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MACRO-NETWORKS

AN APPLICATION TO THE EURO AREA FINANCIAL ACCOUNTS

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MACROPRUDENTIAL RESEARCH NETWORK

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Abstract

We use financial accounts data at sector level to construct financial networks for individual euro area countries. We then connect the country-level networks to one large "Macro Network", using information on cross-border linkages between the national banking sectors. We then evaluate the features of the resulting framework using various network statistics. Shock simulations reveal that the structural features of the bilateral linkages are a key determinant of the losses that may be generated when the shocks propagate in the system. The network structures evolve over time, showing increasing interconnectedness in different instrument categories before the financial crisis hit in 2007, and a sharp retrenchment from bilateral exposures after the crisis started. This reflects the surge in counterparty risk and the de-leveraging processes which were triggered by the initial asset price losses and were further amplified by the economic downturn. As a consequence, there was a marked deterioration in financial integration both within economies and across countries in the euro area. Nonetheless, our analysis suggests that the risk of contagion is not reduced, while a more diversified portfolio of cross-border exposures might mitigate shocks effects.

Keywords: Financial networks, Balance sheet contagion, Cross-border exposures, Interconnectedness, Financial crises

JEL Classifications: E44, F36, G01, G15, G21

Non-technical Summary

Financial interlinkages are an important mechanism through which financial flows in deposits, loans and securities products are transmitted within the financial system. A well-integrated financial system is an important element of financial efficiency since it facilitates financial risk sharing, promotes access to credit and reduces costs for households, firms and financial intermediaries.

However, while increased financial interconnectedness undoubtedly has favourable impacts during tranquil times, financial linkages also act as transmitters of local shocks and disturbances wider to the financial system. In the recent financial crisis, such adverse side-effects have been witnessed in the form of rapid propagation of losses within countries and across the borders. As a response, economic agents became increasingly aware of the risk associated with their financial counterparties and started to withdraw from bilateral transactions in many different market segments. This means that financial integration, which had seen major advances particularly in the euro area throughout the first 10 years of the Economic and Monetary Union, went partially into reverse. The 2012 ECB Financial Integration Report (ECB, 2012, page 8) states that:

"In the recent years, the financial crisis has led to a marked deterioration in European financial integration. Specifically, during 2011 the intensification of the European sovereign bond market crisis strongly affected the euro area financial system, whose degree of integration has deteriorated further… Since 2007, the integration of pan-European financial services suffered a clear setback. In light of this development, it is important to acknowledge the benefits that have resulted from financial integration coming from European initiatives during the past 25 years."

This paper applies new techniques of financial network analysis to study the changes in financial interlinkages in the euro area between 1999 and 2011. Rather than looking at financial transactions between individual financial firms, our focus is on the sector level of the economy. More precisely, we build on the work by Castrén and Kavonius (2009) and construct networks that depict the connections between the main financial and non-financial sectors of the economy in various financial instrument categories. Our main contribution is to take the previous work to a cross border level by constructing networks in two dimensions. First, we replicate the country-level networks developed by Castrén and Kavonius (2009) for 11 euro area countries. Second, we set up a separate network using data on cross-border linkages between the national banking sectors in the euro area. By combining these two sets of networks, we finally arrive at a large-scale financial network for the euro area where each individual sector in each individual country is connected to all other sectors in the system, either directly or via the cross-border links of the domestic banking sector. We call this aggregate system a "Macro Network", owing to its focus on the sector level and its ability to capture the main features that are relevant for the analysis of the financial system at the macro-prudential level.

We analyse the intertemporal network statistics of the Macro Network to gauge information about the evolution of financial integration among financial and non-financial sectors throughout our sample period. We also use the model to simulate various propagation and contagion scenarios to find out how financial losses that originate from different parts of the system multiply in the process where they propagate throughout the network. We find that the euro area Macro Network provides a very suitable platform for simulating contagion and shock propagation.

The 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 financial instrument, economic sector and country of origin. In this way we are able to identify specific sectors in particular countries which are the most prominent ones in terms of their potential of generating system-wide losses in the euro area. Second, we unearth large differences in post-propagation losses not only in quantitative but also in qualitative terms: the country-specific structures of linkages between domestic sectors and to other countries are key drivers of the propagation mechanisms, the speed of contagion and the iterative feedbacks in the model. Third, the network structures and the propagation losses are rather strongly time-variant. We perform simulations quarter-by-quarter throughout the years 2003-2011, covering also the recent financial crisis. We observe a general increase in potential economic losses caused by a standardized 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 hit, the volumes of the linkages contracted sharply due to the reduction in counterparty exposures and de-leveraging processes which ensued as endogenous responses to the financial crisis. Fourth, we show 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.

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

1. INTRODUCTION

The financial crisis which erupted in August 2007 generated global peacetime economic losses not seen since the 1930's great depression. 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. Subsequent large-scale government support measures to 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 sizes of banking sectors are large relative to GDP and government financial positions face constraints due to the fiscal rules laid down in the Maastricht Treaty. Furthermore, faced by sudden losses in their asset values, banks stepped back from their lending exposures to domestic and foreign non-financial sectors. Banks also sharply scaled back their cross-border wholesale financing exposures to counter 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, via the deteriorating debtor credit quality, the banks themselves. The end results 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 ECB, 2012).

Dudley (2009) and Stiglitz (2008) analyze the potential of 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 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 analysis to study how financial linkages between institutional sectors developed since the launch of the single European currency in 1999 and how they reacted to the financial crisis. We estimate stylized networks of sectors at the euro area country level which capture financial exposures both between 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 analyze the static and dynamic features of the financial interconnections at the euro area level. Our findings suggest that despite the deleveraging process contagion risks have not decreased; on the other hand more diversified cross-border exposures might contribute to enhance financial stability.

Network analysis has recently emerged as an appealing approach in modeling financial contagion and systemic risk. However, despite the obvious usefulness of network tools in modeling interconnections, financial applications are still relatively limited. A key reason is that a network representation requires detailed data on counterparty exposures, which is still rarely available, at least from public sources. To deal with 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), Wells (2004), Degryse and Nguyen (2007), Mistrulli (2011)). Another strand of 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 resilience to systemic risk. Gai and Kapadia (2010) investigate the effects of failures of individual institutions and how the likelihood of contagion risk depends on market conditions and network structures. In Gai, Haldane and Kapadia (2011) numerical simulations are used to study the interbank market and derive policy implications. Other papers, construct credit network and study the static and dynamic properties of financial propagation effects (Eisenberg and Noe (2001) and Battiston et al. (2012)).

Our chosen methodology relates to both these strands of literature. However, our approach differs substantially from previous applications in that we develop networks at more aggregated, or *macro*-level. Extending on the work by Castrén and Kavonius (2009), our starting point is the balance sheets of the main institutional sectors of the economy which form the nodes of the estimated networks. However, unlike in Castrén and Kavonius who use sector balance sheets at the euro area aggregate level, we use sector balance sheets at the country level for 11 countries of the euro area. The resulting networks, which are constructed separately for different instrument categories, are necessarily stylized: macro data do not allow us to capture all the complexity and interconnections which are present in the euro area financial system.[1] This notwithstanding, our approach also provides some advantages. First, it paints a broad picture of 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 shock propagation simulations, both across countries and across sectors within countries. The methodological novelties in the present paper are the inclusion of some of the cross-border elements which exist within the euro-area, additional shock propagation simulations and advances in estimating the sector level networks. Regarding the latter, we analyze the complexity of the system considering not only the direct bilateral linkages but also the indirect connections between sectors. Indeed, recent developments in network techniques allow us to identify important structural heterogeneity in 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, analyses of economy-wide contagion effects via balance sheets (interlinked claims and obligations) and liquidity spiral effects from asset fire sales and de-leveraging have mostly been contained to theory models with limited empirical data (see e.g. Kiyotaki and Moore (1997), Adrian and Shin (2008) and Shin (2008)). Recent empirical work by Degryse, Elahi and Penas (2010) use gross bilateral exposures at banking system level to investigate the transmission of shocks over the period 1999-2006. In our setting, we are interested in understanding how shocks propagate both domestically and across the borders in the euro area financial system and what is the extent of financial losses that may be generated in these processes. In this sense, our work complement theoretical studies which analyze how shocks propagate in the system as a function of network architecture (Allen and Gale (2000), Elliott, Golub and Jackson (2012) and Cabrales, Gottardi and Vega-Redondo (2011)). Particularly, Elliott, Golub and Jackson (2012) and Cabrales, Gottardi and Vega-Redondo (2011) model 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 financial instrument, economic sector and country of origin. In this way we are able to identify specific sectors in particular countries which are the most prominent ones in terms of their

[1] In general, financial agents interact with each other in complex and adaptive ways. As a result, financial systems form *complex* networks where the various channels of interdependence are hard to capture even with detailed micro-data.

potential of generating system-wide losses in the euro area. Second, we unearth large differences in post-propagation losses not only in quantitative but also in qualitative terms: the country-specific structures of linkages between domestic sectors and to other countries are key drivers of the propagation mechanisms, the speed of contagion and the iterative feedbacks in the model. Third, the network structures and the propagation losses are strongly time-variant. We perform simulations quarter-by-quarter throughout the years 2003-2011, covering also the recent financial crisis. We observe a general increase in potential economic losses caused by a standardized 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 hit, the volumes of the bilateral linkages contracted sharply, due to the reduction in counterparty exposures and de-leveraging processes which ensued as endogenous responses to the financial crisis. Nevertheless, as a result of the propagation shocks, in 2011 and 2012 vulnerabilities have not reduced in the euro area financial system. Fourth, we show 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 post-propagation losses are reduced. Sixth, we compare the results from the propagation exercise in our estimated network with results from a network which is based on true bilateral links.

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

The remainder of the paper is organized 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 some methodological aspects. Section 4 contains the simulation analyses and the shock propagation exercises, and compares the results to the predictions which arise from the various measures of network statistics. Section 5 assesses the accuracy of network estimation techniques using some limited information on true bilateral sector-level linkages. Section 6 concludes.

2. Data and Methodology

2.1. Data

Our data comes from the euro area accounts (henceforth EEA), or flow of fund statistics, at the individual country level. The flow of funds provide a record of 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.[2] 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); those 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 counterparties at the sector level. BSI statistics are available from Q1 of 2003.

Our final sample consists of quarterly data for 11 euro area countries. In terms of financial instruments, we focus our analysis on deposits, debt securities, loans and equity shares. Additional instrument categories are available but these tend to be either rather 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. Links between the nodes are computed using the EEA data and the BSI statistics in the following way. As a first step we compute, using the EEA data, financial networks connecting sectors at the individual country level. Because we do not observe directly the bilateral links between the various sectors we estimate them by using the maximum entropy method.[3] Previous literature in financial economics has mainly applied maximum entropy to estimate bilateral interbank exposures (see Upper and Worms (2004)). Castren and Kavonius (2009) extended the use of this methodology to sector level accounts by using the EEA statistics at the euro area aggregate level. Similarly, in the present paper we use the maximum entropy method to construct the matrix of bilateral links between sectors for each country.

