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Antonio Sánchez Serrano **Sectoral interconnectedness in the euro area economies: insights from network analysis**

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Abstract

Using who-to-whom data for the last quarter of 2024, I build networks of financial interconnections in the euro area countries. After representing them in chord diagrams, I consider centrality metrics and find that banks dominate, with four exceptions: Cyprus, Ireland, Luxembourg and Malta. In these countries, other financial institutions and investment funds are at the core, with limited links to domestic sectors and strong ones with the rest of the world. A comparison across countries reveals substantial homogeneity between networks in the sixteen euro area countries and large differences with Cyprus, Ireland, Luxembourg and Malta. For each country, two communities are identified, one focused on the real economy and including banks, and the second comprising other financial intermediaries and the rest of the world. The consistent mapping of sectoral linkages and the accompanying descriptive analysis can be useful for policymakers and may also serve as platform for further analytical work.

Keywords: flow of funds, financial interlinkages, contagion, centrality.

JEL codes: D85, G10, G20, G51.

Non-technical summary

Network analysis studies the relationships between a group of connected data points (usually called nodes) to understand complex systems. It has been applied to fields like social sciences (to assess, among others, how people interact in a social group), medicine (for example, to understand how a disease may spread across a population) and transportation (for instance, to find potential vulnerabilities and bottlenecks in railroad systems). The main objectives of network analysis are to define the network structure, identify patterns and key components, and to understand dynamics in the network. To do so, it proposes several visualisation methods, such as maps, and defines a wide range of metrics and indicators.

Network analysis has also been applied in economics and finance. Since the global financial crisis, interest on network analysis as a tool for monitoring systemic risk in the financial system by macroprudential authorities has increased substantially. Actually, interconnectedness in the financial system is usually identified as one of the main sources of systemic risk in the financial system, calling for increased attention by macroprudential authorities. In this vein, research has focused on issues such as the definition of the network structure of the banking system, the identification of the largest components of the network of the global financial system or simulations of shock transmission and contagion.

This paper presents networks of cross-sectoral financial exposures for the twenty countries in the euro area, using who-to-whom data from the quarterly sectoral accounts and following the methodology of Andersen and Sánchez Serrano (2024). Quarterly sectoral accounts are compiled according to a sound and well-established methodology, defined by the United Nations, at global level, and by Eurostat at the EU level. They compute data to build balance sheets of the main sectors of activity (households, non-financial corporations, government, banks, insurance corporations, pension funds, investment funds, other financial institutions, money market funds) and the rest of the world. For listed shares, debt securities, deposits and loans, quarterly sectoral accounts require data on exposures across sectors (who-to-whom).

Based on data for the twenty euro area countries at the end of 2024, this paper builds sectoral balance sheets, aggregates cross-sectoral exposures through listed shares, debt securities, deposits and loans, and then applies network analysis to the resulting dataset. After a brief description of the networks, it computes several network metrics to identify which sectors are at the core of the

network, how stress can spread through the networks, how dense the networks are, and which networks are more similar to each other.

As expected, banks are placed at the core of national networks with only four exceptions: Cyprus, Ireland, Luxembourg and Malta. Banks have large interconnections with both other financial sectors and with the real economy, but limited exposures to and from the rest of the world. This points to the domestic reach of the provision of banking services in the euro area. In Cyprus, Ireland, Luxembourg and Malta, investment funds and other financial institutions dwarf the size of other sectors, particularly those linked to the real economy. There are massive exposures between other financial institutions, investment funds and the rest of the world, but limited interconnections to the domestic real economy. As such, other financial institutions and investment funds seem to serve as vehicles to channel foreign savings into foreign investments.

Considering how shocks can be potentially transmitted, these results must be complemented with an analysis of the existing vulnerabilities in sectoral balance sheets or with a fully-fledged contagion model. Results are heterogeneous across countries, except for pension funds, which seem less likely to act as a potential transmitter of shocks to other parts of the network. Besides, the network structure of several countries is consistent with vulnerabilities to shocks originated abroad or with small sectors potentially acting as transmitters of shocks, such as money market funds or insurance corporations. In a comparison across countries, the networks of Cyprus, Ireland, Luxembourg and Malta stand out like outliers, being much different to the networks of the other sixteen countries. Among this group of sixteen euro area countries, Spain, Austria, Portugal and Germany exhibit the highest degree of similarity to each other. Finally, running algorithms to identify parts of each network that are particularly interconnected among them (called communities in network analysis) shows that most euro area countries have two communities: one comprising banks and the main sectors in the real economy (i.e., households, non-financial corporations and pensions), and the second community comprising other financial intermediaries and the rest of the world. This confirms the key role of banks as providers of financial services to the real economy and suggests that cross-border financial flows tend to dominate now over similar flows linked to international trade and the real economy.

