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Macro-Networks: An application to euro area financial accounts ☆

Olli Castrén [a,1], Michela Rancan [b,*]

[a] European Central Bank, Germany
[b] Robert Schuman Centre for Advanced Studies, European University Institute, Italy

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ABSTRACT

This paper develops a financial network, designated the "Macro-Network", that depicts the connections between the main financial and non-financial sectors of the economy in the various financial instruments of the euro area. The Macro-Network comprises of linkages across financial and non-financial sectors in each country. These country-level sector networks are then connected by the cross-border links between the individual banking sectors. Using the Macro-Network to simulate financial shocks, we find that the propagation effects depend on the underlying network structure, which evolves over time. After the financial crisis, bilateral linkages contracted sharply, reflecting the surge in counterparty risk and the de-leveraging processes. Nonetheless, our analysis suggests that even after this process, vulnerabilities remained in the euro area financial system, while a more diversified portfolio of cross-border exposures might mitigate the shock effects. We identify sectors which are most relevant for the propagation of financial shocks in the Macro-Network.

1. Introduction

The financial crisis that erupted in August 2007 generated global peacetime economic losses that had not been experienced since the Great Depression of the 1930s. The crisis, which originated from a relatively minor segment of the US housing market, spread across sectors and countries via financial markets and balance sheet exposures. The subsequent large-scale government support measures for the financial sectors, combined with an economic downturn, stretched government balance sheets and caused a sharp deterioration in public finances in most advanced economies. These losses were particularly acute in the euro area, where the size of the banking sectors are large relative to the GDP, and government financial positions face constraints due to the fiscal rules outlined in the Maastricht Treaty. Furthermore, faced with sudden losses in their asset values, banks stepped back from their lending exposures to the domestic and foreign non-financial sectors. Banks also sharply scaled back their cross-border wholesale financing exposures to counter the unforeseen counterparty risk exposures. This de-leveraging process acted as a financial accelerator and added to the losses faced by the banks' borrowers, governments and, as a result of the deteriorating debtor credit quality, the banks themselves. The end result was a malicious feedback loop between the financial and non-financial sectors and a marked deterioration in financial integration in the euro area and globally (see European Central Bank, 2012).

Dudley (2009) and Stiglitz (2008) discuss the potential for systemic risk in financially interdependent economies. They note that the speed and scope at which losses may propagate in the global financial system is partly facilitated by the growing interconnectedness of the balance sheets of firms, households, financial institutions and governments both at the national and at the cross-border level. Our paper focuses on these balance sheet interconnections and applies techniques from financial network analy-

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* Corresponding author. Address: European University Institute, Robert Schuman Centre for Advanced Studies, Via delle Palazzine 17-19, I-50014 San Domenico di Fiesole, Italy. Tel.: +39 0332 78 3608.

E-mail address: michela.rancan@eui.eu (M. Rancan).

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sis to study how the financial linkages between the institutional sectors have developed since the launch of the single European currency in 1999 and how they have reacted to the financial crisis. We estimate stylised networks of the sectors at the euro area–country level that capture the financial exposures both between the financial and non-financial sectors. These country-level networks are then connected by a cross-border network of national banking sectors. The resulting "Macro-Network" allows us to perform simulations of shock propagation and to analyse the static and dynamic features of the financial interconnections at the euro area level. Our findings suggest that despite the deleveraging process that followed the first round of the financial crisis in 2007–2008, the contagion risks did not meaningfully decrease.

Network analysis has recently emerged as an appealing approach to analyse financial contagion and systemic risk. However, despite the obvious usefulness of network tools in modelling interconnections, the financial applications are still relatively limited. A key reason is that a network representation requires detailed data on counterparty exposures, which are still rarely available, at least from public sources. To address the data limitation issues, previous empirical studies have often based the analysis on estimated linkages. For instance, estimated bilateral exposures have been used to depict the networks of national interbank payment systems (e.g., Upper and Worms, 2004; Degryse and Nguyen, 2007; Mistrulli, 2011). Another strand of the literature has adopted methods applied in epidemiology and biology to construct financial networks using mathematical methods. In this vein, Nier et al. (2007) exploit a banking system network to study contagious defaults and banking sectors resilience to systemic risk. Gai and Kapadia (2010) investigate the effects of the failures of individual institutions and how the likelihood of contagion risk depends on the market conditions and the network structures. In Gai et al. (2011), numerical simulations are used to study the interbank market and derive policy implications. Other papers construct credit networks and study the static and dynamic properties of financial propagation effects (Eisenberg and Noe, 2001; Battiston et al., 2012; Co-Pierre, 2013).

Our chosen methodology relates to both these strands of literature. However, our approach differs substantially from previous applications in that we develop networks at a more aggregated level or macro-level. Extending the work by Castrén and Kavonius (2013),[2] our starting point is the balance sheets of the main institutional sectors of the economy that form the nodes of the estimated networks. While linkages among the sectors at the country level need to be estimated from the balance sheets, the linkages at the cross-border level are observed for the banking sector. The resulting networks, which are constructed separately for the different instrument categories, connect the individual sectors of the 11 countries of the euro area. This representation is necessarily stylized: The macro data do not allow us to capture the complexity and interconnections that are present in the euro area financial system.

This notwithstanding, our approach provides certain advantages. First, it paints a broad picture of the financial linkages at the euro area level and collects the financial exposures of the various sectors in a unique setting. Second, it makes a useful framework for the shock propagation simulations, both across sectors within the countries and across the countries. The main methodological novelties of the present paper are to include some of the cross-border elements that exist within the euro area and to exploit recent advances in estimating the sector level networks. Regarding the latter, we analyse the complexity of the system in term of not only the direct bilateral linkages but also the indirect connections between sectors. In this way, we are able to identify the important structural heterogeneity in the interconnections across sectors and countries.

We find that the euro area Macro-Network provides a suitable platform for simulating contagion and shock propagation. Thus far, the analyses of the economy-wide contagion effects via balance sheets (interlinked claims and obligations) and the liquidity spiral effects from asset fire sales and de-leveraging have for the most part been limited to theory models with limited empirical data (see e.g. Kiyotaki and Moore, 1997; Adrian and Shin, 2010; Shin, 2008). The recent empirical work by Degryse et al. (2010) use gross bilateral exposures at the banking system level to investigate the transmission of shocks over the period 1999-2006. For our setting, we are interested in understanding how the shocks propagate both domestically and across the borders in the euro area financial system and the extent of the financial losses that may be generated in these processes. In this sense, our work complements the theoretical studies that analyse how shocks propagate in the system as a function of the network architecture (Allen and Gale, 2000; Elliott et al., 2013; Cabrales et al., 2013). In particular, Elliott et al. (2013) and Cabrales et al. (2013) model the networks of firms linked by cross-holding positions and study the resulting contagion effects.

Our main findings are as follows. First, the global economic impact of a shock of a given magnitude strongly depends on its initial location, in terms of the financial instrument, economic sector and country of origin. In this way, we are able to identify the specific sectors in particular countries that are the most prominent in terms of the potential of generating system-wide losses in the euro area. Second, we uncover the large differences in the post-propagation losses not only in quantitative but also in qualitative terms. The country-specific structures of the linkages between the domestic sectors and to foreign countries are the key drivers of the propagation mechanisms, the speed of contagion and the iterative feedbacks in the model. Third, we find that the network structures and the propagation losses are strongly time-variant. We perform simulations quarter-by-quarter throughout the years 2003–2012, covering also the recent financial crisis. We observe a general increase in the potential economic losses caused by a standardised shock between 2003 and 2007, owing to the increase in volume of the bilateral linkages in the Macro-Network throughout this time period. After the financial crisis, the volumes of the bilateral linkages contracted sharply, due to the reduction in counterparty exposures and the de-leveraging processes that ensued as endogenous and procyclical responses to the financial crisis. Nevertheless, in terms of the propagation of shocks, vulnerabilities were not meaningfully reduced in the euro area financial system. Fourth, we demonstrate that network statistics may provide useful predictions of the ways shocks propagate in the system and, more generally, of the sensitivity and resilience of different types of financial systems to shocks. Fifth, considering a different network configuration we show that under a diversified structure of cross-border exposures, the post-propagation losses can be reduced.

Overall, our findings confirm the importance of understanding the pattern of interconnectedness in the financial systems. The multiple channels through which the financial shocks may spread between sectors underlines the potential for the systemic financial stability risks what are latent in closely integrated economies. We conclude that the trade-off between efficiency and stability in the financial networks is an important element to be considered in any welfare analysis of financial integration. In addition, by shedding light on the more remote links and connections in the financial system, the analysis provides new insights for counterparty risk management at the aggregated level.

The remainder of the paper is organised as follows. Section 2 presents the data and the methodology. Section 3 provides the key definitions and describes the constructed network and its topological properties, considering in detail certain methodological aspects. Section 4 contains the simulation analyses and the shock propagation exercises, and formulates financial stability

[2] They use sector balance sheets at the euro-area aggregate level.

considerations that arise from the main results. Section 6 assesses the accuracy of the network estimation techniques using certain limited information on the true bilateral sector-level linkages. Section 6 concludes.

2. Data and methodology

2.1. Data

Our data come from the euro area accounts (henceforth EAA), also called the flow of fund statistics, at the individual country level. The flow of funds provides a record of the financial transactions in terms of assets and liabilities, broken down into instrument categories, for the various institutional sectors: non-financial corporations (henceforth NFC); banks (monetary financing 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 financial balance sheets are valued at market prices, at each point in time.[3] For most of the euro area countries, these data are available from the first quarter of 1999 and our sample extends to the first quarter of 2012, resulting in a total of 52 periods. We also use the euro area Balance Sheet Items statistics (henceforth BSI); the BSI data provide the aggregated (or consolidated) balance sheets of the MFI sector. They include the main instrument breakdowns and, importantly, information on the identity of the counterparties at the sector level, including also foreign MFI sectors. The BSI statistics are available from Q1 of 2003. Our final sample consists of quarterly data for the 11 euro area countries. In terms of the financial instruments, we focus our analysis on the deposits, debt securities, loans and equity shares. Additional instrument categories are available but tend to be either minor in terms of volumes or specific to certain institutional sectors only.

2.2. Methodology

A network is a set of points, called nodes or vertices, with relationships, called links, between them. In our context, each sector is considered as one node in the network. Our sample consists of 11 countries that correspond to 77 sector-level nodes for each network n. Networks which feature different types of nodes are defined as heterogeneous. Two nodes i and j are connected through edges, labelled with x_{ji}, in case we take into account only the presence or the absence of a link ($x_{ij} = 1$ or $x_{ij} = 0$, respectively). If we consider also the strength, or intensity of the connections, the link connecting two nodes is defined as w_{ij}. For example, for the instrument category loans, $w_{ij} = 12{,}000$ means that there is a loan of that value extended from node i to node j. This immediately provides another property of our network: the links are directed, because w is not symmetric in a way that $w_{ij} \neq w_{ji}$ (and similarly $x_{ij} \neq x_{ji}$). Our variable of interest w_{ij}, the financial link between any two sectors, is computed using the EAA data and the BSI statistics in the following way. As a first step, using the EAA data, we compute the financial networks connecting sectors at the individual country level. Because we do not directly observe the bilateral links between the various sectors, we estimate them using the maximum entropy method. Previous literature in financial economics has mainly applied maximum entropy to estimate the bilateral interbank exposures (see Upper and Worms, 2004). Castrén and Kavonius (2013) extended the use of this methodology to sector-level accounts using the EAA statistics at the euro area aggregate level. Similarly, in the present paper, we use the maximum entropy method to construct the matrix of the bilateral links between sectors for each country (see Appendix A for details). To enhance the accuracy of the estimated bilateral links, we add two constraints to the standard maximum entropy method:

- The realised data on the links between the banking (MFI) sector and all other sectors is used from the BSI statistics;
- The intrasector transactions within the ROW sector are set equal to zero.