To enhance the accuracy of the estimated bilateral links, we add two constraints to the standard maximum entropy method:

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[2] The methodological framework is defined in the European System of Accounts 1995 (ESA95).

[3] Bilateral links at country level might be represented as follow

$$W = \begin{pmatrix} w_{ij} & \cdots & w_{iN} \\ \vdots & \ddots & \vdots \\ w_{Nj} & \cdots & w_{NN} \end{pmatrix}$$

Where $a_i = \sum_{j=1}^{N} w_{ij}$ and $l_j = \sum_{i=1}^{N} w_{ij}$ are, respectively, the total amount of assets instrument specific held by a sector i and issued by the other sectors, and the total amount of liabilities instrument specific 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^*, minimizing the Kullback-Leibler distance subject to constraints.

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

s.t. $\sum_{i=1}^{N} \widehat{w}_{ij} = a_i \qquad \sum_{j=1}^{N} \widehat{w}_{ij} = l_j \qquad \widehat{w}_{ij} \geq 0$

Then, RAS algorithm is used to estimate $\widehat{w}_{ij}$. In case some additional information are available it is possible to include further constraints specifying the appropriate linear equations and inequalities.

1. True (or realized) data on the links between the banking (MFI) sector and all other sectors is used from the BSI statistics;

2. Intrasector transactions within the ROW sector are set equal zero.

Regarding the first constraint, the BSI data are not fully consistent with the EEA data but with reasonable accuracy, they provide additional information on the true links between the MFI sector and all the other sectors in selected instrument categories. Note that the inclusion of these two constraints on the MFI and ROW sectors affects all other values in the estimated matrix of bilateral exposures.

Data from the BSI allow us to study also the cross-border flows between 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 the institutional sectors in our system but data limitations prevent such an exercise for the time being. However, we argue that we are able to capture a meaningful share of all cross-border linkages. This is because in the euro area, the banking sector is the main driver of cross-border exposures owing to the traditionally strong reliance of other sectors of bank intermediation services.

2.3. NETWORK DEFINITIONS

Our sample consists of 11 countries that correspond to altogether 77 sector-level nodes for each network n. Networks with different types of nodes are defined as *heterogeneous*. Two nodes i and j are connected through edges, labelled with x_{ij}, 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: links are *directed*, because w is not symmetric in a way that $w_{ij} \neq w_{ji}$ (and similarly $x_{ij} \neq x_{ji}$).

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.

Network theory provides tools to analyze 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 all direct links that each node has with other nodes. A high number of links means the node has a central position in the network and a large number of connections.

- *Betweenness* captures the absolute position of a 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.

Links in the network can also have *weights* and sometimes the heterogeneity in the intensity of links can be very large. The importance to incorporate this aspect in network analysis was stressed by Barrat et al. (2004), who provide centrality measures for weighted graphs. More recently, measures for weighted networks have been improved by Opsahl et al. (2010), who introduced an algorithm which computes the number of *ties* in the network. The algorithm involves selecting a positive value for a parameter α. For values $\alpha < 1$, links have a positive impact on a high number of connections; for $\alpha > 1$, there is a negative impact. 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 where, by construction, the MFI sectors feature more links than the other sectors. The algorithms used to compute these measures allow us to take into account also the *direction* of the links. For the mathematical details see Table 8 in the Appendix.

We also compute the *clustering coefficient* which is defined, for a given vertex *i*, as the number of actual links to the other vertices within its neighborhood, divided by the maximum possible number of links. The value of *CC* ranges between 0 and 1. The clustering coefficient *CC* for the entire graph is defined as the average *CC* of all node-specific *CCs*.

These measures characterize 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, network statistics also provide a first glance of what could happen in case the system is 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 where the banking sector acts as the connecting cross-border element. Given the importance of the estimated connections to the overall results presented below, in the last part of this section we evaluate the accuracy of the results in light of the characteristics of the maximum entropy methodology.

3.1. SECTOR NETWORKS AT THE COUNTRY LEVEL

As the first step, we construct and analyze the structures of the networks at the individual country level (as an example, depicts the graph for country 5, taking a snapshot of 2010 Q3, using instrument category "loans"). Each instrument category provides its unique type of network, depending on the particular structure of cross-sector interlinkages in that instrument category. The networks shown in Figure 1 are estimated using the "pure" maximum entropy method + constraints. The network structures at the country level are (nearly) *complete,* in other words each node is linked to (almost) all other nodes. However, when considering the directions and the weights of the links, even in the same instrument category the patterns of connections may differ substantially across countries, reflecting the individual structural characteristics of the different economies.

The time series of the centrality measures shed some 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 considering the cross-border links (which will be introduced in the next sub-section), is a common element to all countries which is testimony to the fairly bank-dominated financial structures in the euro area economies. Finally, the ROW sector appears to be important in countries 8, 7 and 4, while the general government sector plays a relatively more prominent role in countries 11 and 9.

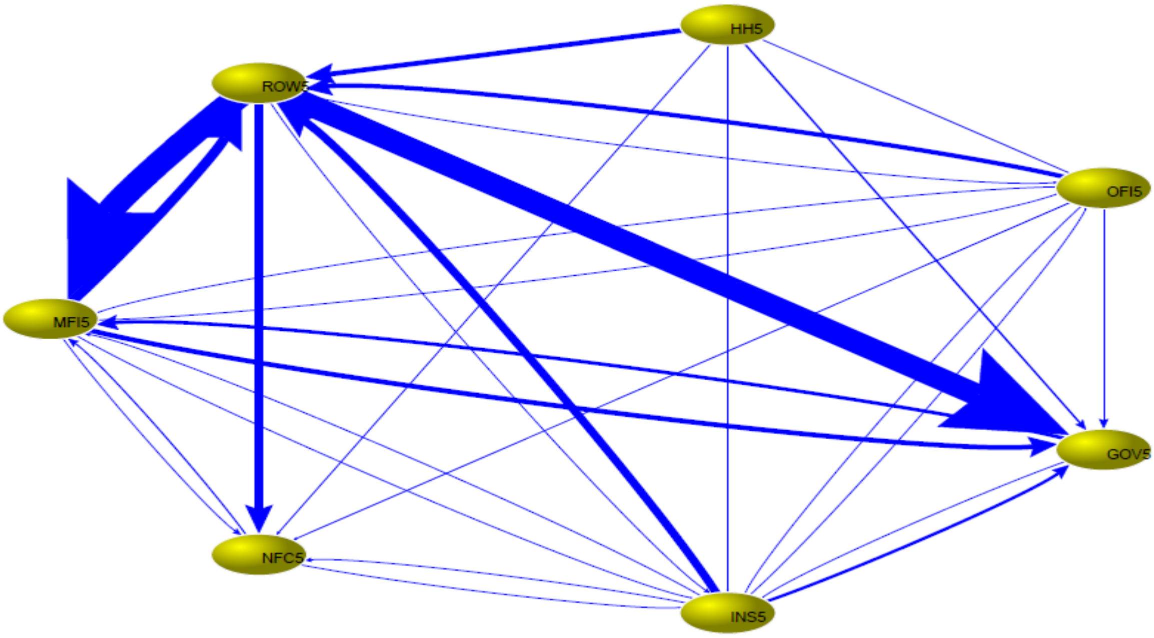

Figure 1 Sector network at the country level. The graph shows the network of sectors for country 5; nodes are the seven institutional sectors of the economy (positions are randomly assigned). Links are estimated with the maximum entropy method (instrument: debt securities, period: Q1 2012). Grey scales and sizes of arrows are used in order to display different weights.

3.2. CROSS-BORDER INTERCONNECTEDNESS OF THE BANKING SECTORS

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 (Chart 1). However, starting from the fourth quarter of 2007 when the crisis first erupted in the global financial markets, the graph shows a sharp contraction in the cross border-banking flows which was most pronounced in deposits (which include interbank deposits).[4]

[4] Similarly, Minoiu and Reyes (2011) find that the financial crisis changed the patterns of banks' cross-border lending activities, thus reshaping the network structure.

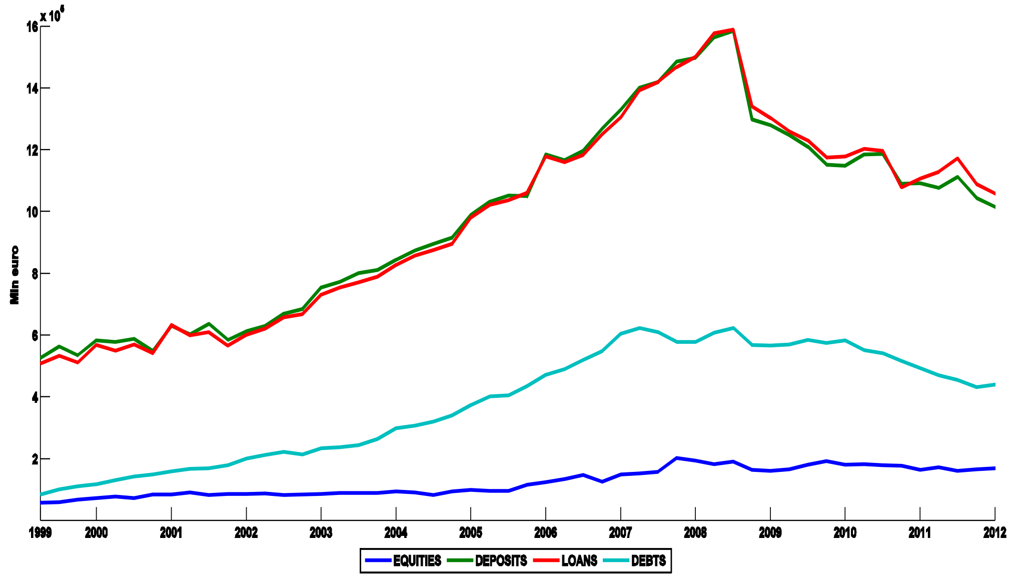

Chart 1 Cross-border financial flows between the MFI sectors of the euro area countries. The chart illustrates the development of cross border exposures (in debt securities, deposits, equities and loans) throughout 1999-2012.

The representation of the cross-border linkages through a network structure is helpful in this context because it allows us to assess the importance of *indirect* linkages between nodes. In principle, the cross-border MFI networks among the euro area countries should be almost complete because there is nearly always a bank in country η with a relationship with a bank in country δ (see Figure 2 left hand side). This means that banks in one country can be affected by shocks to banks in another country, and the shocks can also be transmitted via banks in a third country. There is a large variability across countries in terms of the intensity of these linkages. We take this aspect into account when we simplify and investigate more deeply the cross-border network of MFIs.