In policy terms, this paper provides several insights. First, the centrality of banks in most euro area countries confirms the need to have a strong and comprehensive prudential regime for

them. Second, the concentration of financial non-bank activities in just four countries with large cross-border flows and little impact on the domestic economy suggests the need to ensure, at least, smooth coordination with authorities in other countries. Finally, the fact that some sectors can potentially act as transmitters of shocks, even if they are of small size, serves as a reminder to relevant authorities to keep them present in relevant policy discussions.

1. Introduction

One of the key areas of work of macroprudential authorities relates to the degree of interconnectedness in the financial system and in the real economy. Among others, Allen and Gale (2000), and Nier et al. (2007) show how the fragility of the banking system depends on the existing linkages among banks. Acemoglu et al. (2015) conclude that, beyond a certain threshold, interconnections serve as a mechanism for the propagation of shocks, leading to a more fragile financial system. Direct linkages between economic agents are the most basic contagion mechanism, as they can spread stress (and losses) throughout the financial system and the real economy. Clerc et al. (2016) examine sources of indirect contagion, where there are no direct contractual links between institutions. Altinoglu and Stiglitz (2023) find that interconnectedness and excessive risk taking reinforce one another and that macroprudential regulation that limits the interconnectedness of risky institutions improves welfare.

This work becomes more relevant given the high degree of interconnections in current financial systems, with multiple types of institutions being tightly interconnected between them through several financial instruments, including derivatives and other off-balance sheet items, such as credit lines. The episode of financial stress in March 2020 highlights how the structural increase in interconnectedness in the financial system can contribute to spread stress at unprecedented speed (Financial Stability Board, 2020).

One of the main difficulties encountered by macroprudential authorities in their assessment of interconnectedness refers to data. Analysing interconnectedness requires balance sheet data from at least the main institutions in the financial system and in the real economy, broken down by instrument and country. This data, when available, is usually defined in sectoral regulatory reporting requirements, with different methodologies, data sharing arrangements and definitions. Unfortunately, it is difficult to combine existing datasets without compromising to a large extent data quality and accuracy. As a result, macroprudential authorities often find themselves in a dead alley, unable to progress on this key area of their responsibilities.

The financial accounts offer a valuable tool to macroprudential authorities to carry out interconnectedness analysis. It offers a solid methodology in their computation, based on the national system of accounts, and large availability of who-to-whom data by instrument and country. Eurostat (2013) and United Nations and European Central Bank (2015) are two

fundamental methodological documents. On the other hand, though, financial accounts can only capture interconnections at sector level, as further granularity is not possible in the current framework.

The idea of using who-to-whom data to analyse interconnectedness in the financial system is not new. Focusing on the euro area, pioneering work by Castrén and Kavonius (2009) use flow of funds data to create a sector-level network of bilateral exposures in the financial system and simulate the transmission of balance sheet shocks in the euro area financial system. Castrén and Rancan (2013) use financial accounts to construct financial networks for individual euro area countries and connect them to a “macro network”, using information on cross-border linkages between the national banking sectors. They find that contagion in the network depends on the location of the initial shock and on the centrality and connectivity of the affected network. Oura (2022) defines a methodology to run a system-wide liquidity stress test based on sectoral balance sheets computed from sectoral accounts, which can provide useful insights to macroprudential policymakers. More recently, who-to-whom data has been used to build maps of the euro area financial system (Andersen and Sánchez Serrano, 2024), and of the financial systems of France, Portugal and Spain (Mouakil et al., 2024; Saldias and Mizinski, 2025; Sánchez Serrano, 2025b). Moving to the United States, Acharya et al. (2024) use expanded data from the US financial accounts to investigate the links between banks and non-banks, focusing on the transformation of risks between the two sectors.

Another avenue of work combines who-to-whom data with data from the international investment position. Kubelec and Sá (2012) create a dataset on external assets and liabilities across eighteen countries from 1980 to 2005, broken down by foreign direct investment, portfolio equity, portfolio debt, and foreign exchange reserves, and apply network analysis to find an increase of interconnections. They also run a simulation exercise to show how shocks can generate large losses across countries in the network. Almeida (2015) combines sectoral accounts with data from the IMF Coordinated Portfolio Investment Survey, the International Investment Position and the BIS to estimate bilateral exposures in three different financial instruments across the euro area, Japan, UK and the US. Similarly, Bijlsma et al. (2019) identify linkages with the most important counterparts in terms of geographical regions and foreign sectors. Peltonen et al. (2019) build a macro network of the euro area financial systems based on four financial instruments (deposits, shares, loans and debt securities) and find that a more

central position of banks in the network increase the probability and severity of banking crises. Finally, Coppola et al. (2021) look at the role of offshore financial centres in channelling investments across countries and find that, in general, portfolio investment from advanced economies to emerging economies is substantially larger than previously thought. They offer the example of the national accounts of the United States, which understate the portfolio investment in China by nearly 600 billion dollars.