Regarding the first constraint, the BSI data are not fully consistent with the EAA data but with reasonable accuracy, they provide additional information on the true links between the MFI sector and the other sectors in the selected instrument categories. The second constraint imposes the absence of transactions within the Rest of the Word because this sector is not explicitly modelled in our framework. Note that the inclusion of these two constraints in the MFI and ROW sectors affects all the other values in the estimated matrix of bilateral exposures. As a second step, the data from the BSI allow us to study the cross-border flows between the individual countries' MFI sectors. In this way, we can construct a cross-border network for the banking sectors in the euro area. Ideally, we would like to have such cross-border information for all of the institutional sectors in our system, but the data limitations prevent such an exercise for the time being. However, we argue that we are able to capture a meaningful share of the cross-border linkages. This is because in the euro area, the banking sector is the main driver of the cross-border exposures owing to the traditionally strong reliance of the other sectors of the bank intermediation services. Finally, we obtain the "Macro-Network" by combining the financial networks connecting sectors at the individual country level with the cross-border network for the banking sectors. Following this methodology, we estimate the networks with both valued and directed links, for each time period and each instrument category. The resulting total number of networks is 193.

2.3. Network measures

Network theory provides the tools to analyse the *positions* of the individual nodes in a network. To this end, the literature has developed several measures such as degree, closeness and betweenness. Degree is the sum of the direct links that each node has with other nodes. A high number of links indicates the node has a central position in the network and a large number of connections. Betweenness captures the absolute position of the node in a network. It measures the extent to which a particular node lies "between" the other nodes in the network. Closeness is a measure of influence. The most central node in the network can reach all other nodes quickly. For the mathematical details, see Table 7 in Appendix B. Links in the network can also have weights, and sometimes the heterogeneity in the intensity of links can be very large. The importance of incorporating this aspect in network analysis was stressed by Barrat et al. (2004), who provided the centrality measures for weighted graphs. More recently, the measures for weighted networks have been improved by Opsahl et al. (2010), who introduced an algorithm that considers the weight links in the network.[4] Taking advantage of these earlier studies we compute not only the standard measures of degree, closeness and centrality but also the weighted versions of these statistics for our networks. These enhanced measures are useful in our framework in which, by construction, the MFI sectors feature a large number of links than the other sectors. The algorithms used to compute these measures

[3] The methodological framework is defined in the European System of Accounts 1995 (ESA95). The data were accessed in October 2012. The data can be downloaded from the ECB web site (http://www.ecb.int/stats/acc/html/index.en.html), and a detailed documentation is available in the section Background.

[4] The algorithm involves selecting a positive value for a parameter α. For values $\alpha < 1$, the links have a positive impact on a high number of connections; for $\alpha > 1$, there is a negative impact.

allow us to take into account the direction of the links. We compute the clustering coefficient (henceforth *CC*), which is defined for a given node i as the number of actual links to the other nodes within its neighbourhood divided by the maximum possible number of links. The value of *CC* ranges between 0 and 1. The clustering coefficient for the entire graph is defined as the average *CC* of the node-specific *CCs*.

These measures characterise both the structure of the network and the position of the individual nodes in relation to the overall network. As will be discussed in detail in Section 4.3, the network statistics provide a first glance of what could happen in case the system were to be confronted by a shock.

3. Description of the network

In this section, we construct networks at the country level and, for the banking sector, at the cross-border level. We then combine the two networks to set up a large euro area "Macro Network", defined as a network of individual country-specific sector networks in which the banking sector acts as the connecting cross-border element.

3.1. Sector networks at the country level

As the first step, we construct and analyse the structures of the networks at the individual country level (as an example, Fig. 1 depicts the graph for country 5, taking a snapshot of 2012 Q1 using instrument category "debt securities"). Each instrument category provides its unique type of network, depending on the particular structure of the cross-sector interlinkages in that instrument category. The network displayed in Fig. 1 is estimated using the maximum entropy method + constraints (ME+C). The network structures at the country level are (nearly) complete, in other words each node is linked to (almost) all of the other nodes. However, when the directions and the weights of the links are considered, even in the same instrument category the patterns of connections may differ substantially across the countries, reflecting the individual structural characteristics of the different economies.

The time series of the centrality measures shed light on the evolution over time of the intersectoral relations and the relative roles of the different sectors in the economy. For example, the increasing importance of the other financial intermediaries (OFI) sector (which includes money market funds, other investment funds and leasing companies) seems particularly clear for countries 7, 10 and 8. The prominence of the MFI sector, even without the consideration of the cross-border links (which will be introduced in the next sub-section), is a common element to all of the countries, which is testimony to the fairly bank-dominated financial structures in the euro area economies. Finally, the general government sector plays a relatively more prominent role in countries 11 and 9, while the ROW sector appears to be important in countries 8, 7 and 4. This is partially related to the important connections between the ROW and the MFI sectors, which is a common element in countries 1 and 10.

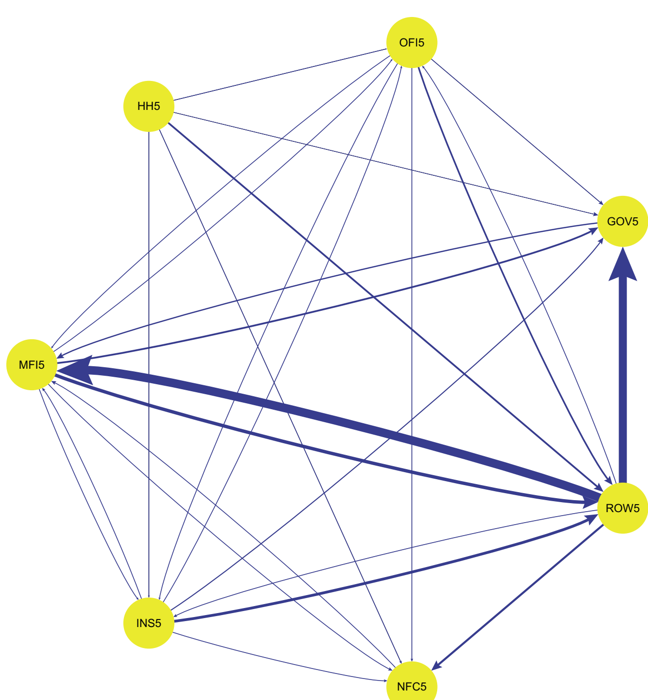

Fig. 1. Sector network at the country level. The graph exhibits the network of sectors for country 5. The nodes are the institutional sectors of the economy: the non-financial corporations (henceforth NFC), the banks (monetary financing institutions, MFI), the insurance and pension fund companies (INS), the other financial intermediaries (OFI), the general government (GOV), the households (HH), and the rest of the world (ROW); the positions are randomly assigned. The links are estimated with the maximum entropy method + constraints (instrument category: debt securities; period: Q1 2012). The different strengths of the arrows reflect the different volumes of the bilateral links.

3.2. Cross-border interconnectedness of the banking sectors

The BSI statistics provide detailed information about the financial exposures between the banking (MFI) sectors of the euro area countries. The time-evolution of the data indicates that throughout the last decade, the MFI sectors of the individual euro-area countries have grown increasingly interdependent on each other in all instrument categories (Fig. 2). However, beginning with the fourth quarter of 2007 when the crisis first erupted in the global financial markets, the graph indicates a sharp contraction in the cross border-banking flows that was most pronounced in deposits (which include interbank deposits).[5]

The representation of the cross-border linkages by a network structure is helpful in this context because it allows us to assess the importance of the indirect linkages between nodes. In principle, the cross-border MFI networks among the euro area countries should be nearly complete because there is frequently a bank in country η with a relationship with a bank in country δ (see Fig. 3). This indicates that banks in one country can be affected by the shocks to banks in another country, and the shocks can also be transmitted via banks in a third country. Two important features should be highlighted. First, although the network is almost complete, there is a large variability across countries in terms of the intensity of these linkages.[6] Second, the data indicate a sharp contraction in the cross border-banking flows; moreover, the exposures to certain peripheral countries were substantially reduced or, in a few cases, severed.

[5] Similarly, Minoiu and Reyes (2013) find that the financial crisis changed the patterns of banks' cross-border lending activities, thus reshaping the network structure.

[6] Taking into account only the most important outgoing connections for each country in each period, we find that the MFI sectors of countries 1 and 10 are the most central in the network, as they are connected to nearly all other countries. In network terminology, they are classified as "hubs", i.e., nodes with the highest number of connections. Countries 8, 4, 9 and 11 are connected to the hubs but they also share a number of linkages among each other. Countries 3, 6, 2 and 7 are in the "periphery" of the network. This analysis casts important light on the structures of the cross-border linkages in the euro area banking sector networks. However, in what follows, we focus on the generalised version of the cross-border network that incorporates all the connections between the individual banking sectors.

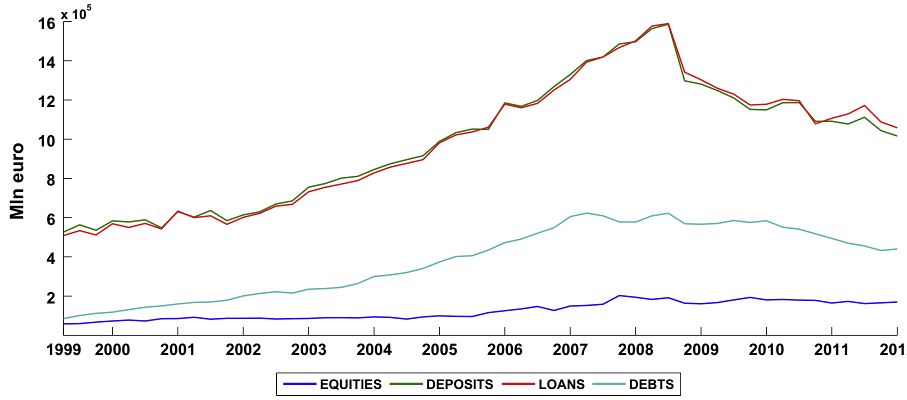

Fig. 2. Cross-border financial flows between the MFI sectors of the euro area countries. The chart illustrates the development of the cross-border exposures (in debt securities, deposits, equities and loans) throughout 1999–2012 (source: BSI data).