We begin the process by considering only the most important outgoing connections for each country in each period.[5] This approach takes into account all countries and their most important linkages. On average, each node (i.e. each country-specific MFI sector) has 3 important counterparties. The resulting network structure is shown on the right hand side of Figure 2. According to this representation, the MFI sectors of countries 1 and 10 are the most central ones in the network, as they are connected to almost 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 some linkages among each other. Finally, countries 3, 6, 2 and 7 are in the "periphery" of the network. Overall, the network is quite centralized, in particular it looks like a "star-network" with a

[5] We start by taking the average value of linkages for each sender-country and in each period. We then delete a link if its value is lower than the average. We could also look at the absolute values and delete the minor links. In this case the resulting network would consist of just 3 or 4 major euro-area countries, depending on the chosen threshold.

somewhat dispersed structure in its core (with some variability over time and across instruments).[6] As a result the average path length between the individual pairs of nodes is 1.62, which means that all nodes are reachable on average in less than two steps.[7]

In network theory the star-like structure is considered an efficient structure for information exchange, given the short communication paths. The structure is also stable in the sense that there are only few hubs. However, the structure is also vulnerable to shocks that affect those central nodes.[8]

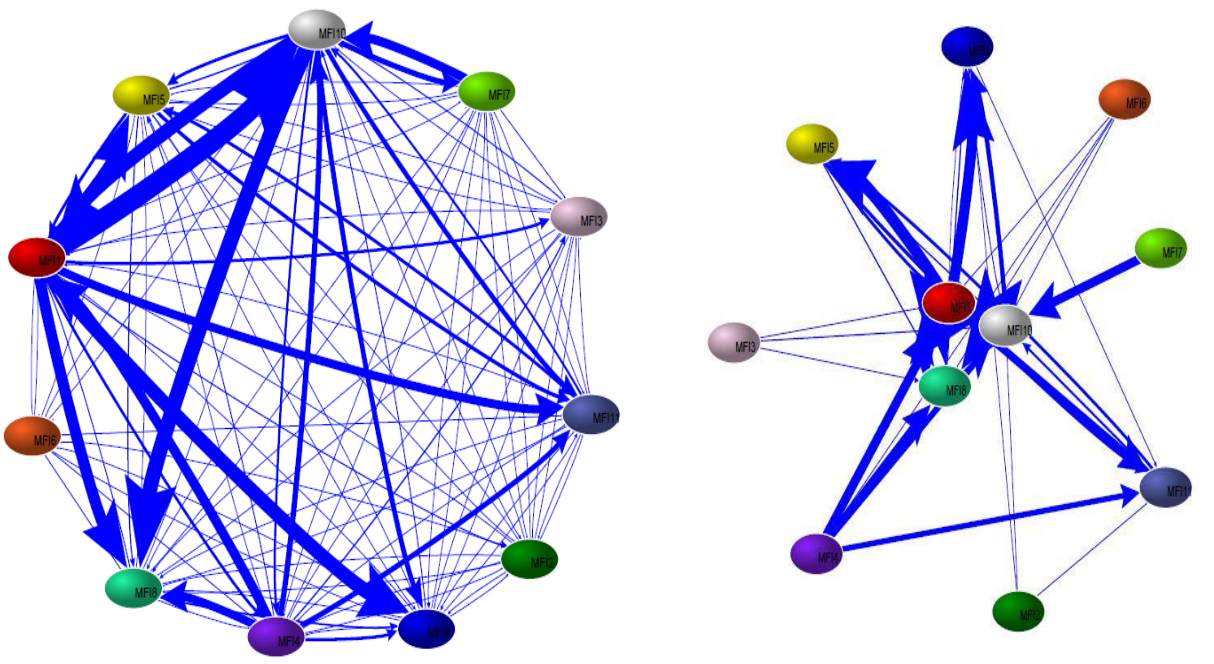

Figure 2 Cross-border exposures of the euro area banking sectors. The left-hand side graph shows all the cross-border exposures. The right hand side graph displays only the largest exposures of each sector (instrument category: debt securities, period: Q1 2012). The different strengths of the arrows reflect the different volumes of the bilateral links.

Results obtained by computing network statistics confirm the intuition from Figure 2. In particular, we focus on the "in-degree" (the number of incoming links), to measure the extent to which banks of country η are the most important counterparties for the banks in all other countries, and the "in-degree strength", or weighted in-degree, which captures the intensity of these linkages. The average number of connections for the MFI sector of countries 1

[6] A "star" structure is a network where one or few nodes are linked to many nodes which themselves have only few other links.

[7] The average path length is defined as the average shortest distance between two nodes.

[8] According to Brede and de Vries (2009) network structures typically show a trade-off between efficiency and resilience.

and 10 is very high, confirming their crucial role in the euro area cross-border banking network. For the more peripheral countries the in-degree is considerably lower.

Next, we focus on the positions of the individual nodes in the network by computing the centrality measures. These measures are not affected by the sizes of the individual countries and they allow us to better figure out the relative importance of each country. Again, closeness and betweenness measures confirm the central role of the MFI sector of countries 1 and 10 in the cross-border network. Also countries 11, 8 and 9 play a central role in networks drawn on instrument categories "equity shares" and "loans". Peripheral countries show low values of betweenness because they are located in the far corners of the network. To note, this does not mean that these countries are less important for the overall network. Rather, they have their main relationships with the banking sectors of countries 1 and 10 which form the hubs of the network, and are much less frequently connected with the "semi-core" countries.[9]

The analysis in this subsection 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 which incorporates all the connections between individual banking sectors.

3.3. THE EURO AREA MACRO NETWORK

We are now ready to combine the various elements to an aggregate network, which consists 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. 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 framework. [10] Around the core banking sector network are the subgraphs of the individual countries' sector networks.

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 all the major institutional sectors at the level of the individual economies, as well as the most relevant cross-border relationships at the level of the monetary union. Figure 3 shows that the network exhibits an almost regular topology: the average path length is 2.50, 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 shares). The diameter of the Macro Network, that is, the greatest distance between 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 centralized.

[9] Details of the analysis are available upon request from the authors.

[10] A subgraph is strongly connected if it contains a direct link from i to j and a direct link from j to i for every pair of vertices i and j.

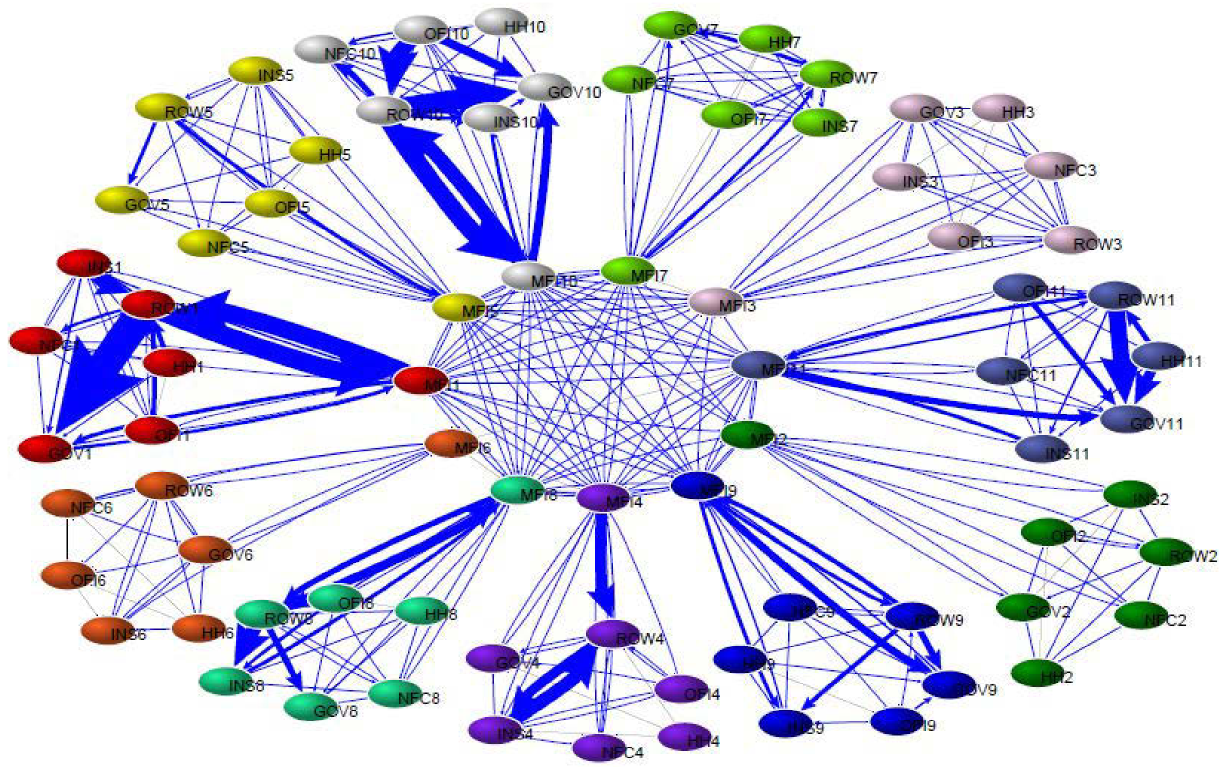

Figure 3 The euro area Macro Network . The graph shows the macro network of eleven euro area countries. We used the Kamada-Kawai energy algorithm in separating the components (instrument: debt securities, period: Q1 2012). Size of arrows are used in order to display different weights.

Focusing the analysis at the individual sector level we find that the average number of in-degree and out-degree is around 10.5 for the MFI sector and 4.8 on average for all the other sectors in the system.

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	99.096154	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	10812.192	3,388	4,060	25.134615	178487.27	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

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

Table 1 shows in detail the average levels of in-strength (average values for out-strength are similar); as already mentioned in section 3.1 there are large differences across countries on this measure. Also, the relative importance of individual sectors varies across instruments.[11] Overall, however, MFI sectors appear to be very important for all 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.

The other centrality measures are shown in Table 10 in Appendix and confirm the heterogeneity across countries and sectors. A high degree of betweenness means that a node has a high importance over what flows in the network, including potential losses in the system. At the same time, a node that is 'close' to many other nodes is more exposed in case there is a shock to any other parts of the network. Nodes lying on several shortest paths between other pairs of nodes are the MFI sectors, and the NFC sector for some countries. In terms of closeness-centrality measures, HH and ROW sectors play an important role in a few countries.

The intensity of linkages among sectors has increased over time, 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, also the shapes of the networks and the centrality measures.

3.4. METHODOLOGY: MAXIMUM ENTROPY VS MAXIMUM ENTROPY + CONSTRAINTS

Before we move 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 nodes are estimated (see Upper (2011) for discussion).