In parallel, since the global financial crisis, there has been a growing use of network analysis for the monitoring of systemic risk in the financial system. In a nutshell, network analysis can be defined as a set of techniques derived from network and graph theories, used to visualise and interpret relationships among entities in a system, with a focus on the degree of interconnectedness and the relative strength of associations within the network. Newman (2010) offers a comprehensive conceptual view of what network analysis covers. Gai and Kapadia (2010) find that the financial system (and other complex systems) tend to be generally robust but fragile to targeted attacks on specific important nodes. Jackson and Pernoud (2021), Espinosa-Vega and Solé (2011) and International Monetary Fund (2009) summarise how network analysis can be applied to the monitor of systemic risk in the financial system. Providing an exhaustive literature review is certainly beyond the scope of this paper, but I would like to mention three relevant contributions in a European context. First, Alves et al. (2013) apply network analysis to the European interbank network using confidential data and performed default and liquidity simulations. They find that small shocks do not lead to substantial stress over the network, although the number of contagious defaults increases non-linearly when the common shock increases from 2% to 3% of non-interbank assets. A different approach is taken by Peralta and Crisóstomo (2016), who define a two-layered multiplex network with collateralized and uncollateralized transactions and run various experiments to analyse the determinants of systemic crisis and the resilience of different financial network configurations. Foglia et al. (2023) explore financial contagion among euro area countries using a multilayer information spillover network framework that includes the sovereign, banking and equity sectors' risk. They find that high interdependence between the different layers can lead to a rapid increase in contagion between markets and countries.

In this paper, I use who-to-whom data to build sectoral balance sheets for the twenty euro area economies, following the methodology of Andersen and Sánchez Serrano (2024), which are then

used to visualise the network of interconnections and to apply network analysis. This paper provides a consistent mapping of sectoral linkages in euro area countries with several network metrics, which can be used as a descriptive exercise for policymakers and as a platform for further research on, for example, contagion simulations. In other words, the contributions of this paper are two. First, it applies the methodology of Andersen and Sánchez Serrano (2024) to the twenty euro area countries and provides a descriptive view of the twenty networks, without entering into other possible exercises involving simulation of shocks or contagion modelling, which can be the core of future exercises. The analysis covers only one period of time, the fourth quarter of 2024, as these structures tend to change little in the short-term. Second, the paper applies the most common network metrics to gain additional insights on the twenty euro area networks. In particular, I look at the centrality of the different sectors in the country networks and compare networks to identify those countries with more similarities. The analysis presented here is also driven by policy purposes. In principle, prudential policies should focus on the most central and connected sectors, as they are likely to be those spreading stress through the system. Besides, this analysis can also serve as a benchmark to compare policy stances between two euro area countries with a similar network of interconnections.

The main findings of the analysis are the following. Banks play a central role in all the national networks with four exceptions: Cyprus, Ireland, Luxembourg and Malta. Banks have large interconnections with both other financial sectors and with the real economy. Interconnections of banks with the rest of the world are limited, suggesting a domestic reach in the provision of financial services among euro area countries. In Cyprus, Ireland, Luxembourg and Malta, investment funds and other financial institutions are substantially larger and more interconnected, particularly with the rest of the world, than the banking system. Investment funds and other financial institutions tend to be much smaller and less interconnected in the other sixteen euro area countries. Contrary to the finding for banks, other financial institutions and investment funds have a clear cross-border reach, serving as vehicles to channel foreign savings into foreign investments. In other words, they attract funding from other countries and invest abroad, leaving little imprint in the domestic real economy. In policy terms, the centrality of banks in the majority of euro area countries confirms the need to have a strong prudential regulatory regime for them. Considering how shocks can be potentially transmitted through the financial sector, results are rather heterogeneous across countries, except for the pension funds,

that seem less likely to transmit shocks to other parts of the system. There are several countries particularly vulnerable to contagion from a shock originating abroad or in apparently small sectors, such as money market funds or insurance corporations. However, it is necessary to thoroughly analyse vulnerabilities in the balance sheet of these entities or to define a contagion model before conclusively associating the position of these sectors in the network to their role as transmitters of shocks.

Turning to the comparison of networks across countries, the networks of Cyprus, Ireland, Luxembourg and Malta stand out like outliers, being different to the networks of the other sixteen countries. Among these sixteen countries, Spain, Austria, Portugal and Germany seem to be particularly close to each other. When running the Louvain and the optimal modularity clustering algorithms for the identification of communities, most networks have two communities, with one usually comprising banks and the main sectors in the real economy (i.e., households, non-financial corporations and pensions), and the second one covering other financial intermediaries and the rest of the world. This is an interesting finding that suggests that cross-border financial flows tend to dominate now over similar flows linked to international trade and the real economy.

This paper is organised as follows. The next section describes the data and methodology used to build the sectoral balance sheets. The analysis is then presented in the following section in terms of visualisation (Section 3). Section 4 introduces the network metrics that are subsequently applied to the networks of the twenty euro area economies in Section 5 (centrality), Section 6 (density and comparison) and Section 7 (communities). Section 8 concludes.