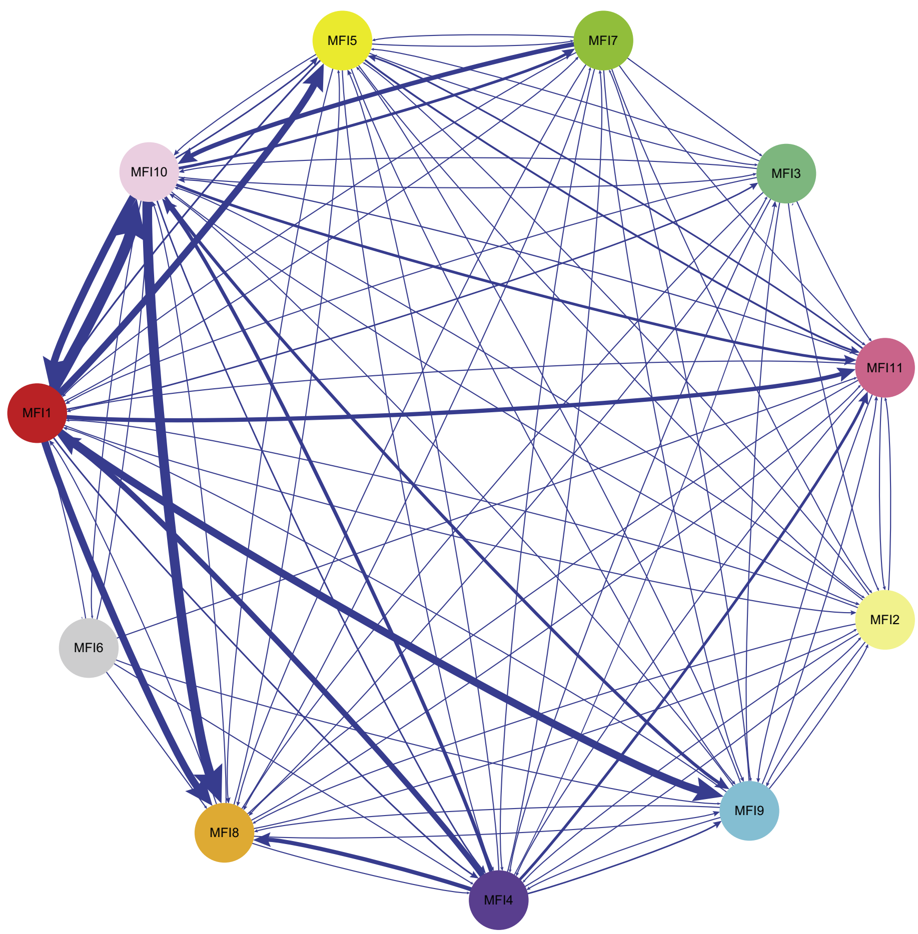

Fig. 3. Cross-border exposures of the euro area banking sectors. The graph exhibits the cross-border exposures of the banking sector of eleven euro area countries; each node represents the banking sector (MFI) of a country η (the positions are randomly assigned). The links are the actual exposures from the BSI statistics (instrument category: debt securities, period: Q1 2012). The varying strengths of the arrows reflect the respective volumes of the bilateral links.

3.3. The euro area Macro-Network

We are now ready to combine the various elements to an aggregate network consisting of both the individual country-level sector networks and the central cross-border network of the banking sectors. The banking sector has a central position by construction, because for this sector we have data on the cross-border relationships. We call the resulting aggregate system a Macro-Network. This alludes to the sector-level aggregation of its primary units (nodes), as well as to its ability to encompass the major institutional sectors at the level of the individual economies and the most relevant cross-border relationships at the level of the monetary union. In terms of network theory jargon, the core banking sector cross-border network forms a strongly connected component given that it is the most strongly connected subgraph of the entire Macro-Network. Around the core banking sector network are the subgraphs of the individual country sector networks. Fig. 4 shows that the network exhibits an almost regular topology: The average

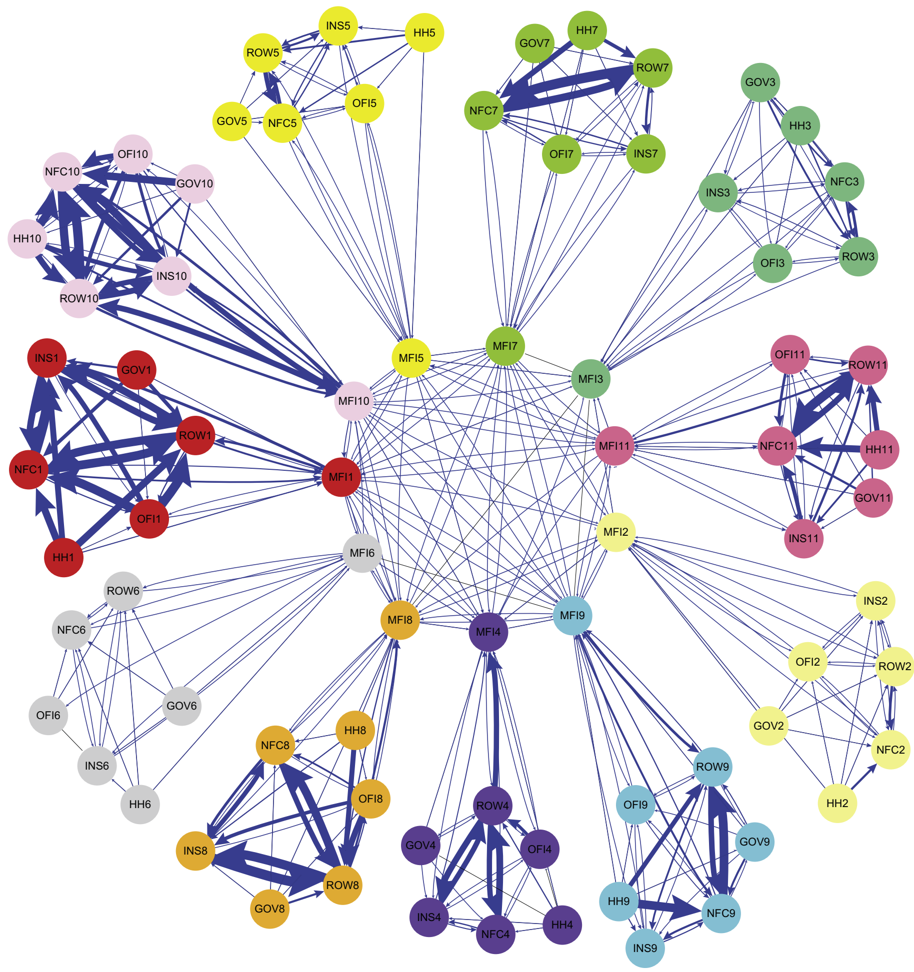

Fig. 4. The euro area Macro-Network. The graph exhibits the Macro-Network of eleven euro area countries. The nodes are the institutional sectors of the economy of each country: the non-financial corporations (henceforth NFC), the banks (monetary financing institutions, MFI), the insurance and pension fund companies (INS), the other financial intermediaries (OFI), the general government (GOV), the households (HH), and the rest of the world (ROW). The numbers η and the colours refer to the countries. We used the Kamada-Kawai energy algorithm in separating the components. The links at the individual country level are estimated with the maximum entropy method + constraints; links at cross-border level for the MFIs are the actual exposures (instrument category: debt securities, period: Q1 2012). The size of the arrows indicates the different weights.

path length is 2.50 and the clustering coefficient is 0.68 (which is quite high, although there are substantial differences across instruments, for example, the clustering coefficient is 0.45 for deposits and 0.90 for quoted shares). The diameter of the Macro-Network, that is, the greatest distance between the individual nodes, varies from 3 to 6 links. The high variance of the cluster coefficient at the node level makes the euro area Macro-Network relatively highly centralised.

Focusing the analysis at the individual-sector level, we find that the average number of the in-degree and out-degree is approximately 10.5 for the MFI sector and 4.8 on average for the other sectors in the system. Table 1 displays in detail the average levels of the in-strength (the average values for out-strength are similar); as already mentioned in Section 3.1, there are large differences across countries on this measure. In addition, the relative importance of the individual sectors varies across instruments. Overall, however, the MFI sectors appear to be important for all of the instrument categories as they are well connected and the sizes of the links that originate from them or terminate at them are on average quite large.[7] Over time, the intensity of the linkages among the sectors increases, as the overall size of balance sheet exposures has increased (at least until 2008). Indeed, the 2008–09 deleveraging episode associated with the global financial crisis strongly affected the magnitudes of the connections and, in certain cases, the shapes of the networks and the centrality measures.

Before we proceed to analyse the propagation of shocks in the system, it is important to stress that the results of these propagation simulations may depend heavily on how the linkages between the nodes are estimated (see Upper, 2011, for discussion).[8] The comparison of the network structures that can be obtained with the "standard" maximum entropy method to the structures that are produced when we include the two constraints introduced in

[7] For brevity, the values of other centrality measures are not reported but confirm those results.

[8] The maximum entropy method allows the researcher to find a unique solution for an undetermined system, favoring uniform and smooth distributions. The algorithm can also include constraints that guide the solution to a desired direction, for example, by excluding underutilized or non-existent links. In this vein, Degryse and Nguyen (2007) and van Lelyveld and Liedorp (2006) exploit the available information on the large bilateral exposures in interbank networks and estimate only the remaining unknown exposures with the ME algorithm. Other methodologies have been used to approximate different network structure, such as skewed solutions (see e.g. Markose, 2012). Recently, Craig and von Peter (2014) have empirically demonstrated the existence of a core-periphery structure in the German interbank market. van Lelyveld et al. (2012) find similar results for the Dutch banking sector. However, these works refer to individual banking institutions. Hence, given the state of the art, the maximum entropy method seems the most appropriate to estimate the domestic linkages for the aggregate level of the institutional sectors.

Table 1
In-strength: summary statistics. The table summarises the average values over time of s^{IN} for all countries and sectors. Instrument category: debt securities.

Country	NFC	MFI	INS	OFI	GOV	HH	ROW
1	97,484	1,004,122	55,286	2,664	1,094,616	0	922,558
2	23,933	44,763	11,244	99	83,548	0	62,016
3	19,461	44,891	1,792	1,044	56,381	0	58,039
4	5,091	141,148	236,455	478	45,308	0	602,935
5	28,552	178,832	7,290	1,125	157,795	0	142,349
6	10,812	3,388	4,060	25	17,8487	0	28,411
7	18,976	77,579	36,192	892	279,250	0	277,448
8	42,936	373,126	605,357	587	236,929	0	443,690
9	13,715	284,866	393,674	214	412,624	0	262,808
10	306,201	693,469	141,320	3,718	1,050,048	0	1,080,023
11	57,386	338,171	136,013	4,117	1,351,342	0	414,044

Section 2.2 is exhibited in Appendix C. Overall, the results suggest that the constraints improve the linkages estimation, adding heterogeneity across both the countries and sectors.