The maximum entropy method allows the researcher to find a unique solution from 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 available information on large bilateral exposures in interbank networks and estimate only the remaining unknown exposures with the ME algorithm. In this section we compare the network structures which can be obtained with the "standard" maximum entropy method to the structures which are produced when we include the two constraints introduced above in section 2.2.

Table 3 shows that the cluster coefficients (*CC*s) of the networks estimated with constraints are, on average, statistically different from the standard ME network *CC*s. At the individual node level, the constraints indirectly affect the entire matrix by changing the values of links, especially when one of the two counterparties of a given node is either the MFI sector or the ROW sector. Table 2 shows that while the values are rather similar on average, for the networks estimated with ME + constraints large values are more frequent. Dropping links happens more

[11] For the sake of brevity in Table 10 (in Appendix) we report only the values for instrument category "debt securities". Results for other instruments are available upon request.

frequently for the MFI and the ROW sectors. The pattern of removed links varies across instruments (it is more frequent for loans), and 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. The 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 3).

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

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**

Table 3 ME vs ME + Constraints: network measures. The table compares average values for macro networks (instrument category: loans), computed with maximum entropy method (ME) and with maximum entropy method with constraints (ME+C), respectively. We show 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, 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.

4. Shock propagation in the Macro Network

After we constructed 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 which exploits the interconnections that exist via shareholder equity ownerships. This mechanism, which is similar to that developed by Castrén and Kavonius (2009), includes a negative credit shock (loan loss) which causes a mark-to-market drop in the value of shareholder equity of the creditors (the banking sector). The shock is transmitted to the rest of the system via counterparty positions in banks' equity.[12]

To be somewhat more specific, we describe the mechanism in a simplified three-sector framework. Suppose that a negative shock, such as a sudden decline in net income, hits sector *A* which can be any private financial or non-financial sector which issues equity shares. Balance sheets are the conduits for the transmission of shocks, indeed deficit in *A's* profit and loss (P&L) account affects the balance sheet items of counterparty sectors *B* and *C* and, on further rounds, the balance sheet of sector *A* itself. We assume that *A* and all the other sectors they have to deduct losses on P&L accounts from shareholder equity on every period as if they adopt mark-to-market accounting.[13]

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 which own *A's* equity, and so the shock propagates in the system reaching sector *B* and *C*. In the subsequent round of the iteration, sector *B* and *C* have to deduct the losses on their asset holdings from their own shareholder's equity (if they issue any; we return to this point in a moment), and so the value of their shareholder equity declines, which again will be suffered by those sectors owning the equity issued by *B* and *C*, and so forth. Adjustments in net financial wealth and shareholder equity positions create negative feedback loops and the propagation mechanism continues as long as losses reach a sector that is not connected to any other sector via shareholder equity.[14] 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, within the financial accounts they do not transmit the shock further.

In our analysis, we are mainly interested in studying shock propagation over time and countries, and so we do not model deleveraging processes which require endogenous responses and might follow different rules. However, our propagation mechanism partially mimics the deleveraging process. In order to restore their balance sheet, agents sell their financial assets, which in turn might trigger price and valuation losses on the debt side of the balance sheets of counterparties issuing the dis-invested assets, inducing further sales by the issuing sectors.

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

[13] The financial sector crisis has been exacerbated by 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 lead to large valuation gains in several asset categories, including housing, corporate stocks and commodities, which leads to stronger balance sheets of all sectors holding such assets or derivatives products. Consequently, agents had additional borrowing capacity and increased their leverage, but in downturns the deterioration in the assets' prices worsened investors' positions and balances.

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

To measure the impact of the shock over discrete periods of time, we apply a round-by-round algorithm which calculates the distribution of the instrument-specific losses in each sector and on each round according to the sizes of the balance sheet linkages to the sectors that were affected in the previous round.

The algorithm allows us to carry out various types of alternative experiments. However, below we only report the results of those simulations which yielded significant results in terms of the dynamics of the model. We start with shocks to banks' cross-border exposures. We then move on to analyze shocks to banks' domestic exposures. Then, in order to gain a better understanding of the model dynamics, we compare the results from the shock propagation simulations with statistical insights from network theory and we repeat the simulations assuming different distributions of international exposures. Finally, we compare the results from the propagation exercise in our estimated network with results from a network which is based on true 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 an 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 domestic holdings of equities of MFI_{η}, and to the banking sectors of all other euro area countries via the cross-border holdings of equity issued by MFI_{η}.

In sum, three different channels are at work. Cross-border connections in interbank loans between banking sectors (effect-1); connections in cross-sector equity holdings at country level (effect-2); and 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 but 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 start the analysis by focusing on the impacts at the country level. The algorithm allows us to choose the instrument category where the shock (unpaid obligations) is placed; first simulation is carried out considering that MFI_{δ} fails to pay its obligations to one other MFI sector (MFI_{η}). The left part of Table 4 shows the average values and standard deviations of the final losses after full propagation of the shock, separately for each country η. The final loss for all sectors is on average 2.3 times larger than the initial shock but it varies substantially from 1.2 when the shock starts from country 4 to 4.7 when it starts from country 10. Taking a closer look at the dynamics within each individual country, MFI_{I} is the banking sector with highest losses. Next, we analyse the extent to which the individual MFI sectors transmit losses to the non-financial sectors of their respective economies, and particularly to the NFC and HH sectors which are the largest borrowers of funds from the banks. We find that these two sectors are most affected in countries 10, 9, 2 and 11. Note that the final impact varies extensively across countries: the outcome of the shock propagation depends on the structure of the economy.

Second, we simulate the propagation of a shock from MFI_{δ} to all the other banking sectors simultaneously. This scenario provides an overall picture of the propagation channels that are at work when more than one banking sector is hit by a shock at the same time. The size of the initial shock is the same as in the previous simulation but, as can be seen in the right part of Table 4, the results are to some extent different. For example, for a shock assigned on the banking sector of country 10, the final loss on all other banking sectors is significantly higher than in the previous scenario (on average the ratio is 5.97). In contrast, if the shock is assigned on countries 3 or 4, the losses are almost unchanged from the previous scenario. Regarding the individual banking sectors, MFIs in countries 10 and 11 are again those suffering the largest losses. In this exercise, country-specific dynamics are magnified by the cross-border effects via the banking sectors, while the results from the first simulation were primarily driven by the dynamics within individual countries and only to a lesser extent by cross-border effects (effect-3).

Finally, we repeat these simulations for all periods for which the networks could be estimated at the euro area level. 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.

	1 country						*11 countries*					
Countryη	All sectors		MFI		NFC+HH		All sectors		MFI		NFC+HH	
	Mean	St.Dev.	Mean	St.Dev.	Mean	St.Dev.	Mean	St.Dev.	Mean	St.Dev.	Mean	St.Dev.
1	2.79	0.28	0.85	0.22	0.91	0.09	2.99	0.30	0.95	0.23	0.95	0.10
2	2.24	0.07	0.40	0.05	1.11	0.05	2.83	0.57	0.65	0.25	1.31	0.18
3	1.88	0.16	0.13	0.03	0.59	0.08	1.95	0.22	0.15	0.06	0.61	0.08
4	1.20	0.02	0.03	0.01	0.06	0.01	1.28	0.06	0.06	0.03	0.06	0.01
5	2.59	0.27	0.80	0.25	0.70	0.07	2.72	0.27	0.87	0.25	0.72	0.07
6	1.57	0.25	0.22	0.23	0.71	0.13	2.20	0.93	0.53	0.59	0.84	0.08
7	1.86	0.14	0.21	0.10	0.74	0.13	2.02	0.21	0.28	0.11	0.79	0.15
8	1.70	0.10	0.34	0.12	0.10	0.01	2.64	0.44	0.81	0.21	0.13	0.02
9	2.51	0.33	0.71	0.27	1.15	0.04	3.58	1.04	1.24	0.61	1.49	0.25
10	4.70	0.26	0.77	0.12	2.09	0.16	5.97	0.60	1.17	0.21	2.55	0.27
11	2.52	1.26	0.97	1.25	0.98	0.02	3.99	2.44	1.86	2.15	1.35	0.25
Average	2.32	0.29	0.49	0.24	0.83	0.07	2.92	0.64	0.78	0.43	0.98	0.13

Table 4 Country effect: Final loss over initial shock. We compute the final losses over the initial shock on MFI_{η}. We perform two sets of simulations: in the left part of the table MFI_{δ} fails to pay its obligations to one other MFI sector (MFI_{η}), whereas in the right part of the table MFI_{δ} defaults on its obligations to all other MFIs simultaneously. We show the final losses for all sectors and, separately, for the banking sector and for the private non-financial sectors. The table shows the average values and the standard deviations based on simulations performed in all time periods.

4.1.2. THE AGGREGATE EFFECT POST CROSS-BORDER PROPAGATION

Next, we study the overall effects of shock propagations by exploiting the full euro area macro network. Chart 2 depicts the values of the initial losses for each country from a shock that hits 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$_{\delta}$ 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 that each country can generate are different. In fact, each line in Chart 2, representing the country where the shock originates from, has different *length.* Differences in absolute values of line length are mostly explained by large differences in sizes across countries. Hence, we could rank the countries based on the size of the losses they can generate to the rest of the system to identify "systemically important" countries in terms of simple shock propagation (of course, our analysis completely ignores any confidence-based contagion effects). Another important feature emerges from the smaller graph within Chart 2 which focuses on the origin of the complete graph to better illustrate the different *slopes* of the lines. Different slopes mean 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 losses originating from countries 1 and 9 get amplified by more than losses originating from country 5.