2. Sectoral balance sheets: data and methodology

The primary source of data for this analysis is the who-to-whom data of the euro area, compiled by the European Central Bank within the quarterly sectoral accounts. In general, quarterly sectoral accounts are compiled according to the European System of Accounts, governed by Eurostat, and go through extensive data quality checks. One component of the quarterly sectoral accounts are the financial accounts, which show the financial assets and liabilities of sectors and how they change over time. These changes can basically result from changes in prices (i.e., revaluations) or changes in volume (i.e., financial transactions). Non-financial assets and liabilities are excluded from financial accounts. I have complemented this data with other datasets

compiled by the European System of Central Banks (ESCB), covering the balance sheet of banks (i.e., monetary financial institutions), insurance corporations, pension funds, investment funds, and money market funds. The compilation of these datasets is governed by a methodology similar to the one in the European System of Accounts, particularly in what regards the definition of sectors, the degree of consolidation and the financial instruments under its scope.

Following the methodology developed by Andersen and Sánchez Serrano (2024) for the euro area, I use these datasets to build a simplified balance sheet of nine sectors of activity, plus an additional one for the rest of the world, for each euro area country on a non-consolidated basis. These sectors comprise the real private non-financial sector (households and non-financial corporations), the public sector (government) and the financial sector, separately showing banks, insurance corporations, (private) pension funds, investment funds, money market funds and other financial institutions. The central bank is not included, as the allocation of the balance sheet items of the Eurosystem across countries would be methodologically problematic. Data is presented on a non-consolidated basis, implying that, for instance, the financial subsidiary (i.e., captive financial institution) of a large non-financial corporation is classified within other financial institutions. Similarly, non-euro area subsidiaries of euro area financial and non-financial institutions are included in the aggregate of the rest of the world, even if the ultimate ownership remains within the euro area.

The sectoral balance sheets focus on financial instruments, such as cash, deposits, debt securities, (listed and unlisted) shares, and investment fund shares, to the extent data is available in the who-to-whom data. Non-financial assets are only shown for investment funds, non-financial corporations and households. For other sectors, they are included in “other assets”.

While able to provide a broad view of interconnections between sectors in euro area countries, there are limitations in this methodology. The first one refers to the valuation of balance sheet items at market prices. For financial instruments which are usually traded in financial markets (such as listed shares or debt securities), the computation of their market value is straightforward. However, issues arise for financial instruments not traded in financial markets, such as loans or unlisted shares. Market values then need to be estimated by national statistical offices. Second, the methodology considers sectors at a high level of aggregation. As such, it does not cover all intra-sectoral exposures and does not allow for a consideration of different

business models within a sector. For instance, life and non-life insurance corporations have very different balance sheets but are presented together in the financial accounts. Similarly, many central clearing counterparties operate with a banking license, so they are included in the banking sector in spite of having a different business model than traditional banks. The third limitation refers to the use of data on a non-consolidated basis, which has been touched upon above. Finally, the aggregate of the rest of the world is rather extensive and, on some occasions, subject to limitations in data availability. Most of the assets and liabilities of the rest of the world have been indirectly derived from amounts related to the world, the domestic economy and other euro area countries. It would be possible to overcome, at least partially, this limitation by using data on the International Investment Position to have a breakdown by country, as proposed in Sánchez Serrano (2025a). This can be the subject of future endeavours.

Even if the methodology of national accounts is well-established, sound and consistent, several methodological issues arose when identifying the data points to use for the map. First, to ensure that total assets equal total liabilities (including net worth) in all cases, the necessary adjustments are made to the captions of “other assets” or “other liabilities”. Similarly, I have checked that there are no negative amounts reported, which has not been the case for “other assets” and “other liabilities” for some countries in the balance sheet of banks. These cases are not material and should not compromise data quality overall. I also made additional adjustments and assumptions to build the balance sheets for each sector. In particular, I assume that non-financial corporations do not have loans nor deposits with the central bank and that investment fund shares issued by monetary financial institutions and held by non-financial corporations refer to money market fund shares. Regarding other financial institutions, I assume that they do not have loans with central banks.

Once the sectoral balance sheets are built for the twenty euro area countries, I have aggregated cross-sectoral exposures across available instruments: deposits, loans, listed shares, investment fund shares and debt securities. Data availability does not allow the inclusion of cross-sectoral exposures for unlisted shares, which are important components of the balance sheet of other financial institutions and non-financial corporations in countries such as Cyprus, Malta or the Netherlands (Table 1).