4. Shock propagation in the Macro-Network

After the construction of the Macro-Network at the euro area level, we are now ready to simulate shock propagation in the system. For this, we apply a channel that exploits the interconnections that exist via shareholder equity ownerships. This mechanism, which is similar to that developed by Castrén and Kavonius (2013), includes a negative credit shock (loan loss) that causes a mark-to-market drop in the value of the shareholder equity of the creditors (the banking sector). The shock is transmitted to the rest of the system via the counterparty position in the banks' equity.[9] Specifically, we describe the mechanism in a simplified three-sector framework. Suppose that a negative shock, such as a sudden decline in net income, impacts sector A, which can be any private financial or non-financial sector that issues equity shares. The balance sheets are the conduits for the transmission of the shocks; indeed the deficit in A's profit and loss (P&L) account affects the balance sheet items of the counterparty sectors B and C and, in further rounds, the balance sheet of sector A itself. We assume that A and the other sectors have to deduct losses on the P&L accounts from the shareholder equity on every period, in line with mark-to-market accounting practices.[10]

More precisely, the drop in the value of A's shareholder equity will be reflected in a decline of the asset-side holdings of those sectors that own equity in A, and thus the shock propagates in the system, reaching sectors B and C. In the subsequent round of the iteration, sectors B and C have to deduct the losses from their own shareholder equity (that is, if they issue any; we return to this point in a moment), and thus the value of the shareholder equity declines, which again will be transmitted to those sectors owning the equity issued by B and C, and so forth. The adjustments in net financial wealth and shareholder equity positions create negative feedback loops and the propagation mechanism continues as long as the losses reach a sector that is not connected to any other sector via shareholder equity.[11] Note that despite the fact that our networks represent "closed" systems, the shocks converge over time because the household and government sectors do not issue equity and therefore do not transmit the shock further.

In our analysis, we are mainly interested in studying the shock propagation over time and across countries, and thus we do not model the deleveraging processes that require endogenous responses and might follow different rules. However, our propagation mechanism partially mimics the deleveraging process. To restore the balance sheet, agents sell their financial assets. This might trigger price and valuation losses on the debt side of the balance sheets of the counterparties that issue the dis-invested assets.

We model a credit shock that begins with the banks cross-border exposures and a credit shock that originates from the banks domestic exposures. In both cases the propagation mechanism evolves as explained above. To measure the impact of the shock over discrete periods of time, we apply a round-by-round algorithm that calculates the distribution of the instrument-specific losses in each sector and of each round according to the sizes of the balance sheet linkages to the sectors that were affected in the previous round. Thus, a shock that originates in a specific sector or country spreads through the financial linkages to the entire Macro-Network. We introduce a measure, the Loss Multiplier, that is the ratio of the final total loss over the size of the initial shock and allows us to compare the effect of a shock over time and across countries. In addition, we evaluate the sectors most affected by the various shocks, the capacity of a country to export a domestic shock, and the recursive effects inside the economy. Below, we report the results of only those simulations that yielded significant results in terms of the dynamics of the model. We begin with the shocks to the banks' cross-border exposures. We then proceed on to analyse the shocks to the banks' domestic exposures. Then, to gain a better understanding of the model dynamics, we compare the results from the shock propagation simulations with the statistical insights from the network theory and repeat the simulations assuming different distributions of international exposure. Finally, we compare the results from the propagation exercise in our estimated network with the results from a network that is fully based on actual bilateral links.

4.1. Shocks to banks' cross-border exposures

The first propagation exercise focuses on the cross-border links between the euro area banking sectors. The scenario is that the banking sector of country δ, MFI_δ, does not honour its foreign obligations to the banking sector of country η, MFI_η. In this simulation, there is a cross-border interbank credit loss for MFI_η, which causes a mark to market loss in that sector's equity. The shock then propagates further both to the non-banking sectors in country η, via the domestic holdings of the equities of MFI_η, and to the banking sectors of the other euro area countries via the cross-border holdings of equity issued by MFI_η.

[9] We do not need to assume sector default.

[10] The financial sector crisis has been exacerbated by the mark-to-market accounting rules accelerating the valuation losses and their spill-over from one sector to another. Prior to the crisis, the same rules contributed to large valuation gains in several asset categories, including housing, corporate stocks and commodities, and balance sheets of the sectors which were holding such assets. Consequently, agents had additional borrowing capacity and increased their leverage, but in downturns the deterioration in asset prices worsened the investor positions and balance sheets.

[11] Alternatively, the recursive effects of the balance sheet spillover might be dissipated by sectors that are not subject to the mark-to-market accounting rules or offset the losses with profits in the P&L accounts. We do not consider such cases in the simulation exercises.

Table 2
Country effect: Final loss. We simulate that MFI_δ fails to pay 40% of its obligations to one other MFI sector (MFI_η). We exhibit the final losses for the domestic sectors of country η and, separately, for the private non-financial sectors (NFC+HH), for the banking sector (MFI), for insurance and other financial intermediaries (INS+OFI) and, for the general government. The table presents the average values and the standard deviations based on the simulations performed for all time periods.

Country	NFC+HH		MFI		INS+OFI		GOV	
	Mean	St.Dev.	Mean	St.Dev.	Mean	St.Dev.	Mean	St.Dev.
1	100,095	18,271	92,732	22,413	46,654	8,768	9,328	3,369
2	11,798	2,357	4,289	1,162	1,778	517	1,034	155
3	502	178	113	48	142	52	256	89
4	1,682	413	697	128	3,806	1,445	203	71
5	9,811	1,946	11,094	2,781	5,073	1,299	1,279	231
6	2,871	1,566	613	391	226	113	806	205
7	51,414	14,596	16,377	12,568	12,538	5,170	1,716	536
8	3,637	562	13,933	7,873	11,321	1,677	429	69
9	36,418	10,497	22,262	8,865	3,121	971	2,035	537
10	223,655	52,271	84,145	27,383	90,947	24,194	24,005	8,032
11	37,145	10,158	32,749	38,079	8,519	2,542	2,814	698

In sum, three different channels are at work. The cross-border connections in interbank loans between the national banking sectors (effect-1); the connections in cross-sector equity holdings at the country level (effect-2); and the cross-border connections in equities of the euro area banking sectors (effect-3). The final results are not a priori obvious because the process is driven by these three distinct though interconnected effects. The ultimate impact of effect-2 depends on effect-1, and the ultimate impact of effect-3 depends on the combination of effect-1 and effect-2. The propagation algorithm stops when the loss is absorbed by the system.

4.1.1. Effects of a foreign shock at the domestic level

We begin the analysis by focusing on the impacts at the country level. The algorithm allows us to choose the instrument category in which the shock (the unpaid obligations) is placed; the first simulation is carried out with the consideration that MFI_δ fails to pay 40% of its obligations to one other MFI sector (MFI_η). We repeat these simulations for each pair of banking sectors MFI_δ–MFI_η and for all periods for which the networks could be estimated at the euro area level. Table 2 presents the average values and the standard deviations of the final losses after the full propagation of the shock, separately for each country η and domestic sector. We analyse the extent to which the individual MFI sectors transmit the losses to the non-financial sectors of their respective economies, and particularly to the NFC and HH sectors that are the largest borrowers of funds from the banks. We find that these two sectors are most affected in countries 10, 1, 7 and 11. However, a closer look at the dynamics within each country reveals that in countries 5 and 8 the banking sector is the one with the highest losses.[12] The losses are more contained for the INS, OFI and GOV sector. Note that the final impact varies extensively across countries: The outcome of the shock propagation depends on the financial structure of the economy. Finally, we find that the results differ over time; this is not entirely surprising given the time-variation in the network measures that we observed above.

4.1.2. The aggregate effect after the cross-border propagation

Next, we study the overall effects of the shock propagations by exploiting the full euro area Macro-Network. Fig. 5 depicts the values of the initial losses for each country from a shock that impacts its system and the final total loss suffered by all euro-area countries after the full propagation of the shock across sectors and countries. This relationship can also be approximated by a line drawn for each MFI_δ from which the shock is assumed to originate. At a first glance, it is clear that the final losses vary substantially across countries because the initial losses generated by each country are different. In fact, each line in Fig. 5[13] representing the country from which the shock originates, has a different length. The differences in absolute values of the line length are to a great extent explained by the large differences in size across countries. Hence, we could rank the countries based on the size of the losses generated to the rest of the system to identify the "systemically important" countries in terms of simple shock propagation (of course, our analysis completely ignores any additional confidence-based contagion effects). Another important feature emerges from the smaller graph within Fig. 5 that focuses on the origin of the complete graph to better illustrate the different slopes of the lines. The slopes indicate that a shock originating from a given country does not necessarily have the same impact than a shock originating from some other country, e.g., in the propagation process, the losses originating from countries 1 and 11 become amplified by more than the losses originating from country 7.

This finding can be further clarified by computing the *"loss multiplier"*, defined as the ratio between the final total loss to the entire system and the initial loss that was caused by the payment default of the triggering country δ. The evolution over time of the loss multiplier values are plotted in Fig. 6. To better clarify this finding, in Fig. 7 we concentrate on two countries 9 and 10. The losses for each period are computed by running the propagation process under the assumption that the shock hits at the time displayed on the horizontal axis. These per-period losses are then plotted after each other to illustrate how the severity of the total losses evolves over time, assuming that a shock of varying size hits at a particular point in time. We find that the same shock would propagate in very different ways if introduced at different points in time. This reflects the changes in the intertemporal network structures that drive the changes in the degree of interconnectedness of the sector-level financial systems.

The dynamics of the loss multipliers differ across countries and over time for two reasons. First, each country generates different propagation dynamics in the system, based on its unique structure of bilateral exposures. For example, country 9 triggers an initial shock (x-axis) that is smaller than the one triggered by country 10, but the post-propagation losses that are generated by the shock originating from country 9 are larger (y-axis). Second, throughout the sample period, the loss multiplier effect first increases over time in all countries. This profile reflects the increasing volumes and interconnectivity across the countries and across the sectors within the countries over the years 2003–2007 that were characterised by rapid financial integration in the euro area. When the

[12] This is verified in country 9 when separately considering the NFC and HH sector.

[13] It refers to period Q1 2012.

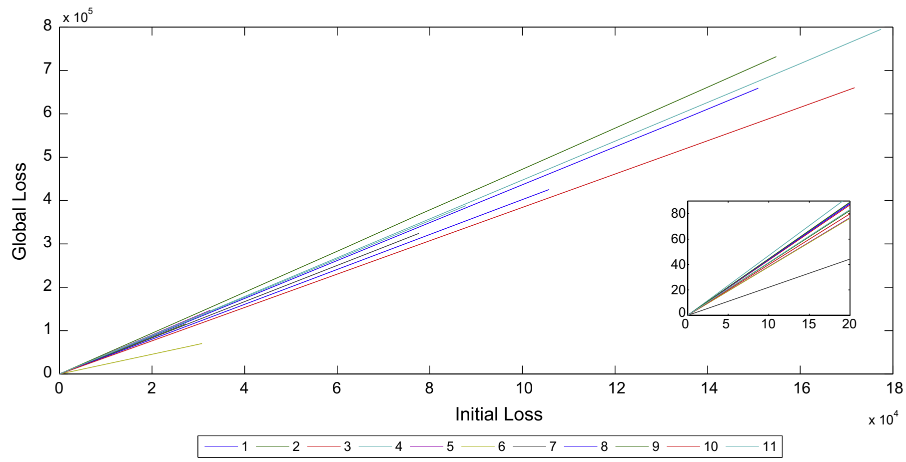

Fig. 5. Global loss in the Euro Area. The chart plots the final global loss suffered by all euro-area countries after the full propagation of the shock in the Macro-Network (on the vertical axis), against the initial loss (on the horizontal axis). Each line represents the country δ from which the shock originates. The small chart focuses on the origin (period: Q1 2012).