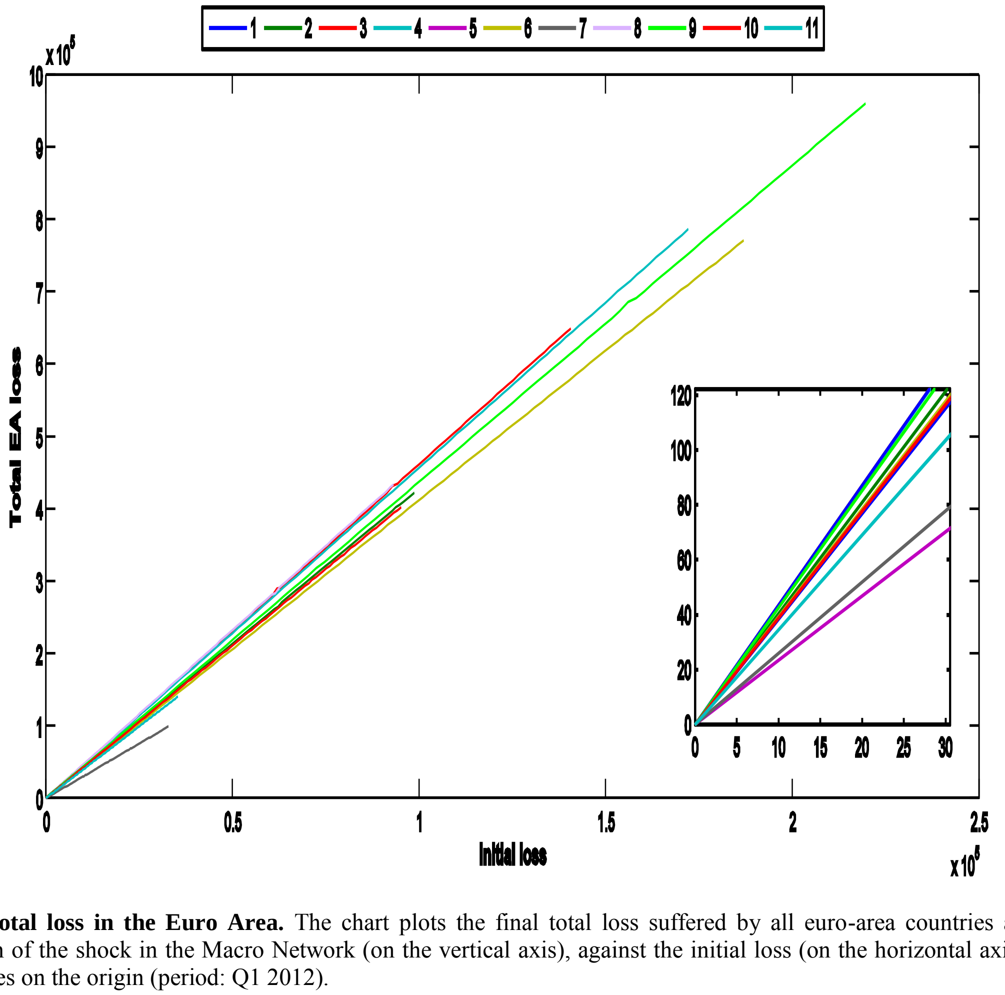

Chart 2 Total loss in the Euro Area. The chart plots the final total loss suffered by all euro-area countries after the full propagation of the shock in the Macro Network (on the vertical axis), against the initial loss (on the horizontal axis).The small chart focuses on the origin (period: Q1 2012).

This finding can be further clarified by computing a *"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 Chart 3.

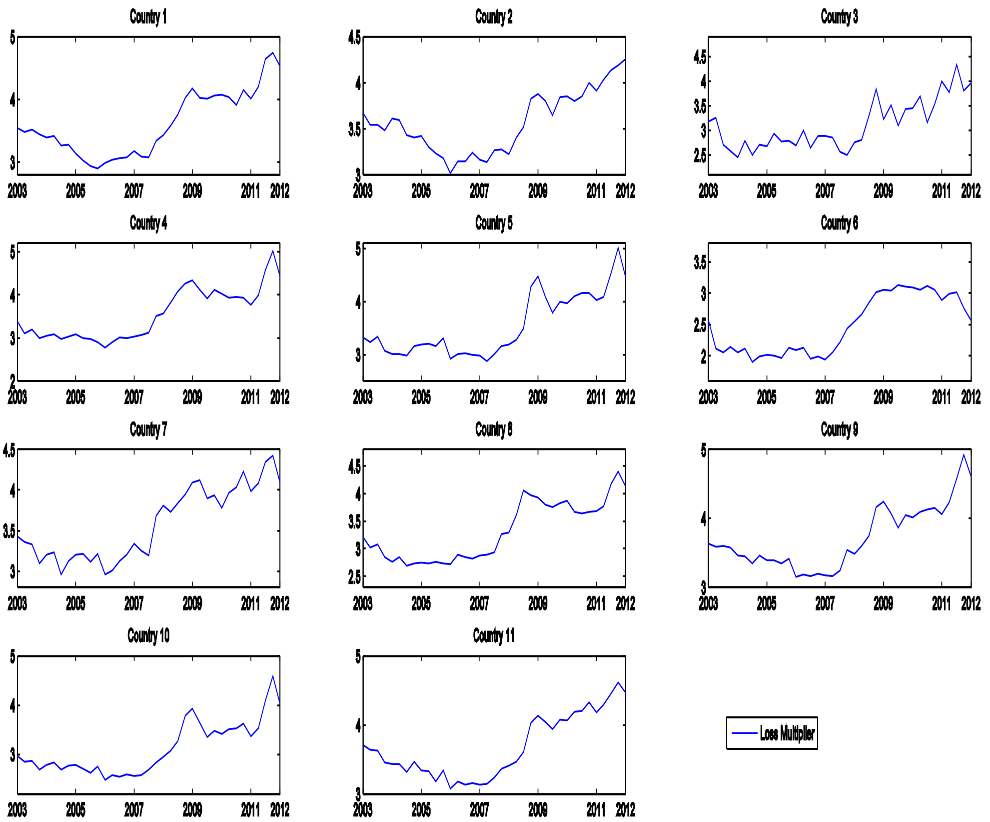

Chart 3 Evolution of loss multipliers over time. Plots show the loss multipliers (final total loss/initial loss) over time for each country. The labeling of each sub-chart denotes the country where the shock is assumed to originate from (i.e. the home country of MFI_{δ}).

Finally, in Chart 4, we exploit the loss multipliers from Chart 3 and repeat the simulation exercises in all periods. The losses for each period are computed by running the propagation process under the assumption that the shock hits at the time shown 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 a varying size hits at a particular point in time. We find that the same shock would propagate in very different ways if it was introduced in 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) which is smaller than the one in country 10, but the post propagation losses is bigger (y-axis). Second, throughout the sample period, the loss multiplier effect first increases over time in all countries. This profile reflects the increasing interconnectivity across countries and across sectors within countries over the years 2003-2007 which were characterized by rapid financial integration in the euro area. When the financial crisis hit, shocks to various sectors propagated along these linkages to other parts of the system. Since 2008-2009, we observe a decline in loss multipliers. This captures the decline in bilateral linkages which took place when sectors pulled back from financial exposures to each other and started a de-leveraging process. Yet, in 2011-2012 shocks are again substantially amplified triggering high levels of post-propagation losses.

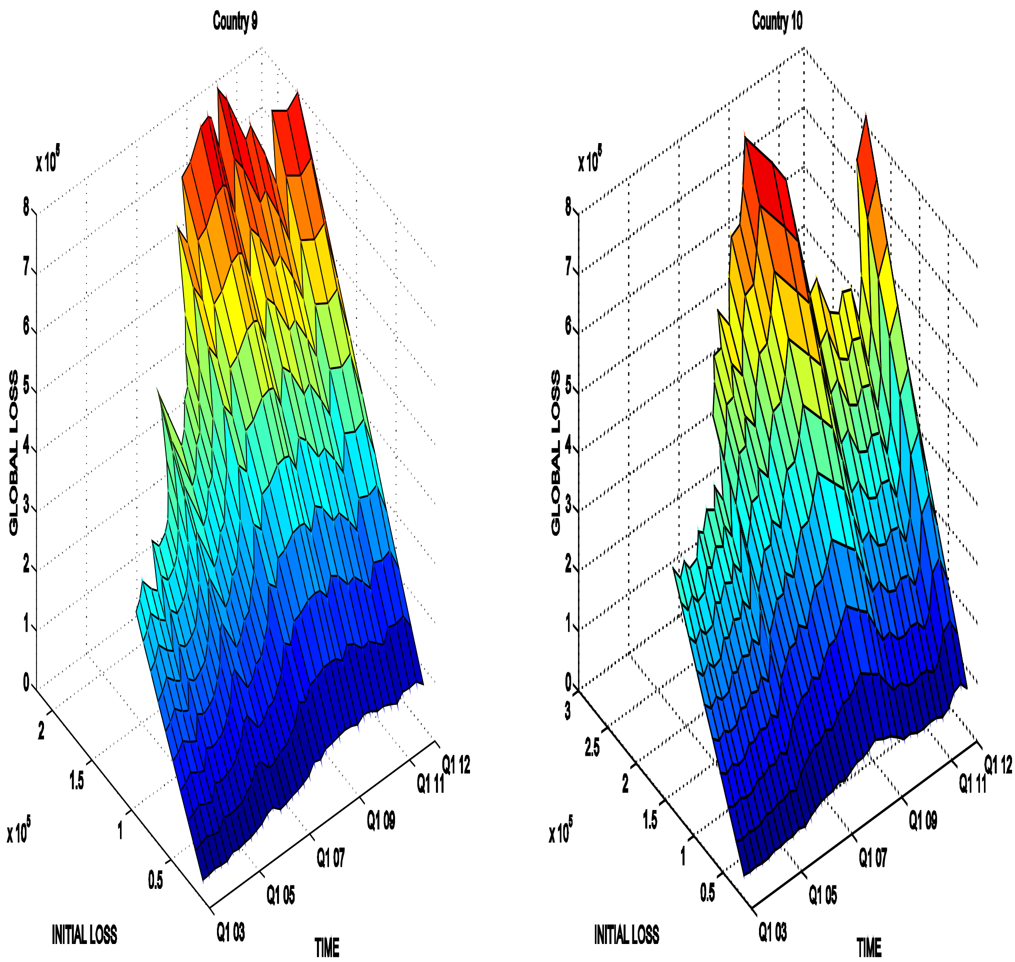

Chart 4 Final loss from a shock in MFI, countries 9 and 10. The graphs show the global losses at the euro area level (y-axis) and the initial loss (x-axis) over time (z-axis). Results are drawn for countries 9 and 10 from which the initial interbank payment shock is assumed to originate. Simulations are performed separately in each time period and for all possible values of initial 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. 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 further to all domestic sectors in country δ which hold equity shares issued by MFI_{δ}, and to the banking sectors of all other euro-area countries via the cross-border equity holdings. Different from the previous exercise, here the cross-border interlinkages come into play only in the second round. However, it turns out that they can still generate important losses.

An interesting question is which are the sectors that can generate shocks that cause the largest losses in the domestic financial system and in the aggregate euro area system? Simulating an initial shock of loan losses of 40% in each sector (in absolute values), HH_1, HH_{10} and ROW_1 are those that generate the largest domestic (panel (a) of Chart 5) and global losses (panel (a) of Chart 6). Panel (b) of Chart 5 reports the final domestic loss divided by the total domestic assets of each sector. It shows that each of the seven sectors has a different impact in its own country's financial system, and the relative impacts differ across countries. On average, HH, NFC and GOV are the sectors which generate the largest losses within the individual countries. Results at the global level are quite similar but in some cases the relative importance of sectors differs (Chart 5). Overall, countries 11 and 6, followed by countries 9, 1 and 5, are those which produce the largest global impacts in case of a shock to one of their domestic non-bank sectors.