Table 1. Share of unlisted shares over total assets of each sector, Q4-2024

	Assets							Liabilities			
	Gov	HH	NFC	Insurance	OFI	Banks	RoW	NFC	Insurance	OFI	RoW
AT	16%	9%	20%	3%	17%	7%	19%	29%	21%	0%	20%
BE	10%	11%	30%	2%	35%	2%	20%	36%	12%	32%	24%
CY	9%	6%	25%	0%	57%	0%	60%	65%	30%	62%	52%
DE	15%	6%	24%	1%	14%	1%	8%	25%	10%	7%	18%
EE	13%	28%	16%	0%	29%	5%	46%	48%	26%	26%	19%
ES	7%	8%	22%	5%	37%	7%	21%	41%	14%	17%	20%
FI	6%	11%	19%	1%	21%	6%	8%	26%	8%	50%	15%
FR	12%	9%	44%	4%	22%	4%	10%	49%	7%	16%	21%
GR	7%	10%	11%	1%	53%	3%	6%	70%	15%	16%	6%
HR	20%	7%	12%	0%	0%	0%	33%	25%	17%	4%	9%
IE	7%	4%	43%	0%	0%	2%	11%	33%	7%	12%	15%
IT	7%	13%	17%	2%	25%	3%	11%	50%	8%	15%	15%
LT	9%	13%	12%	0%	53%	1%	35%	33%	31%	50%	14%
LU	13%	7%	31%	0%	63%	1%	21%	21%	3%	61%	29%
LV	19%	15%	8%	0%	31%	-1%	37%	48%	21%	35%	11%
MT	8%	12%	15%	0%	47%	1%	67%	27%	37%	72%	42%
NL	10%	10%	35%	3%	49%	2%	39%	50%	13%	44%	37%
PT	23%	16%	19%	2%	44%	2%	25%	48%	10%	45%	17%
SI	18%	10%	14%	3%	11%	3%	25%	38%	15%	3%	12%
SK	9%	3%	3%	0%	1%	1%	28%	22%	2%	3%	5%

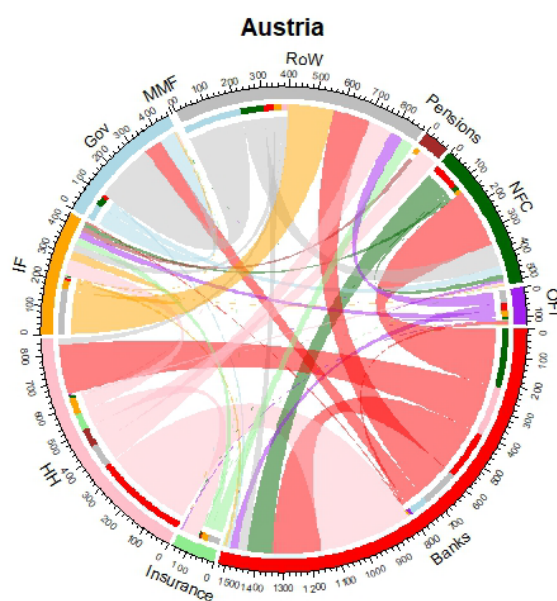
Source: ECB and author's calculations. Notes: RoW stands for rest of the world, OFI for other financial institutions, NFC for non-financial corporations, HH for households and Gov for government. Cells in blue refer to shares of unlisted shares over total assets above 40%.

The reference date for the analysis is the fourth quarter of 2024. Given the descriptive nature of this paper, it makes sense to consider only one period to build and describe the financial networks in the twenty euro area countries. It would be possible to collect data from previous periods and build a time series, allowing, for instance, a deeper analysis of flows and financial transactions during episodes of financial stress, as partially done by Andersen and Sánchez Serrano (2024). However, for the purposes of this paper, focusing on one period, in this case, the fourth quarter of 2024, should be enough. The networks of cross-sectoral financial interconnections tend to persist over time, with limited changes over short time horizons. Annex 1 compares the main network metrics for the fourth quarter of 2019 with the ones discussed later in Sections 5, 6 and 7, referred to the fourth quarter of 2024. It documents limited changes in the structure of the networks in five years, despite the COVID-19 pandemic, the start of the Russian invasion of Ukraine and the subsequent surge of inflation.

3. A brief description of cross-sectoral interconnections

Chord diagrams (also known as dependency wheels) constitute a straightforward and intuitive tool to visualise exposures across sectors. Chart A2 in Annex 2 displays the chord diagrams of the twenty euro area countries, based on balance sheet data at the end of 2024. Each chord diagram shows the financial assets and liabilities with other sectors of the economy, excluding therefore non-financial assets and liabilities, such as real estate owned by households. Besides, net worth is not shown either. Within each sector, assets and liabilities are separately represented. There is a smaller inner circle signalling the destination circle of assets, while that inner circle does not exist for liabilities. For example, in the case of Austria, banks have assets with non-financial corporations, households, other banks, the rest of the world, the government and investment funds (Chart 1). These assets account to around 800 billion euros. In turn, the main liabilities of Austrian banks are with households, banks and non-financial corporations.