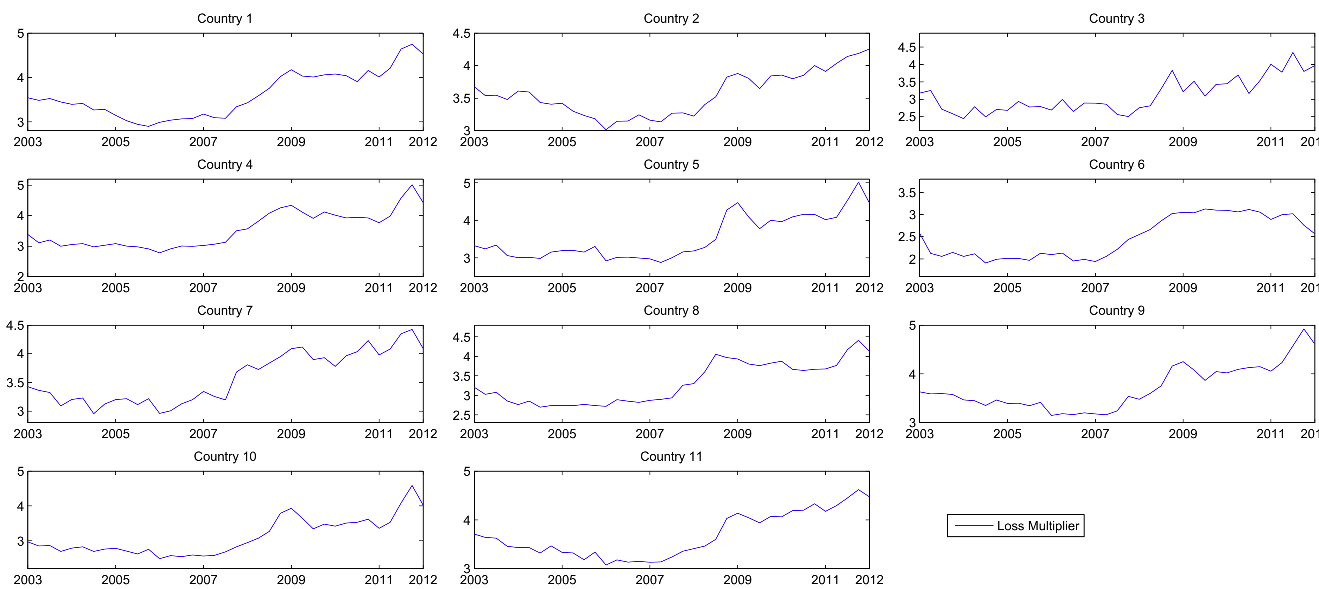

Fig. 6. Evolution of loss multipliers over time. The plots exhibit the loss multipliers (final total loss/initial loss) for each country throughout 2003–2012. The labelling of each sub-chart denotes the country from which the shock is assumed to originate (i.e., the home country of MFI_δ).

financial crisis hit, the shocks to various sectors propagated along these linkages to the other parts of the system. Since 2008–2009, we observe a decline in the loss multipliers. This captures the decline in the bilateral linkages that took place when the sectors pulled back from financial exposures to each other and started the de-leveraging process. Beginning in 2011, the shocks were again substantially amplified, generating high levels of post-propagation losses.

4.2. Shocks to banks' domestic exposures

We now focus on the propagation of domestic shocks. We assume that the MFI_δ sector is hit by unpaid claims (loans) on a domestic non-financial sector (e.g., the households of country δ). As in the previous experiment, the loss implies a deduction in the banking sector's assets, which in turn implies a corresponding loss in its equity capital. The shock then propagates to the domestic sectors in country δ that hold the equity shares issued by MFI_δ and to the banking sectors of the other euro area countries via the cross-border equity holdings. As opposed to the previous exercise, here the cross-border interlinkages come into play only in the second round. However, it is still the case that they can generate important losses.

An interesting question is which of the sectors can generate shocks that cause the largest losses in the domestic financial system and in the aggregate euro area system. Given a simulation of an initial shock of loan losses of 40% in each sector (in absolute values), HH_1, HH_{10} and NFC_{11} are the sectors that generate the largest domestic losses (panel (a) of Fig. 8). Panel (b) of Fig. 8 presents the final domestic loss divided by the total domestic assets of each sector. It indicates that each of the seven sectors has a different impact on its country's financial system, and the relative impacts differ across countries. On average, HH, NFC and GOV are the sectors that generate the largest losses within the individual countries.[14] The

[14] We do not consider shocks that originate from the ROW sector. We think that our setup is well suited to represent shocks triggered by all sectors with the exception of the Rest of the World. A framework that enables us to analyse the shocks initiated by foreign countries in a more accurate way is left for future research.

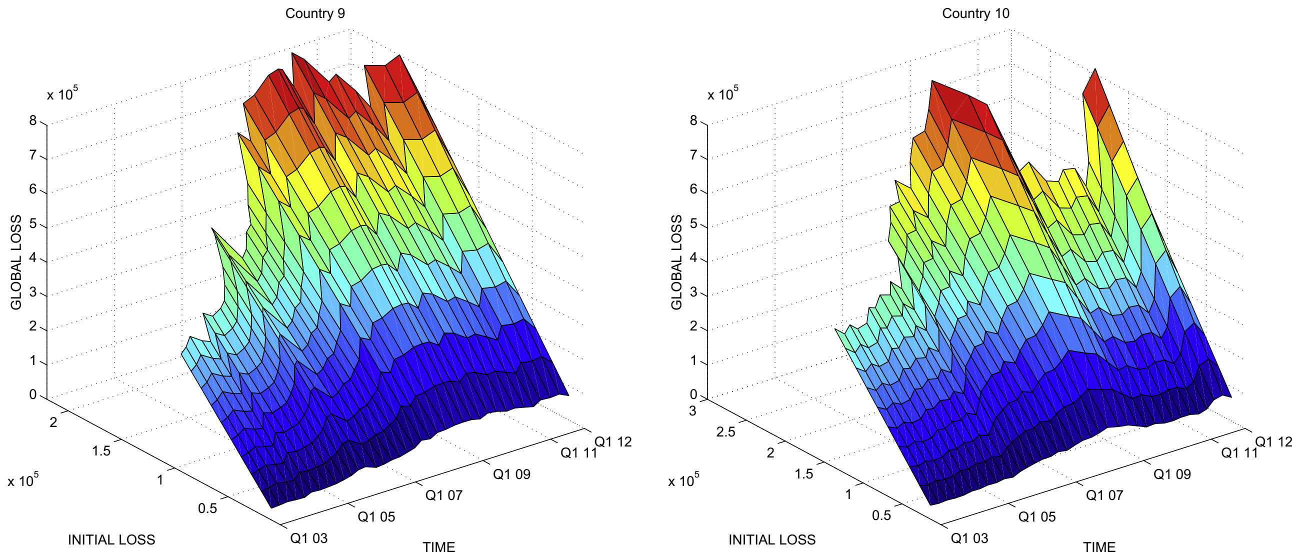

Fig. 7. Final loss from a shock in the banking sector (MFI), countries 9 and 10. The graphs exhibit the global losses at the euro area level (y-axis) and the initial loss (x-axis) over time (z-axis). The results are drawn for countries 9 (left) and 10 (right) from which the initial interbank payment shock is assumed to originate. The simulations are performed separately in each time period (2003–2012) and for all possible values of the initial losses.

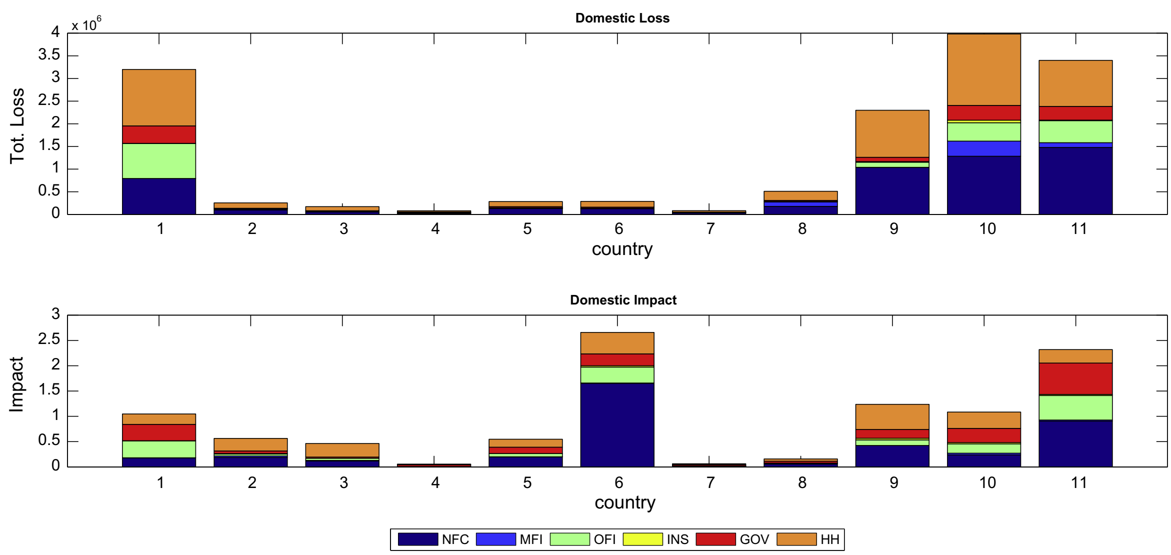

Fig. 8. Domestic shock: loss and impact on the domestic system. Panel (a) exhibits the domestic post-propagation loss given a shock originating in a sector δ. Panel (b) exhibits the total post-propagation economic impact (the final loss on all domestic sectors/total assets of sector$_\delta$) of an initial asset shock (40% loss on the loans extended) on each domestic sector (period: Q1 2012). The graphs plot the results for the sectors NFC, MFI, OFI, INS, GOV, HH for each country (identified by the numbers on the x-axis).

results at the global level are quite similar, but in some cases the relative importance of the sectors differs. Overall, countries 11 and 6, followed by countries 9, 1 and 5, produce the largest global impacts in cases of a shock to the domestic non-bank sectors. In Table 3, we exhibit the results for the loss multiplier (LM) defined as in the previous section. This measure varies across countries depending both on the particular linkages among sectors and the extent to which the country is connected with other countries via its banking sector. The results indicate that countries 10, 5 and 1 amplify the losses more than the other countries.

We also define an "*export multiplier*" (EM), measured as the ratio between the final global loss in all EA countries and the final domestic loss in the country where the shock originated from. A reading of the EM equal to 1.55 for country 5 indicates that a final loss in country 5 of 1 billion euros generates a loss for each of the other euro area countries of 550 million euros on average, i.e., half as large as the loss suffered by the country that was originally hit by the shock. Countries 8 and 7 also exhibit high values, meaning that they diffuse losses rapidly to the other countries in the network. The export ratios vary substantially across countries depending on their interconnectiveness. For a similar reason, the speed at which losses are absorbed by the system varies across countries: For shocks originating from certain countries, a couple of rounds are needed for the shock to disappear, whilst for shocks originating from other countries the process takes substantially longer. It is also possible to simulate the propagation of a shock that hits more than one sector simultaneously. In this case the results are quantitatively different because, as regards the cross-border exposures, what matters now are the net rather than the gross positions. In addition, this experiment demonstrates that there are marked differences in the dynamic responses across countries and sectors.