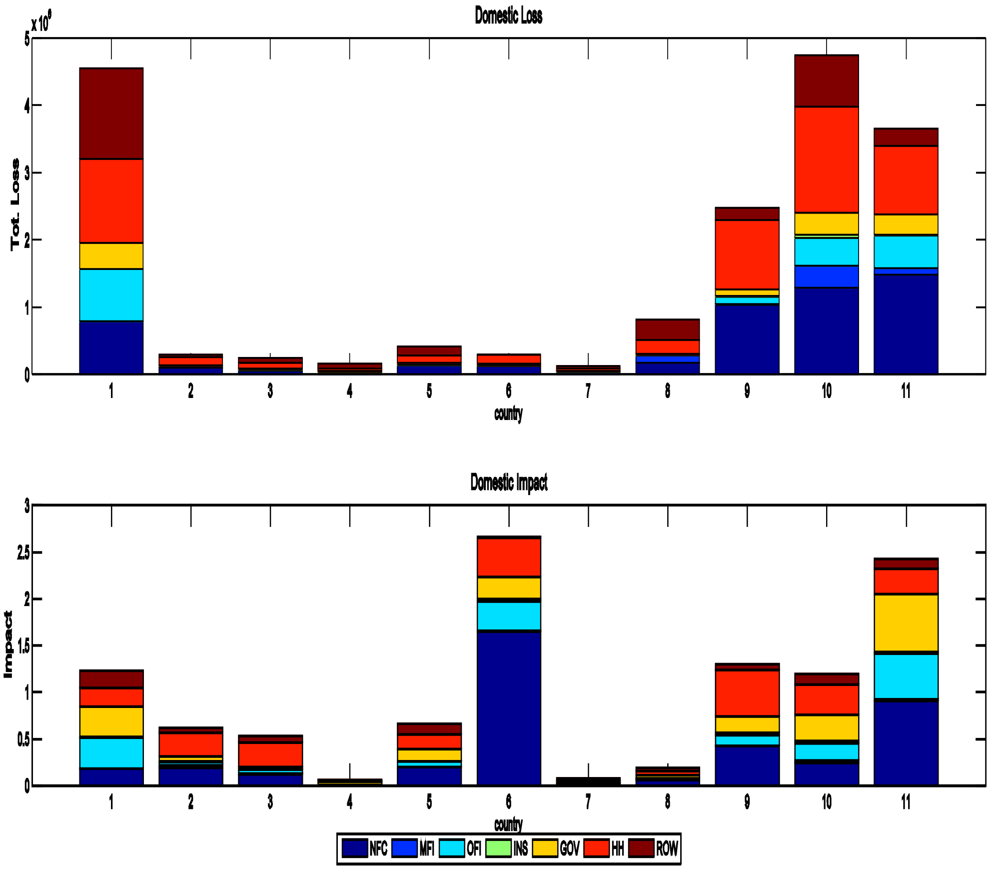

Chart 5 Domestic shock: loss and impact on the domestic system. Panel (a) shows the domestic post-propagation loss from a shock to sector δ. Panel (b) shows the total post-propagation economic impact (final loss on all domestic sectors/total assets of sector$_\delta$) of an initial asset shock (40% loss on loans extended) on each domestic sector (period: Q1 2012).

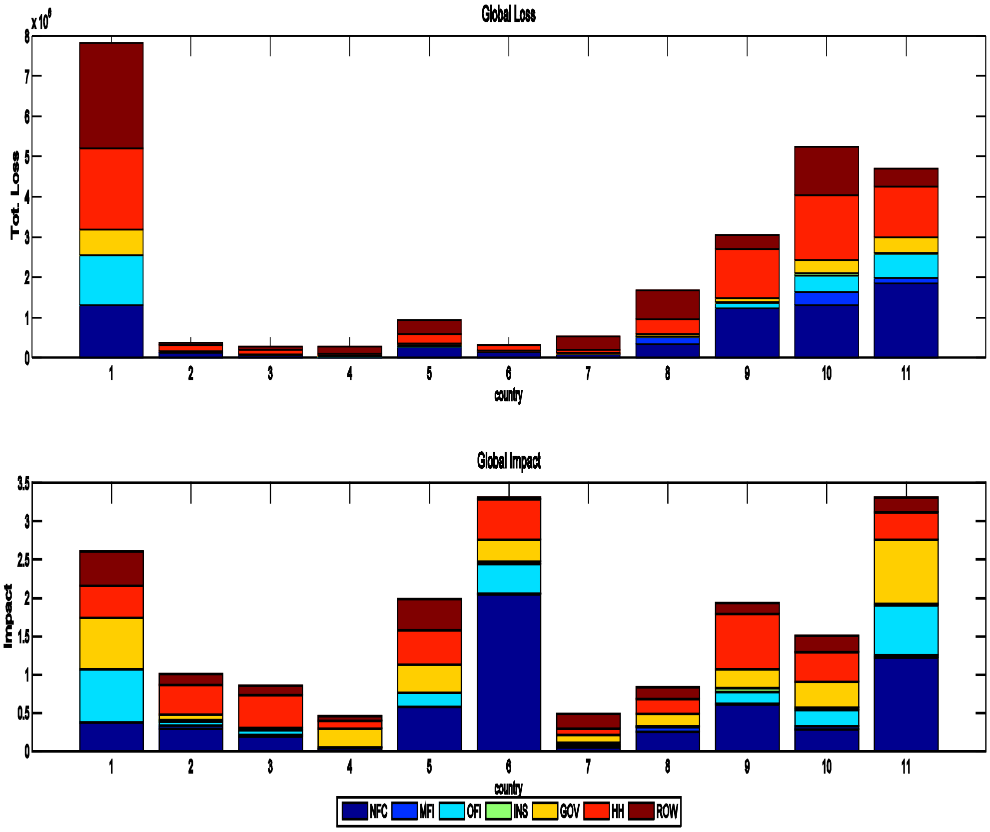

Chart 6 Global shock: loss and impact on the global system. Panel (a) shows the global post-propagation loss from a shock to sector δ. Panel (b) shows the global post-propagation economic impact (final global loss/total assets of sector$_\delta$) of an initial asset shock (40% loss on loans extended) on each domestic sector (period: Q1 2012).

In Table 5 we show 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. Results show that countries 10, 5 and 1 amplify 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 EM equal to 1.55 for country 5 means that a final loss in country 5 of 5 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 which was originally hit by the shock. Countries 8 and 7 also show high values, meaning that they diffuse losses rapidly to the other countries in the network. 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 only a couple of rounds are needed for the shock to disappear, whilst for shocks originating from some other countries the process takes substantially longer.

Country	LM		EM		Rounds	
	Mean	St.dev.	Mean	St.dev.	Mean	St.dev.
1	3.54	0.54	1.28	0.17	25	14
2	2.68	0.32	1.17	0.07	15	7
3	2.16	0.26	1.11	0.06	12	7
4	1.44	0.23	1.12	0.03	11	9
5	3.94	0.71	1.55	0.27	18	10
6	2.12	1.40	1.02	0.02	9	7
7	3.15	0.66	1.72	0.42	20	7
8	3.18	0.49	1.86	0.25	25	6
9	2.92	0.49	1.14	0.06	21	10
10	4.62	0.49	1.01	0.00	34	6
11	2.98	1.48	1.14	0.08	25	11
Average	2.98	0.64	1.28	0.13	20	8

Table 5 Impact of shocks. The table reports statistics of the loss multiplier (LM), the export multiplier (EM) and the number of rounds needed for the shock to dissipate (averaged across sectors). 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.

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.[15] Also this experiment shows that there are marked differences in the dynamic responses across countries and sectors.

Lastly, Chart 7 illustrates the dynamics of global losses, both over time and as percentage of the initial loss, from a shock which originates from the non-financial corporate sector in a given country. Also in this case the patterns of countries 9 and 10 (shown in the chart) appear substantially different than the others. Note that the evolution of the loss over time is rather different than what could be observed in Chart 4. Country 9 shows a substantial increase in the size of initial shock (x-axis), and, combined with the pattern of loss multiplier, towards the end of the period, triggers high levels of post-propagation losses. In 2011-2012, shocks are again substantially amplified not just in countries 9 and 10 but in all countries of our sample.

[15] We could also simulate scenarios which are contained only to a subset of countries. Quantitatively, the results would depend on the domestic structures and the cross-border linkages of the selected countries.

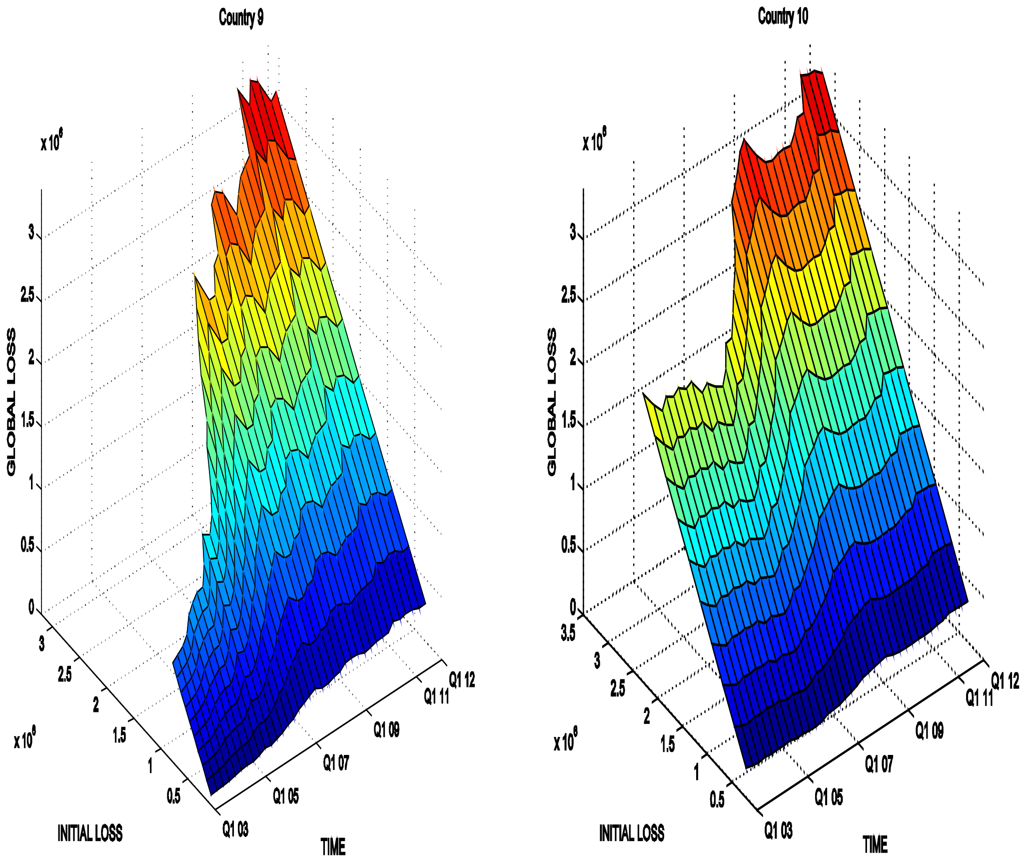

Chart 7 Final loss from a shock to the NFC sector, countries 9 and 10. The graphs show the global losses at the euro area level (y-axis) and the initial loss (x-axis) over time (z-axis). Results are drawn for NFC_9 and NFC_{10} from which the shock is assumed to originate. Simulations are performed separately in each time period and for all possible values of initial losses.