Chart 1. Chord diagram of Austria, Q4- 2024, billion euros

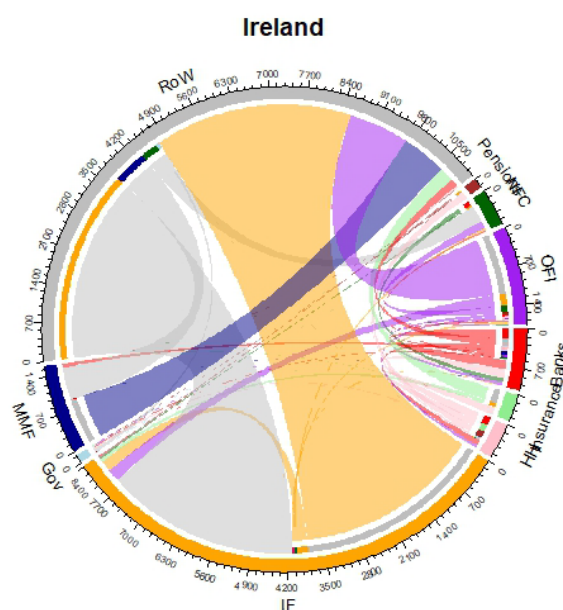


Source: Source: European Central Bank and author's calculations. Notes: HH stands for households, IF for investment funds, Gov for government, MMF for money-market funds, RoW for rest of the world, NFC for non-financial corporations, and OFI for other financial institutions.

The chord diagrams in Chart A2 provide interesting insights on the structure of financial systems. With four exceptions (Cyprus, Ireland, Luxembourg and Malta), the banking sector shows the largest connections with other sectors. As an illustration, Chart 1 represents the cross-

sectoral exposures in a bank-centric country, Austria, while Chart 2 shows the chord diagram of Ireland, where domestic banks are not the main sector in the economy. In Chart 1, representing Austria, and in the majority of chord diagrams in Chart A2, banks occupy the bottom-right quadrant, covering, approximately one quarter of all interconnections. France, where banks are clearly going beyond that quadrant, and the Netherlands, where banks play a smaller role in favour of other financial institutions and pension funds, would be the two extremes. Within banks, the largest exposures are with households, usually in the form of loans and deposits, with lower exposures to and from non-financial corporations. The fact that households, and not non-financial corporations, are the main counterpart of banks tends to confirm the finding in Beck et al. (2023) that banks are moving their lending activities away from non-financial corporations towards households and real estate.

Chart 2. Chord diagram of Ireland, Q4-2024, billion euros



Source: Source: European Central Bank and author's calculations. Notes: HH stands for households, IF for investment funds, Gov for government, MMF for money-market funds, RoW for rest of the world, NFC for non-financial corporations, and OFI for other financial institutions.

Cyprus and Malta have the largest interconnections between other financial institutions and the rest of the world, suggesting the use of captive financial institutions in these countries by large multinational groups. The chord diagrams in Chart A2 capture the liabilities of the rest of the world against other financial institutions based in Cyprus and Malta, but data availability does not allow to show the assets, which are normally in the form of unlisted shares. Furthermore, the

links between domestic other financial institutions and domestic non-financial corporations are rather small (if not zero) for most euro area countries. This suggests that captive financial institutions are mainly used across borders, trying to gain advantages that cannot be achieved in the country of domiciliation of the non-financial corporation. Ireland and Luxembourg have large investment fund sectors, where funds from the rest of the world are coming as liabilities of investment funds (foreign investors) and leaving in the form of assets (debt securities, listed shares,...). These interconnections are massive when compared to those of the domestic non-financial economy.

Looking at the relative size of other sectors in each country, pensions seem to be larger in the Netherlands and, to a lesser extent, in Latvia and Croatia, while money-market funds are only visible for Luxembourg, Ireland and France. Interconnections of the government tend to be large in countries like Italy and Spain. The rest of the world constitutes an important investor in government debt in most countries. Finally, the relative size of the insurance sector tends to be rather homogenous across the twenty euro area countries, with France and Italy showing the largest ones.

At this stage, a mere visual inspection of Chart A2 has led to a separation of the twenty euro area countries into two large groups. The first one comprises sixteen countries where banks have the largest interconnections to other sectors (particularly, households and non-financial corporations), while the second one comprises only four countries (Cyprus, Ireland, Luxembourg and Malta) that have the largest interconnections between the rest of the world, other financial institutions and investment funds. Network analysis can be useful in distilling further insights that may not be evident in Chart A2. This constitutes the main purpose of the following sections.

4. Methodology for the computation of network metrics

This section serves as a brief introduction to the network metrics and indicators that are applied later on the twenty country networks.¹

¹ For further information, Newman (2010) constitutes the basic reading as it covers these metrics and many other topics in network analysis.

Let's start with a weighted directed sectoral network $G = \{V, E\}$, where each node $i \in V$ represents an institutional sector, and each directed edge $\omega_{i,j} \in E$ denotes the amount of financial assets held by sector i that were issued by sector j . In other words, the adjacency matrix of the network of exposures across sectors ($W = [\omega_{i,j}]$) shows the sector of origin in rows (recognising it as an asset) and the sector of destination in columns (recognising it as a liability).

4.1. Centrality indicators

Degree centrality and centralisation

Degree centrality counts the number of edges connected to a node i :

$$C_{Deg}(i) = deg(i) \quad (1)$$

Centralisation extends degree centrality of a node to the whole network. If i^* represents the node with the highest degree centrality in $G = \{V, E\}$, centrality can be defined as:

$$C_{Deg}(G) = \frac{\sum_i^Y (C_{Deg}(i^*) - (C_{Deg}(i_i)))}{\sum_j^Y (C_{Deg}(y^*) - (C_{Deg}(y_j)))} \quad (2)$$

where the denominator refers to the Y -node connected graph that maximises $\sum_j^Y (C_{Deg}(y^*) - (C_{Deg}(y_j)))$ and y^* is the node with the highest degree centrality in that graph.