Lastly, Fig. 9 illustrates the dynamics of the global losses, both over time and as a percentage of the initial loss, from a shock that originates from the non-financial corporate sector in country 9 and

Table 3
Impact of shocks. The table reports the statistics of the loss multiplier (LM), the export multiplier (EM) and the number of rounds needed for the shock to dissipate (averaged across sectors, except the ROW). The LM is the ratio between the final total loss in the Euro Area and the initial loss in the triggering country. EM is the ratio between the final total loss in the Euro Area and the final domestic loss in the triggering country. "Rounds" indicates the number of rounds that the system requires to absorb the shock.

Countries	LM		EM		Rounds	
	Mean	St.dev.	Mean	St.dev.	Mean	St.dev.
1	3.56	0.55	1.28	0.17	23	14
2	2.60	0.25	1.17	0.07	14	6
3	2.13	0.27	1.11	0.06	11	7
4	1.35	0.06	1.12	0.03	9	6
5	3.96	0.71	1.55	0.27	16	10
6	1.62	0.32	1.02	0.02	8	6
7	3.16	0.70	1.72	0.42	18	6
8	3.17	0.50	1.86	0.25	24	6
9	2.86	0.48	1.14	0.06	20	10
10	4.77	0.26	1.01	0.00	33	6
11	2.93	1.55	1.14	0.08	24	11
Average	2.92	0.51	1.28	0.13	18	8

country 10. In addition, in this case the patterns of countries 9 and 10 appear substantially different from each other. Note that the evolution of the loss over time is rather different than what could be observed in Fig. 7. Country 9 displays a substantial increase in the size of the initial shock (x-axis), and combined with the pattern of the loss multiplier, triggers high levels of post-propagation losses towards the end of the period. In 2011–2012, the shocks are again substantially amplified not just in countries 9 and 10 but in all countries of our sample.

4.3. Shocks, network analysis and financial stability

The recent financial crisis unearthed the close financial connections between seemingly unrelated economic sectors. In this way, it created new challenges for financial stability analysis. We argue that network theory is a tool that can be helpful in quantifying both the complexity that is inherent in the financial systems and how various type of shocks can spread in these systems. In that sense, the stylized setting presented in this paper provides a number of insights.

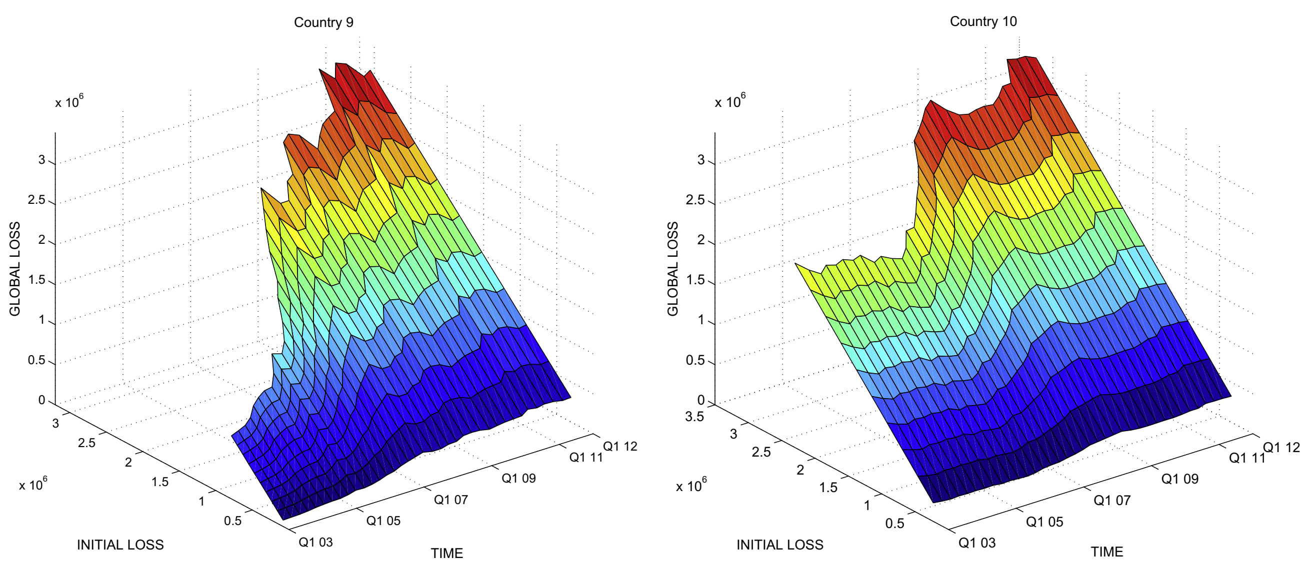

Fig. 9. Final loss from a shock in the non-financial corporations (NFC), countries 9 and 10. The graphs exhibit the global losses at the euro area level (y-axis) and the initial loss (x-axis) over time (z-axis). The results are drawn for NFC_9 and NFC_{10} from which the shock is assumed to originate. The simulations are performed separately in each time period (2003–2012) and for all possible values of the initial losses.

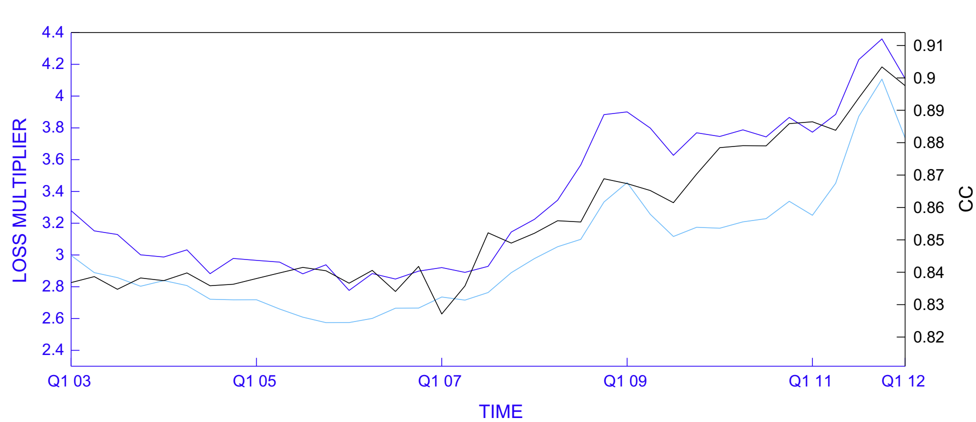

Fig. 10. Loss multiplier vs. cluster coefficient. The chart exhibits (i) the loss multiplier computed from the shock simulations on the cross-border exposures in blue (averaged across countries); (ii) the loss multiplier computed from the shock simulations on the domestic exposures in light blue (averaged across countries and sectors); and (iii) the cluster coefficient (CC is a network measure quantifying the transitivity of the Macro-Network and is computed for shares) in black, throughout 2003–2012.

Table 4
Cross border exposures of the banking sector. The table exhibits the proportions p of the exposure of the MFI_η towards its foreign banking sector counterparties (Instrument category: deposits, period: Q1-2012).

Country	1	2	3	4	5	6	7	8	9	10	11
1	0.00	0.16	0.52	0.13	0.69	0.07	0.11	0.30	0.20	0.33	0.22
2	0.01	0.00	0.00	0.00	0.00	0.05	0.02	0.00	0.06	0.02	0.00
3	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
4	0.05	0.00	0.08	0.00	0.01	0.69	0.03	0.08	0.01	0.12	0.10
5	0.13	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.02	0.02
6	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00
7	0.21	0.10	0.00	0.30	0.06	0.00	0.00	0.33	0.05	0.17	0.01
8	0.10	0.00	0.16	0.11	0.02	0.03	0.30	0.00	0.05	0.13	0.03
9	0.06	0.45	0.00	0.00	0.02	0.01	0.13	0.06	0.00	0.06	0.08
10	0.31	0.28	0.23	0.32	0.18	0.15	0.34	0.17	0.55	0.00	0.54
11	0.12	0.00	0.00	0.14	0.02	0.00	0.05	0.05	0.08	0.14	0.00

Table 5
Final loss with true (or realised) and diversified exposures. The table presents the global losses (column 2 and 3) at the euro area level after a shock originated in each country in turn (column 1). The results refer to the simulations performed with the true cross-border exposures (status quo) and the diversified cross-border exposures (diversification), for the period Q1-2012.

Country	Status quo	Diversification
1	131,488	107,946
2	22,893	20,179
3	3,885	3,476
4	77,413	68,202
5	29,041	22,439
6	13,876	22,999
7	64,570	57,055
8	84,806	78,564
9	145,925	112,917
10	131,797	120,580
11	158,581	122,368

When illustrating the results of our simulations, we introduced the loss multiplier, which allows us to compare the impact of a shock across time, countries and sectors. Importantly, we notice that on average, the loss multipliers computed for shocks both on the cross-border exposures and on the domestic exposures show dynamic patterns that are somewhat similar to the Cluster Coefficients (*CC*; see Fig. 10);[15] this confirms that the pattern in interconnectedness indeed explains the shock amplification effect. As we demonstrated previously, the reversed integration process triggered by the global crisis at the end of 2008 partially reversed the dynamics in the country-specific loss multipliers. However, the reductions are somewhat smaller in the overall *CC* (although there was a decrease in the cross-border links between the MFI sectors, see Fig. 2) and in the average loss multipliers. Despite the protracted deleveraging process and the partial reversal in the financial integration between domestic sectors and across the borders, the evidence suggests that on these measures, the risk of financial contagion was not substantially reduced.[16]

The identification of the specific measures that would effectively mitigate the risks of spill-overs and strengthen financial stability is by and large an on-going process. In our simulations, the cross-border interlinkages are demonstrated to play a crucial role in the propagation mechanisms, allowing the shocks to spread from one country to another. In this way, our framework provides a useful setting to investigate how reshaping the international exposures could mitigate the malicious feedback loops.

To accomplish this, in Table 4 we apply the BSI data to show the proportions p of the total foreign exposure of the MFI sector of country η vis-á-vis to the other countries' MFI sectors (so that the sum of the proportions of all bilateral exposures equals one in the columns of Table 4). The results in Table 4 indicate an uneven and concentrated distribution of the cross-border exposures in the banking sectors. This finding is further confirmed when we compute the Gini coefficients for each country η, which range from 0.49 to 0.8.[17]

Next, we repeat the simulation exercise of Section 4.1.2 assuming different distributions of the cross-border exposures. As a benchmark, we choose a distribution in which the exposures of the banking sectors of each country η are perfectly balanced across all counterparty banking sectors. Table 5 compares the propagation losses from using the actual exposure distributions from Table 4 and the hypothetical evenly distributed exposures, after a shock to each country in turn. The results suggest that the final losses would be mitigated if the exposures were more diversified. The magnitude of the reduction in the final losses ranges between 7% and 22%, depending on the country.[18]

In a theoretical model, Elliott et al. (2013) find that in networks, the effect of exposure diversification is not linear. A higher level of diversification reduces the extent of contagion only after a certain threshold has been passed. In addition, Allen and Gale (2000) demonstrate that under certain assumptions a complete network absorbs shocks better than a sparse network. In our framework, we compare the diversified cross-border exposures, which resemble a complete network structure in the terminology of Allen and Gale, to a sparse network of actual cross-border exposures. We find that in all network structures, certain countries absorb shocks more quickly while others generate recursive feedback loops. However, in a complete network structure the first effect tends to dominate the second one. The only exception in our sample seems to be country 6, which suggests that it is already closely connected to other countries that are dissipating shocks and would not benefit greatly from additional diversification.

