B5 Banking sector centrality measures on the cross-border banking network: summary statistics

	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)

Note. 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.

TABLE B6 Individual centrality measures in early-warning models

	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
$U_r(\mu)$																
$\mu = 0.6$	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
$\mu = 0.7$	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
$\mu = 0.8$	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
$\mu = 0.9$	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

Note. The table reports the estimates and predictive performance of logit models. All models include the banking sector and macro-financial controls (coefficients not reported). 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 time level. ·Statistical significance at 0.10 level. *Statistical significance at 0.05 level. **Statistical significance at 0.01 level. ****Statistical significance at 0.001 level.

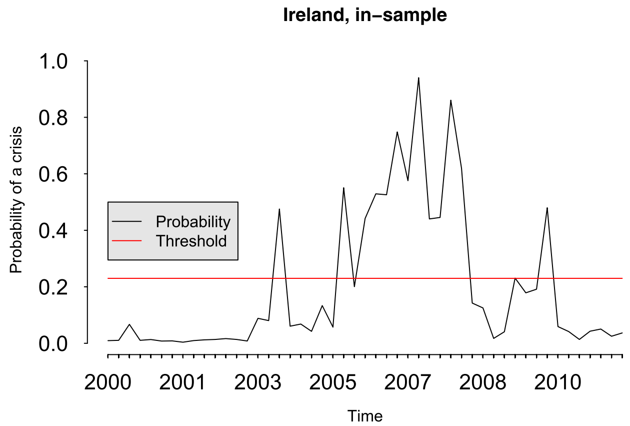
TABLE B7 Additional variables employed in the empirical analysis, definitions, and data sources

Indicator	Definition	Source
Financial development and legal variables:		
Rule of law	measure of quality of enforcement	La Porta et al. (1998)
Stock market turnover	Value of total shares traded/ Average real market capitalization	Financial Development and Structure dataset Čihák et al. (2013)
Bond market	(Private domestic debt securities issued by financial institutions and corporation + Public domestic debt securities issued by government)/GDP	Financial Development and Structure dataset Čihák et al. (2013)
Outstanding private debt	Total amount of domestic private debt securities (amounts outstanding) issued in domestic markets/GDP	World Bank
Economic freedom	Score to an economy's economic and financial freedom	Heritage Foundation
Civil law	Dummy variable equal 1 if a country has a civil law, 0 otherwise	La Porta et al. (1998)
Rule of law	measure of quality of enforcement	La Porta et al. (1998)
Creditors rights	Aggregated index of different creditor rights	La Porta et al. (1998)
Banking variables:		
Concentration	Assets of three largest banks as a share of assets of all commercial banks	Financial Development and Structure dataset Čihák et al. (2013)
Z-score	(ROA+ Equity+/Assets)/ standard deviation(ROA)	Financial Development and Structure dataset Čihák et al. (2013)
Activity restrictions	Measure of the extent to which banks may engage in i) underwriting, brokering and dealing in securities, and all aspects of the mutual fund industry; ii) insurance underwriting and selling, and iii) real estate investment, development and management	Barth et al. (2013)
Capital stringency	Overall capital stringency	Barth et al. (2013)
Strength external audit	Effectiveness of external audits of banks	Barth et al. (2013)

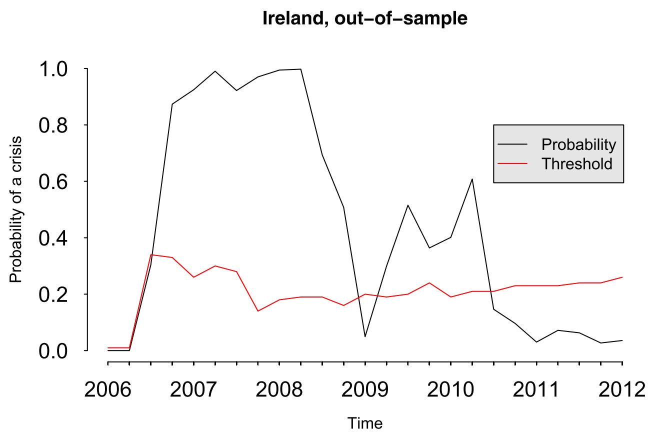
TABLE B8 Estimated network versus real network, instrument loans

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

Note. The table reports the centrality measures of the banking sectors computed on the macronetwork 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.



(a) Ireland's probabilities and thresholds (in sample)



(b) Ireland's probabilities and thresholds (out of sample)

FIGURE B1 Ireland. We plot predicted probabilities and thresholds for Ireland. The upper panel (lower panel) refers to the in-sample (out-of-sample) analysis [Colour figure can be viewed at wileyonlinelibrary.com]