Betweenness

The betweenness of a node v in a graph $G = \{V, E\}$ is computed in three steps. First, for each pair of nodes (i, j) , the shortest path between them is computed. Second, for each pair of nodes (i, j) , we determine the share of shortest paths that pass through node v . Finally, these shares are summed over all pairs of nodes (i, j) .

On that basis, betweenness can be expressed as:

$$C_{Bet}(v) = \sum_{i \neq v \neq j \in V} \frac{\sigma_{ij}(v)}{\sigma_{ij}} \quad (3)$$

where σ_{ij} represents the shortest paths from node i to node j and $\sigma_{ij}(v)$ those passing through node v .

In the weighted network $G = \{V, E\}$, the shortest path from node i to node j ($s(i, j)$) minimises the sum of the edge weights through the path:

$$s(i, j) = \min_{P_{ij}} \sum_{(i, j) \in P_{ij}} \omega_{ij} \quad (4)$$

where P_{ij} is the set of all possible paths from node i to node j .

Closeness

Closeness is the reciprocal of farness (i.e., the distance between two nodes). In mathematical terms, it is equal to:

$$C_{Clo}(i) = [\sum_j d(i, j)]^{-1} \quad (5)$$

where $d(i, j)$ is the distance between nodes i and j .

Strength

As an indicator of centrality, strength is the sum of the weights (or size) of all edges connected to a node. It considers separately inbound edges ($C_{Istr}(i)$) and outbound edges ($C_{Ostr}(i)$):

$$C_{Str}(i) = C_{Istr}(i) + C_{Ostr}(i) = \sum_j \omega_{ji} + \sum_j \omega_{ij} \quad (6)$$

where ω_{ij} is the weight (or size) of the edge connecting node i and node j .

In a financial network showing sectoral exposures, inbound strength measures the financial instruments issued by a sector and held by other sectors, while outbound strength shows the financial instruments issued by other sectors and hold by a sector.

Eigenvalue centrality

To compute eigenvalue centrality of node i , let's make that a_{ij} takes the value 1 when the node i is connected to node j and the value zero when it is not, and let's define x_i as the centrality of node i . Eigenvalue centrality is then equal to the greatest eigenvalue (λ) that solves the equation:

$$x_i = \frac{1}{\lambda} \sum_{j \in G} a_{ij} x_j \quad (7)$$

Eigenvalue centrality implicitly assumes that the centrality of a node i can stem from the node having many large connections or from the node having connections to important nodes.

Page rank

Page rank is based on the algorithm used in Google and other search engines. It satisfies the following equation:

$$x_i = \alpha \sum_j a_{ji} \frac{x_j}{k_j^{out}} + \frac{1-\alpha}{N} \quad (8)$$

where α is a factor taking values between 0 and 1, N is the number of nodes in the network and k_j^{out} is the number of outbound links of node j .

Authority and hub scores

The authority and hub scores are based on a centrality algorithm called hyperlink-induced topic search (HITS), introduced by Kleinberg (1999).

The authority and the hub scores of node i are equal to:

$$Aut_i = \sum_j \omega_{ji} Hub_j \quad (9)$$

$$Hub_i = \sum_j \omega_{ij} Aut_j \quad (10)$$

In a directed network of financial exposures, sectors with high authority scores issue financial instruments that are owned by important investors. Similarly, sectors with high hub scores are those providing funding to other important sectors.

4.2. Other metrics

Edge density

In a weighted directed sectoral network $G = \{V, E\}$ with n nodes and m directed edges, edge density is defined as the number of edges in the network divided by the total possible number of edges in the network. Edge density only looks at the existence of an edge, regardless of its size.

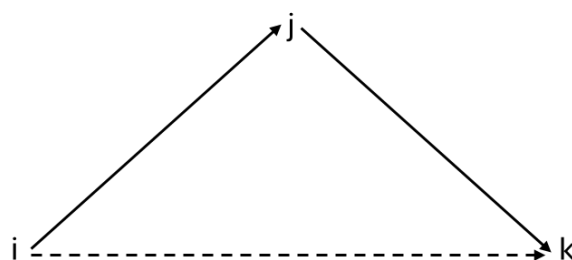
Therefore, edge density is equal to:

$$D_{Edge}(G) = \frac{m}{n(n-1)} \quad (11)$$

Clustering coefficient

To compute the clustering coefficient (or transitivity) of a network, it is useful to first consider three nodes, i , j and k . If i is linked to j and j is linked to k , the nodes i , j and k are connected to each other through a path of two edges. If i is also linked to k (the dashed line in Figure 1), then the path is closed, forming a triangle.

Figure 1. Connections between nodes i , j and k



Source: author.