The financial crisis has also underscored the risks of cross-border propagations via the balance sheets of large individual financial institutions. However, Allen et al. (2011) argue that the cross-border exposures also carry substantial benefits, not only costs. Our findings contribute to this debate by indicating that the shape of the network exposures is important. A more diversified portfolio

[15] In addition, the loss multipliers at the node level exhibit a pattern similar to the closeness (see Appendix D).

[16] Indeed, the *CC* measures how interconnected each node's neighbours are. It characterises the cohesiveness and the transitivity of the system. In the aftermath of the financial crisis, the values of *CC* are increased as feedback loops become more important at the domestic level; thus the recursive effects are magnified.

[17] The average value of the Gini coefficients across countries increases over time, confirming the results of Section 3.2.

[18] The results refer to period Q1 2012 and the initial loss is assumed to be 20% of the exposures. We obtain similar results for the different periods and the values of the initial losses.

of exposures might reduce the negative propagation effects, while a non-coordinated shedding of bilateral exposures per se does not necessarily strengthen the resilience of the system at large.[19]

5. Estimated linkages versus observed linkages from national data

This section compares the network statistics resulting from the estimated linkages and observed linkages. Among the countries included in our sample, only one provides the information on the actual linkages between the individual sectors (the so-called "who to whom accounts"). For this country, we can thus compare the estimated linkages (using both the maximum entropy and maximum entropy + constraints techniques) between sectors with the true linkages to evaluate the accuracy of the estimations. We can also contrast the results obtained from the shock simulations using either the estimated or the true networks. Although this comparison is limited to one country, it provides a rough assessment of our results given the important role played by the patterns and structures of the networks.

5.1. Methodology

One euro area country collects the complete data on the flow of funds between the individual sectors. This who-to-whom information is collected for the following instruments: the short-term and the long-term debt securities, the short-term and long-term loans, and the shares and other equity (excluding mutual fund shares). However, the data do not provide detailed information on deposits or for mutual fund shares. Furthermore, the sectoral aggregation of the data varies slightly from the one used in the previous sections of this paper (see Table 10 panel A in Appendix E). In the observed data the banking sector, the insurance and pension fund sector and the other financial intermediaries sector are aggregated under a single category "Financial Corporations". Hence, for the sake of consistency, we need to adjust our framework, summing up the values for the MFI, INS and OFI sectors for all instruments; thus, the comparison between the true linkages and the estimated linkages is undertaken according to the framework displayed in Table 10 panel B in Appendix E.

Table 6 exhibits the differences between the observed and estimated values of the linkages for the following instrument categories: debt securities, loans and equity shares. We can observe that the estimated values are not very different, on average, from the true values, especially for the debt securities. Regarding the numbers of linkages that may result from the estimations that rely on the ME+C technique, two types of errors are possible. The estimation method may either identify non-existent linkages (type-1 error), or it may fail to identify linkages that are actually present in the true data (type-2 error). Type-1 errors are more frequent with the ME+C because by definition, the method distributes the aggregate values across all sectors (albeit subject to the constraints). Compared to the networks estimated with the standard ME technique, the ME+C technique correctly identifies and drops a large number of non-existent linkages (ranging between 19% for debt securities and 39% for loans). We conclude that the maximum entropy method that is enhanced by the two constraints introduced in Section 2.2 is successful in moving the estimations closer to the true observed linkages. Crucially, by including the constraints we are able to capture the most relevant linkages between the various sectors of the economy while preserving the heterogeneity across the financial structures in individual countries.

Table 6
Estimated vs. observed linkages. The table compares the estimated vs. the observed linkages for one country, which provides detailed information on the true who-to-whom statistics. The difference reported in the table is the average difference between the estimated and observed linkages. A type-1 error indicates the average number of links identified by the ME+C method that are not present in the true data. A type-2 error indicates the average number of links that are present in the true data but are not identified by ME+C. Type-1 and Type-2 errors are expressed in percentages.

	Debt securities	Equities	Loans
Difference	143	−440	227
Type-1 error	24.86%	16.60%	13.44%
Type-2 error	3.01%	0.08%	10.35%

5.2. Shock propagation

Finally, we follow Mistrulli (2011), who analyses the shock propagation in the Italian interbank market using both the actual bilateral exposures and the connections estimated with the ME method. His results demonstrate that the ME method generally underestimates the extent of the shock propagation. We compare the effects of a shock using the true observed linkages and the linkages estimated with ME+C. This serves to provide guidance about the bias that is potentially incorporated in our simulations presented in the previous sections.

Building on the findings in Section 5.1, we find that the estimated responses of the networks using the ME+C method are quite similar to the responses of the networks computed with the observed linkages. Our estimated network tends to overestimate the reaction of the NFC sector, while for the other sectors the differences are more modest. While this outcome may be encouraging, one should nevertheless be cautious when generalising these results to other countries given the different structures of bilateral linkages across the individual countries.

6. Conclusion

In this paper we applied data from the Euro Area Accounts (flow of funds) to construct the financial networks for seven economic sectors in the 11 major euro area countries. The individual country networks were then connected to one large "Macro-Network" using information on the banking sector cross-border linkages. We evaluated the properties of these systems using the tools of network analysis. In particular, we identified the most central nodes and the key network characteristics.

While our estimated Macro-Network is a simplified representation of the true observed interlinkages within the euro area financial system, it nevertheless provides useful insights into how the financial shocks may propagate across sectors and countries. We find that the propagation effects crucially depend on two things. First, the location of the original shock (the financial instrument, economic sector and country) is crucial in terms of the aggregate post-propagation losses. For example, the shocks to bank loans in countries where the banking sectors play an important role in the financial intermediation process typically generate large losses. Second, the underlying financial network structure, that is, the centrality and connectivity of the networks of the sectors and countries, determines the speed and the extent of the propagation of the shock in the system. For example, the countries that during

[19] Note that we do not claim that a full diversification would necessarily minimise the potential losses. Indeed, the optimal distribution would be to concentrate the cross-border exposures on those countries that are able to absorb shocks without transmitting them further. See also Battiston et al. (2012), who find that the probability of default does not decrease monotonically with diversification. Similarly, in our set-up, the post-propagation effect of a shock does not decrease monotonically with the degree of cross-border diversification.

Table 7
Measures of network statistics. The table presents the formulas that are used for computing the centrality measures. The degree is the sum of all direct 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. The table reports unweighted, weighted and weighted-α versions of the statistics.

	Unweighted	Weighted	Weighted-α
Degree	$k_i = C_D(i) = \sum_j^N x_{ij}$	$s_i = C_D^w(i) = \sum_j^N w_{ij}$	$s_i = C_D^{w\alpha}(i) = \sum_j^N w_{ij}^{\alpha}$
Betweenness	$C_B(i) = \frac{g_{ij}(i)}{g_{ij}}$	$C_B^w(i) = \frac{g_{ij}^w(i)}{g_{ij}^w}$	$C_B^{w\alpha}(i) = \frac{g_{ij}^{w\alpha}(i)}{g_{ij}^{w\alpha}}$
Closeness	$C_C(i) = \sum_j^N \left[\min\left(\frac{1}{x_{ih}} + \cdots + \frac{1}{x_{hj}}\right)\right]$	$C_C^w(i) = \sum_j^N \left[\min\left(\frac{1}{w_{ih}} + \cdots + \frac{1}{w_{hj}}\right)\right]$	$C_C^{w\alpha}(i) = \sum_j^N \left[\min\left(\frac{1}{(w_{ih})^{\alpha}} + \cdots + \frac{1}{(w_{hj})^{\alpha}}\right)\right]$

Table 8
ME vs. ME + Constraints: summary statistics. The tables exhibit the estimated links using the maximum entropy method (ME) and the maximum entropy method + constraints (ME+C). The values are averaged over time and across countries for each instrument.

	Mean	St.dev.	Min	Max
ME				
Debt securities	27,179	76,287	0	762,039
Deposits	30,413	134,842	0	2,391,991
Equities	35,565	96,241	0	1,750,318
Loans	27,042	91,911	0	1,168,828
MEC				
Debt securities	27,438	91,695	0	1,297,237
Deposits	30,049	135,223	0	1,915,258
Equities	35,211	132,755	0	3,584,861
Loans	26,751	94,717	0	1,434,091

Table 9
ME vs. ME + Constraints: network measures. The table compares the average values for the Macro-Networks (instrument category: loans), computed with the maximum entropy method (ME) and with the maximum entropy method with constraints (ME+C), respectively. We exhibit the values for diameter, D (the average shortest distance), CC (the cluster coefficient), $k^{IN} - k^{OUT}$ (in- and out-degree), $s^{IN} - s^{OUT}$ (weighted in- and out-degree), C_C^w (weighted closeness), and C_B^w (weighted betweenness). For brevity, the measures with weighted-α as well as the results for all other instrument categories are omitted. However, we note that the differences between the results from the two methodologies are statistically significant in all cases. Column 4 and column 5 report, respectively, the differences in averages and statistical significance.

Network measure	ME	ME+C	Difference
Diameter	4.86	5.49	-0.63^{***}
D	2.63	2.74	-0.11^{***}
CC	0.69	0.65	0.04^{***}
$k^{IN} - k^{OUT}$	6.37	5.81	0.56^{***}
$s^{IN} - s^{OUT}$	185,823	217,646	$-31,823^{***}$
C_C^w	5.39	7.89	-2.50^{**}
C_B^w	3.28	8.90	-5.62^{**}

the years prior to the financial crisis witnessed more extensive financial integration across the individual domestic sectors and/or the sectors that witnessed growing cross-border activity unexpectedly became vulnerable to shocks that hit even remote parts of the system. This finding provides evidence of the classic knife-edge property of financial networks. Initiatives that in normal times are viewed as beneficial in terms of financial efficiency and enhanced risk sharing may become malicious in times of financial panics. Third, when confronted by losses or potential losses, the economic agents typically change their behaviour and sever the linkages to counterparties with uncertain credit quality. This is clearly demonstrated in the results for the years 2008-09, when the losses from the first rounds of the global financial crisis had propagated in the system and the sectors started to step back massively from bilateral transactions (both cross-sector and cross-border). Despite this process, our simulations also revealed that the vulnerabilities persisted in the euro area financial system, providing the channels for further loss propagation. Finally, we demonstrated that the networks that are characterised by highly diversified exposures are less prone to the shock-amplifying feedback loops, suggesting that the systems with incomplete degrees of financial integration may prove to be the least resilient to propagating shocks.