4.3. Shocks, network analysis and financial stability

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

First, centrality measures are to some extent useful in predicting the impact of negative shocks. Chart 8 shows this in two ways. First, it displays the average values over time of the ratio between the final loss for each sector and the initial shocks. Second, it plots the closeness and centrality measures for the networks in instrument category equity shares.[16] The graphs show that for most of the nodes, closeness has a pattern similar to the behavior of the final-loss-over-initial-shock ratio. For example, the highest values for both the ratio and the closeness measures appear in

[16] We consider the average of the final loss/initial shock from the exercise which simulates a shock to all banking sectors simultaneously. Closeness is rescaled and averaged over time.

country 10 for the NFC and INS sectors, in country 1 for the MFI sector, in country 9 for the HH sector and in country 8 for the ROW sector.

From a methodological point of view this is an interesting result: while network statistics provide a quantification of the importance of a node in the system, they are also helpful in identifying some behavioral patterns at the various stages of the propagation. This does not mean that 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 which 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 the connections in the system, the ratio mainly reflects 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.

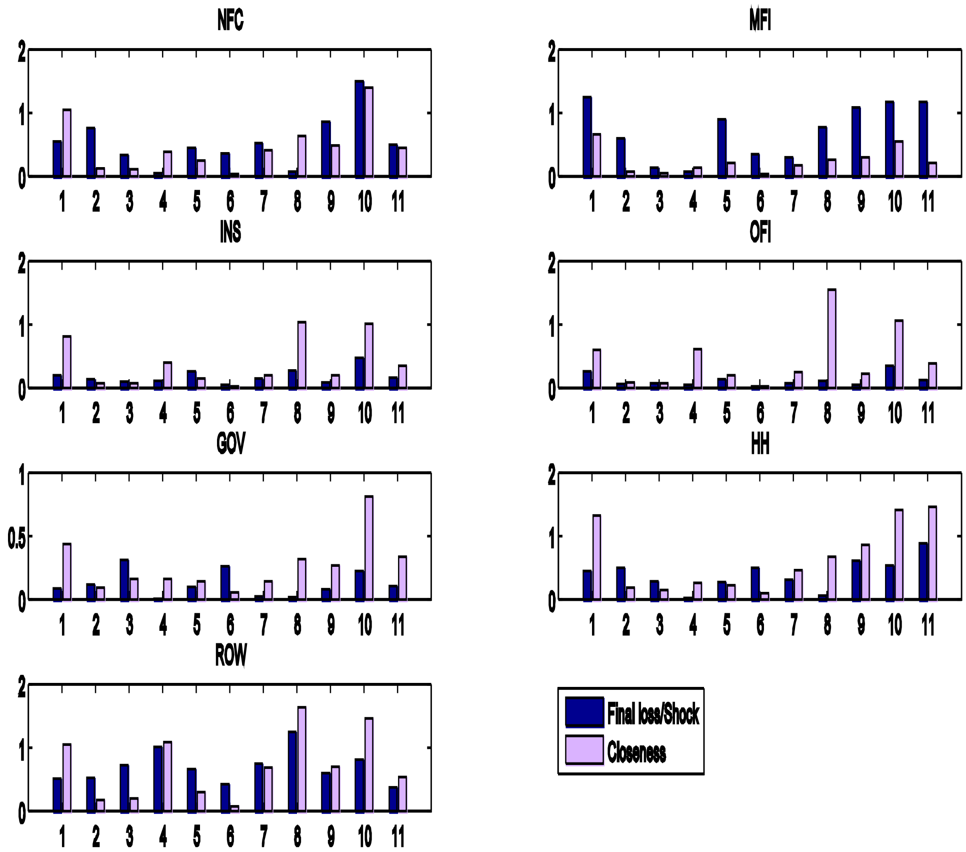

Chart 8 The final loss/initial shock ratio vs closeness centrality measures. The charts show the final-loss-to-initial-shock ratio, and the closeness centrality measures for each sector and country. Values are averaged over time.

Second, 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 cross-border exposures and on domestic exposures show dynamic patterns which are somewhat similar to the cluster coefficients (Chart 9); this confirms that the growth in interconnectedness indeed explains the stronger shock amplification effect in 2003-2007 shown in Chart 4. As we showed before, 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 Chart 1) and in the average loss multipliers. Despite the protracted deleveraging process and the partial reversal in the financial integration between domestic sectors and across borders the evidence suggests that on these measures, the risk of financial contagion was not substantially reduced and in late 2011-early 2012 it remained very high.

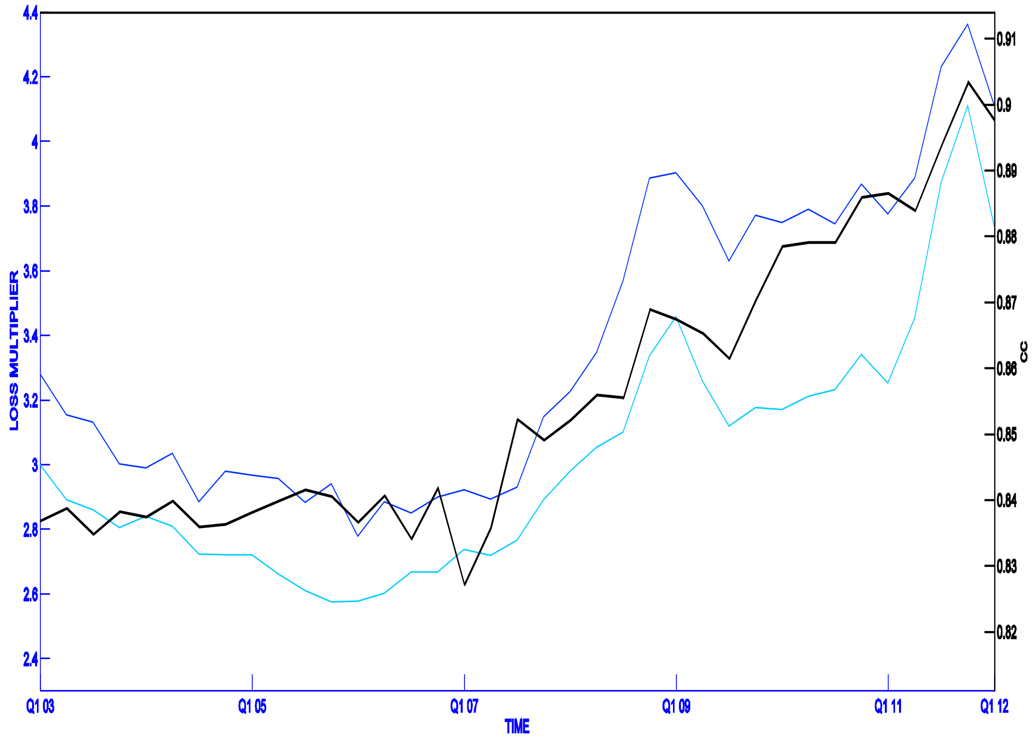

Chart 9 Loss multiplier vs Cluster coefficient. The chart shows (i) the loss multiplier computed from a shock simulation on cross-border exposures, in blue, (averaged across countries); (ii) the loss multiplier computed from a shock simulation on domestic exposures, in light blue (averaged across countries and sectors); and (iii) the cluster coefficient (*CC*, for shares), in black.

Third, the identification of specific measures which would effectively mitigate the risks of spill-overs and strengthen financial stability is, by and large, still an ongoing process. In our simulations, cross border interlinkages are shown 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 international exposures could mitigate malicious feedback loops.

To do this, in Table 6 we apply the BSI data to show the proportions p of the total foreign exposure of the MFI sector of country η vis-à-vis all the other countries' MFIs sectors (so that that the sum of the proportions of all bilateral exposures equals one in the columns of Table 6). The results in Table 6 show an uneven and concentrated distribution of cross-border exposures in the banking sectors. This finding is further confirmed when we compute the Gini indices for each individual country μ, which range between 0.5 to 0.7.[17]

Country	1	2	3	4	5	6	7	8	9	10	11
1	0.0000	0.1598	0.5211	0.1270	0.6898	0.0692	0.1066	0.3018	0.2045	0.3346	0.2206
2	0.0054	0.0000	0.0000	0.0000	0.0006	0.0465	0.0171	0.0001	0.0565	0.0221	0.0010
3	0.0102	0.0000	0.0000	0.0000	0.0015	0.0000	0.0013	0.0026	0.0003	0.0020	0.0003
4	0.0507	0.0013	0.0830	0.0000	0.0067	0.6923	0.0273	0.0776	0.0104	0.1241	0.1015
5	0.1265	0.0047	0.0012	0.0017	0.0000	0.0000	0.0147	0.0037	0.0011	0.0162	0.0174
6	0.0057	0.0066	0.0000	0.0000	0.0000	0.0000	0.0016	0.0085	0.0010	0.0023	0.0000
7	0.2083	0.0954	0.0002	0.3015	0.0589	0.0031	0.0000	0.3293	0.0510	0.1705	0.0071
8	0.1043	0.0012	0.1607	0.1071	0.0218	0.0320	0.3020	0.0000	0.0526	0.1271	0.0280
9	0.0601	0.4517	0.0006	0.0030	0.0197	0.0104	0.1321	0.0563	0.0000	0.0646	0.0807
10	0.3103	0.2790	0.2330	0.3239	0.1845	0.1464	0.3426	0.1712	0.5470	0.0000	0.5435
11	0.1187	0.0003	0.0002	0.1358	0.0166	0.0002	0.0547	0.0490	0.0757	0.1364	0.0000

Table 6 Cross border exposures of the banking sector. The table shows the proportions p of the exposure of MFI_η towards its foreign banking sector counterparties (Instrument category: deposits, period: Q1-2012).

Next, we repeat the simulation exercise of section 4.1.2, but assuming different distributions of cross border exposures. As a benchmark, we choose a distribution where the exposures of the banking sectors of each country η are perfectly balanced across all counterparty banking sectors. Table 7 compares the propagation losses from using the actual exposure distributions from Table 6 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 Elliot, Golub and Jackson (2012) find that in networks, the effect of exposure diversification to organizations failing is not linear. A high level of diversification reduces the extent of contagion only after a certain threshold has been passed. Also, Allen and Gale (2000) show that under some assumptions a complete network absorbs shocks better than a sparse network. In our framework we compare diversified cross-border

[17] Regarding this point, see also Section 3.2.

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

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, some 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 which are dissipating shocks and would not benefit 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 cross-border exposures also carry substantial benefits and not only costs. Our findings contribute to this debate showing that the shape of the network exposures is important. A more diversified portfolio of exposures might reduce the negative propagation effects, while a non-coordinated reduction in bilateral exposures and in financial integration *per se* does not necessarily strengthen the resilience of the system at large.[19]

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

Table 7 Final loss with true (or realized) and diversified exposures. The table shows the global losses (column 2 and 3) at the euro area level after a shock originated in each country in turn (column 1). Results refer to simulations performed with true cross-border exposures (status quo) and diversified cross-border exposures (diversification), period Q1-2012.

[19] Note that we do not claim that a full diversification would necessarily minimize potential losses. Indeed, the optimal distribution would be to concentrate cross border exposures on those countries which 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.

5. ESTIMATED LINKAGES VERSUS OBSERVED LINKAGES USING NATIONAL DATA

This section compares the network statistics resulting from 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 in order to evaluate the accuracy of the estimations. We can also contrast the results obtained from shock simulations using either the estimated or the true networks. Although this comparison is limited to one country only, 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 complete data on the flow of funds between individual sectors. This who-to-whom information is collected according to a framework presented in Table 11 in Appendix B for the following instruments: short-term and long-term debt securities, short-term and long-term loans, and shares and other equity (excluding mutual fund shares). 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: the banking sector, the insurance and pension fund sector and the other financial intermediaries sector are all aggregated under one single category "Financial Corporations". Hence, for the sake of consistency we need to adjust our framework here (see Table 12), 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 done according to the framework shown in Table 13 in Appendix B.

Table 8 shows the differences between the observed and estimated values of linkages for the following instrument categories: debt securities, loans and equity shares. We can see that the estimated values are not very different, on average, from the true values, especially for 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 present in the true data (type-2 error). Type-1 errors are more frequent under 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 currently 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 which 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 financial structures in individual countries.

	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%

Table 8 Observed linkages versus estimated linkages. The table compares estimated vs observed linkages for one country which provides detailed information on true who-to-whom statistics. The difference reported in the table is the average difference between estimated and observed linkages. Type-1 error indicates the average number of links identified by the ME+C method which are not present in the true data. Type-2 error indicates the average number of links which are present in the true data but are not identified by ME+C. Type-1 and Type-2 errors are expressed in percentages.

5.2. SHOCK PROPAGATION

Finally, we follow Mistrulli (2011) who analyses shock propagation in the Italian interbank market using both actual bilateral exposures and connections estimated with the ME method. His results shows that the ME method generally underestimates the extent of 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 some guidance about the bias that is potentially incorporated in our simulations presented in the previous sections.

Building on the findings in section 5.1, Chart 10 shows the cumulated losses over the number of rounds in which the shock dissipates across five sectors (the sector "Financial Corporations" includes the MFI, OFI and INS sectors). Our results show 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 encouraging per se, one should nevertheless be cautious when generalising these results to other countries given the different structures of bilateral linkages across the individual EA countries.

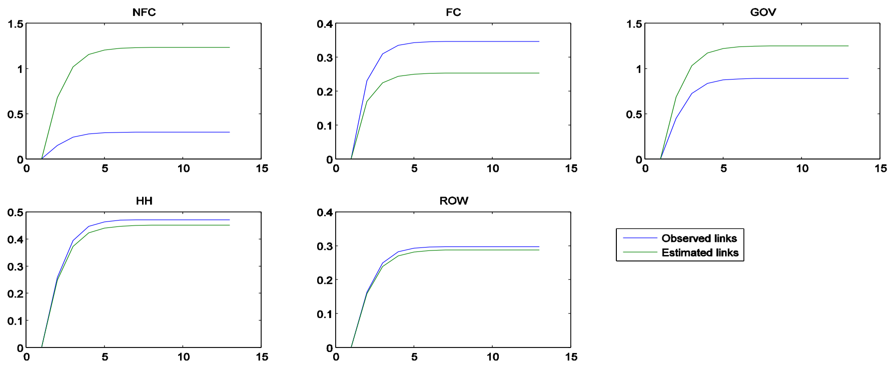

Chart 10 Dissipation of shocks in networks using observed vs estimated linkages.

6. CONCLUSION

In this paper we applied data from the Euro Area Accounts (flow of funds) to construct financial networks for 7 economic sectors in eleven major euro area countries. The individual country networks were then connected to one large “Macro Network” using information on banking sector cross-border linkages. We evaluated the properties of these systems using 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 financial shocks may propagate across sectors and countries. We find that propagation effects crucially depend on two things. First, the location of the original shock (the financial instrument, economic sector and country) matters a lot for the aggregate post-propagation losses. For example, shocks to bank loans in countries where 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 sectors and countries, determines the speed of and the extent to which shocks propagate in the system. For example, countries which during the years prior to the financial crisis saw more extensive financial integration across individual domestic sectors, and/or sectors which saw growing cross-border activity, unexpectedly became vulnerable for shocks that could hit even remote parts of the system. This finding provides evidence of the classic knife-edge property of financial networks at play. Initiatives that in normal times are seen beneficial in terms of financial efficiency and enhanced risk sharing may turn malicious in times of financial panics and closely integrated systems thus feature a tradeoff between efficiency and resilience. Third, when confronted by losses or potential losses, economic agents typically change their behaviour and severe the linkages to counterparties with uncertain credit quality. This is clearly shown in our results for the years 2008-09 when losses from the first rounds of the global financial crisis had propagated in the system and sectors started to step back massively from bilateral transactions (both cross-sector and cross-border). Despite this process, our intertemporal simulations also revealed that vulnerabilities persisted in the euro area financial system, providing channels for further loss propagation in the first half of 2011. Finally, we showed that networks which are characterized by highly diversified exposures are less prone to shock-amplifying feedback loops, suggesting that systems with incomplete degrees of financial integration may prove to be 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 economies and across economic regions, causing widespread economic losses, emphasize that more work is needed to identify and analyze the financial networks at different levels of aggregation. Given the dearth of information on true bilateral linkages between individual financial agents, obvious avenues for future research are tools which can improve on the accuracy of the estimated bilateral linkages. Improvements on the availability of data on 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 more complex propagation algorithms which are capable of incorporating behavioral responses of 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 so as to create more complete tools for the analysis of financial shocks and financial structures in the macroeconomic environment.

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A. Appendix – Centrality measures

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

Table 9 Measures of network statistics. The table shows the formulas that are used for computing centrality measures. *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.

OUT-DEGREE							
Country	NFC	MFI	INS	OFI	GOV	HH	ROW
1	147,877	743,916	453,414	149,969	31,898	270,620	1,419,391
2	3,868	42,391	15,987	38,125	6,889	17,453	92,323
3	6,177	17,599	10,230	18,942	34,586	3,899	89,463
4	4,020	471,450	201,811	43,161	3,385	208	353,034
5	10,369	96,478	72,830	29,384	16,920	32,031	247,225
6	2,798	58,332	5,220	4,337	9,343	25,461	120,008
7	16,922	234,628	35,730	102,511	14,136	110,417	188,527
8	21,263	286,569	74,427	371,703	6,665	45,150	860,506
9	36,016	426,650	103,361	175,300	37,405	41,340	490,068
10	65,497	905,631	314,740	799,992	48,063	65,753	1,129,361
11	55,032	198,083	224,374	282,479	19,390	680,812	801,872

BETWEENNESS							
Country	NFC	MFI	INS	OFI	GOV	HH	ROW
1	0.00	3,294.90	10.85	0.00	0.00	0.00	413.10
2	0.00	685.67	0.00	0.00	0.00	0.00	351.50
3	0.00	695.56	0.00	0.00	253.90	0.00	476.35
4	0.00	733.02	1.19	0.00	0.00	0.00	408.04
5	0.00	702.52	0.00	0.00	0.00	0.00	456.77
6	0.00	679.52	0.00	0.00	326.13	0.00	227.75
7	0.00	717.54	0.00	0.00	0.00	0.00	390.42
8	0.00	735.87	0.00	0.00	0.00	0.00	469.25
9	0.00	916.85	5.48	0.00	9.60	0.00	298.63
10	0.00	2,020.37	0.00	0.00	0.00	0.00	345.27
11	0.00	744.83	0.00	0.00	8.69	0.00	367.21

CLOSENESS							
Country	NFC	MFI	INS	OFI	GOV	HH	ROW
1	16.07	32.76	32.07	19.58	9.75	26.34	55.06
2	0.85	1.99	1.60	2.55	1.05	1.74	3.35
3	1.57	2.34	2.02	2.74	3.19	1.48	4.33
4	2.93	24.42	15.90	10.13	2.56	0.33	17.52
5	4.04	9.18	9.27	6.61	5.57	6.87	13.34
6	0.42	2.44	0.55	0.55	0.73	1.31	3.88
7	4.24	12.53	5.50	8.92	5.00	10.01	10.77
8	4.94	15.99	9.28	23.86	2.37	8.00	30.63
9	4.54	17.05	8.42	10.92	5.40	5.30	17.63
10	13.61	38.59	25.69	45.19	14.29	13.53	45.91
11	5.04	10.19	12.65	14.50	4.71	28.36	27.86

Table 10 Centrality measures. The table shows the average values of out-degree, betweenness and closeness (instrument category: debt securities). All measures are computed both as weighted and directed measures.

B. Appendix- Estimated linkages versus observed linkages

	Sender						
Receiver	NFC	MFI	INS	OFI	GOV	HH	ROW
NFC							
Financial Corporations							
GOV							
HH							
ROW							

Table 11 Framework of Observed linkages.

	Sender						
Receiver	NFC	MFI	INS	OFI	GOV	HH	ROW
NFC							
MFI							
INS							
OFI							
GOV							
HH							
ROW							

Table 12 Flow of funds framework estimated with the ME method + Constraints

		Sender						
Receiver		NFC	MFI	INS	OFI	GOV	HH	ROW
	NFC	✓	✓	✓	✓	✓	✓	✓
MFI INS OFI	∑(MFI, INS, OFI)	✓	✓	✓	✓	✓	✓	✓
	GOV	✓	✓	✓	✓	✓	✓	✓
	HH	✓	✓	✓	✓	✓	✓	✓
	ROW	✓	✓	✓	✓	✓	✓	✓

Table 13 Framework used to compare observed linkages and estimated linkages