The recent global financial crisis has indeed highlighted the role of financial interconnections as a key shock-amplification mechanism. The speed at which financial shocks have spread across countries and economic regions, causing widespread economic losses, emphasises that more work is needed to identify and analyse the financial networks at different levels of aggregation. Given the dearth of information on the true bilateral linkages between the individual financial agents, obvious avenues for future research are tools that can improve on the accuracy of the estimated bilateral linkages. Improvements in the availability of the data on the cross-border interconnections beyond the banking sectors would also substantially enhance the empirical relevance of network architectures such as those developed in this paper. More work is also needed in developing the more complex propagation algorithms that are capable of incorporating the behavioural responses of the different types of financial agents to a wide range of shocks. Finally, novel theoretical contributions are needed to facilitate better communication between financial networks and traditional macroeconomic models to create more adequate tools for the analysis of financial shocks and financial structures in the macroeconomic environment.

Appendix A. Maximum Entropy

Bilateral links at the country level might be represented as follows

$$\mathbf{W} = \left(\begin{array}{ccccc|c} w_{11} & \cdots & w_{1j} & \cdots & w_{1N} & a_1 \\ \vdots & \ddots & \vdots & \ddots & \vdots & \vdots \\ w_{i1} & \cdots & w_{ij} & \cdots & w_{iN} & a_i \\ \vdots & \ddots & \vdots & \ddots & \vdots & \vdots \\ w_{N1} & \cdots & w_{Nj} & \cdots & w_{NN} & a_N \\ \hline l_1 & \cdots & l_j & \cdots & l_N & \end{array}\right)$$

where $a_i = \sum_{j=1}^N w_i j$ and $l_j = \sum_{i=1}^N w_i j$ are, respectively, the total amount of instrument-specific assets held by a sector i and issued by the other sectors and the total amount of instrument-specific liabilities of sector j claimed by the other sectors. Matrix W is not identified unless other information are available. The standard approach in the literature is to estimate $\widehat{W}$ given a prior matrix W^*, minimising the Kullback-Leibler distance subject to constraints.

$$\min_{\widehat{w_{ij}}} \sum_{j=1}^{N}\sum_{i=1}^{N} \ln\left(\frac{\widehat{W_{ij}}}{W_{ij}^*}\right) \quad (1)$$

s.t. $\sum_{j=1}^N \widehat{w_{ij}} = a_i \sum_{i=1}^N \widehat{w_{ij}} = l_j \ \widehat{w_{ij}} \geqslant 0.$

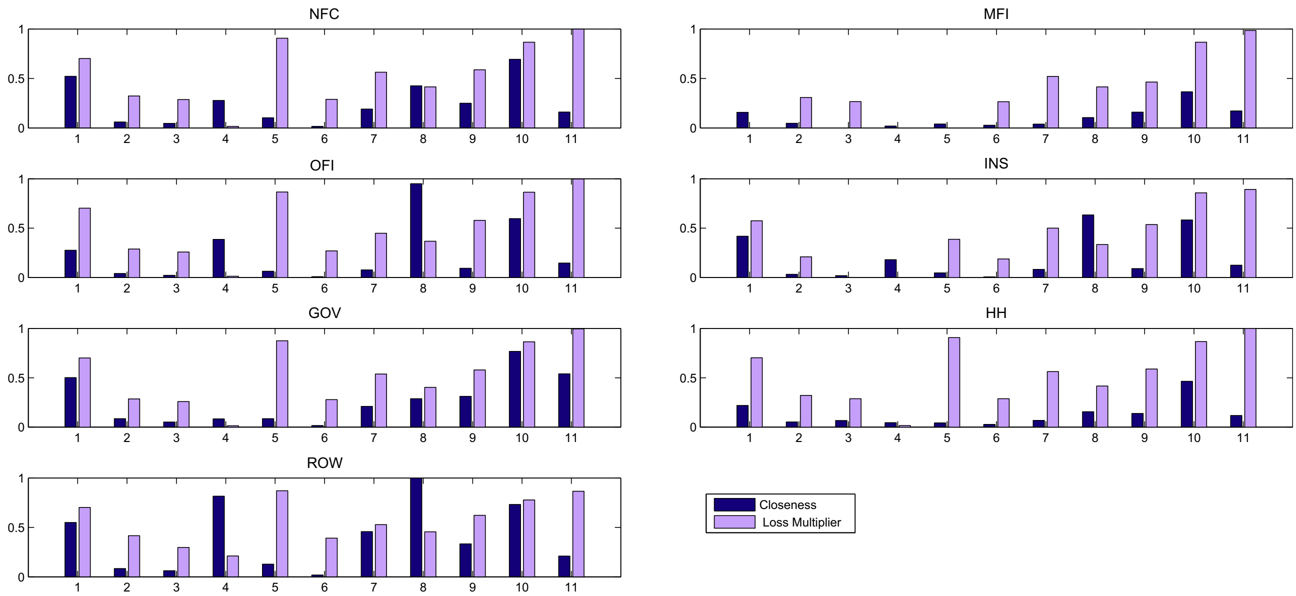

Fig. 11. The loss multiplier vs. closeness centrality measures. The charts exhibit the loss multiplier (final total loss/initial loss) after a shock originated in each sector-country and the closeness centrality measures for each sector and country (period: Q1 2012).

Table 10
Framework of the estimated and observed linkages. Panel A presents the flow of funds framework of the estimated linkages. Panel B exhibits the framework used to compare the observed linkages and estimated linkages. In both tables, w_{ij} corresponds to a financial linkage from one sector i to sector j. The institutional sectors are: non-financial corporations (NFC); banks (monetary financing institutions, MFI); insurance and pension fund companies (INS); other financial intermediaries (OFI); general government (GOV); households (HH); the rest of the world (ROW); and financial corporations (FC).

	NFC	MFI	INS	OFI	GOV	HH	ROW
Panel A							
NFC	$w_{NFC,NFC}$	$w_{NFC,MFI}$	$w_{NFC,INS}$	$w_{NFC,OFI}$	$w_{NFC,GOV}$	$w_{NFC,HH}$	$w_{NFC,ROW}$
MFI	$w_{MFI,NFC}$	$w_{MFI,MFI}$	$w_{MFI,INS}$	$w_{MFI,OFI}$	$w_{MFI,GOV}$	$w_{MFI,HH}$	$w_{NFC,ROW}$
INS	$w_{INS,NFC}$	$w_{INS,MFI}$	$w_{INS,INS}$	$w_{INS,OFI}$	$w_{INS,GOV}$	$w_{INS,HH}$	$w_{INS,ROW}$
OFI	$w_{OFI,NFC}$	$w_{OFI,MFI}$	$w_{OFI,INS}$	$w_{OFI,OFI}$	$w_{OFI,GOV}$	$w_{OFI,HH}$	$w_{OFI,ROW}$
GOV	$w_{GOV,NFC}$	$w_{GOV,MFI}$	$w_{GOV,INS}$	$w_{GOV,OFI}$	$w_{GOV,GOV}$	$w_{GOV,HH}$	$w_{GOV,ROW}$
HH	$w_{HH,NFC}$	$w_{HH,MFI}$	$w_{HH,INS}$	$w_{HH,OFI}$	$w_{HH,GOV}$	$w_{HH,HH}$	$w_{HH,ROW}$
ROW	$w_{ROW,NFC}$	$w_{ROW,MFI}$	$w_{ROW,INS}$	$w_{ROW,OFI}$	$w_{ROW,GOV}$	$w_{ROW,HH}$	$w_{ROW,ROW}$
Panel B							
NFC	$w_{NFC,NFC}$	$w_{NFC,MFI}$	$w_{NFC,INS}$	$w_{NFC,OFI}$	$w_{NFC,GOV}$	$w_{NFC,HH}$	$w_{NFC,ROW}$
$\left.\begin{array}{l}\text{MFI}\\\text{INS}\\\text{OFI}\end{array}\right\}$ FC	$w_{FC,NFC}$	$w_{FC,MFI}$	$w_{FC,INS}$	$w_{FC,OFI}$	$w_{FC,GOV}$	$w_{FC,HH}$	$w_{FC,ROW}$
GOV	$w_{GOV,NFC}$	$w_{GOV,MFI}$	$w_{GOV,INS}$	$w_{GOV,OFI}$	$w_{GOV,GOV}$	$w_{GOV,HH}$	$w_{GOV,ROW}$
HH	$w_{HH,NFC}$	$w_{HH,MFI}$	$w_{HH,INS}$	$w_{HH,OFI}$	$w_{HH,GOV}$	$w_{HH,HH}$	$w_{HH,ROW}$
ROW	$w_{ROW,NFC}$	$w_{ROW,MFI}$	$w_{ROW,INS}$	$w_{ROW,OFI}$	$w_{ROW,GOV}$	$w_{ROW,HH}$	$w_{ROW,ROW}$

Then, the RAS algorithm is used to estimate w_{ij}. In case additional information is available, it is possible to include further constraints specifying the appropriate linear equations and inequalities. Specifically, we add two constraints:

The realised data on the links between the banking (MFI) sector and all other sectors is used from the BSI statistics;

The intrasector transactions within the ROW sector are set equal to zero.

Appendix B. Network measures

See Table 7.

Appendix C. Comparison ME vs. ME+C

We compare the network structures that can be obtained with the "standard" maximum entropy method to the structures that are produced by including the two constraints. Table 9 indicates that the cluster coefficients (*CCs*) of the networks estimated with constraints are, on average, statistically different from the standard ME network *CCs*. At the individual node level, the constraints indirectly affect the entire matrix by changing the values of the links, especially when one of the two counterparties of a given node is either the MFI sector or the ROW sector. Table 8 indicates that while the values are rather similar on average, for the networks estimated with the ME + constraints, large values are more frequent. Cutting links happens more frequently for the MFI and the ROW sectors. The pattern of removed links changes over instruments (it is more frequent for loans), and varies across countries. Overall, the key contribution of the constraints is that the estimated networks are no longer all symmetric and complete, or almost complete, unlike the networks resulting from the standard ME estimation. These differences in the network structures are confirmed by the changes observed in the network metrics both at the network level and at the individual node level (Table 9).

Appendix D. Closeness and loss multiplier

Centrality measures are to some extent useful in predicting the impact of negative shocks. Fig. 11 demonstrates this in two ways. First, it displays the values of the loss multiplier for each sector and country. Second, it plots the closeness for the network in the instrument category equity shares. We consider the average of the final loss/initial shock from the exercise that simulates a shock to the banks' domestic exposures (Section 4.2). The values are rescaled. The graphs indicate that for most of the nodes, the closeness has a pattern similar to the behaviour of the loss multiplier at the node level.

From a methodological point of view, the following is an interesting result: While the network statistics provide a quantification of the importance of a node in the system, they are also helpful in identifying certain behavioural patterns at the various stages of the propagation. This does not mean that the network metrics could perfectly predict the consequences of shocks because the final effects also depend on model-specific assumptions. For example, in our specific case the absorption effect, which results from nodes that are not transmitting shocks further in the networks, cannot be captured by the centrality measures. In addition, while the closeness measures take into account all of the connections in the system, the ratio mainly reflects the linkages among the MFI sectors. Nevertheless, we argue that the network metrics applied here can provide rough ideas of how the shock dynamics of the model would look like.

Appendix E. Estimated linkages versus observed linkages: framework

See Table 10.

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