The clustering coefficient is calculated as the share of closed paths of length two in a network divided by the total number of paths of length two. It can take thus values from zero (no closed paths at all, like branches in a tree) to one (implying perfect transitivity, all edges are connected through triangles).

Cosine similarity

In general, cosine similarity is a measure of similarity between two non-zero vectors. To compare two undirected networks, the adjacency matrixes need to be transformed to two vectors, A and B . In geometry, the inner product of two vectors is given by the following expression:

$$A \cdot B = |A||B|\cos(\theta) \quad (12)$$

where $|A|$ and $|B|$ are the magnitudes of A and B , respectively, and θ is the angle between the two vectors.

The cosine similarity of vectors A and B is then equal to:

$$S_{cos}(A, B) = \cos(\theta) = \frac{A \cdot B}{|A||B|} = \frac{\sum_{i=1}^N A_i B_i}{\sqrt{\sum_{i=1}^N A_i^2} \sqrt{\sum_{i=1}^N B_i^2}} \quad (13)$$

where A_i and B_i are the components of the vectors A and B .

If the vectors do not have negative values, the cosine similarity can take values from zero, showing no similarity between the vectors, to 1, implying that the two vectors have a very similar structure.

Global efficiency

First proposed by Latora and Marchiori (2001), global efficiency in a weighted directed network is defined as:

$$GE(G) = \frac{1}{n(n-1)} \sum_{i \neq j} \frac{1}{d_{ij}} \quad (14)$$

where n is the number of nodes (sectors) in the network and d_{ij} is the weighted distance between nodes i and j . In a financial network like $G = \{V, E\}$, distances are defined as the reciprocal of edges between i and j ($1/\omega_{ij}$), so stronger exposures imply shorter distances and higher global efficiency.

4.3. Identifying communities through the Louvain algorithm

The Louvain method of community detection is based on the optimisation of modularity, defined as a measure of the density of links inside communities compared to links between communities. In a weighted network, modularity is equal to:

$$Q = \frac{1}{2m} \sum_{i=1}^N \sum_{j=1}^N \left(\omega_{ij} - \frac{k_i k_j}{2m} \right) \delta(c_i, c_j) \quad (15)$$

where m is the sum of all edge weights in the network, N is the total number of nodes in the network, ω_{ij} is the edge weight between node i and node j , k_i and k_j are the sum of the weights linked to node i and to node j , respectively, c_i and c_j are the communities to which nodes i and j belong, and $\delta(c_i, c_j)$ is the Kronecker delta function, which takes the value 1 if the nodes i and j belong to the same community, and zero otherwise.

The modularity of community c would then be equal to:

$$Q_c = \frac{\sum in}{2m} - \left(\frac{\sum tot}{2m} \right)^2 \quad (16)$$

where $\sum in$ is the sum of edge weights between nodes in the community c and $\sum tot$ is the sum of all edge weights of nodes in the community, including edges to nodes outside the community.

From Equation (15) and Equation (16), modularity of a network can be expressed as the sum of the modularity of its communities:

$$Q = \sum_{c=1}^C Q_c \quad (17)$$

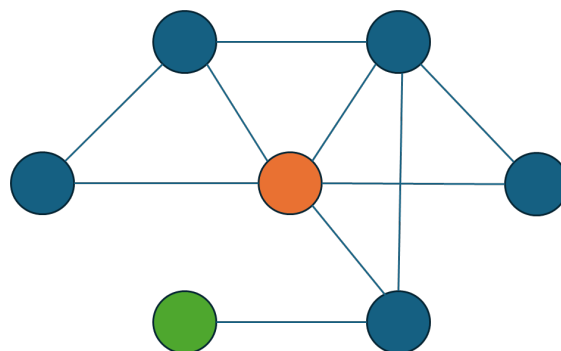
The Louvain algorithm works in two phases. First, each node is considered to be its own community. Then, the algorithm assesses how moving each node into a neighbouring community would affect the modularity of the network. The algorithm selects the community with the largest positive change and incorporates the new node into it. The process continues until there is no further improvement in modularity. In the second phase, communities are treated as if they were nodes, trying to optimise modularity as in the first phase. The process goes on until an optimal level of modularity is achieved.

4.4. Using network metrics for the identification of contagion

Before discussing the values of the network metrics defined in this section, it is useful to consider how these metrics indirectly relate to the capacity of a member of the network to transmit shocks through the network. While reaching final conclusions requires a fully-fledged contagion model or a thorough assessment of balance sheet vulnerabilities, the position that each node occupies in the network can signal whether it can potentially contribute to the transmission of a shock throughout the network.

In principle, higher values of degree centrality for a node, signalling that it has a relatively high number of edges, are linked to a central position of the node and, as such, a potential for transmitting shocks to other nodes. For example, the orange node in Figure 2 has a degree centrality of 5 and could possibly act as a transmitter of a shock originated in it, while the green node, with a degree centrality of 1, could be expected to lead, in principle, to limited contagion of a shock originating in it.

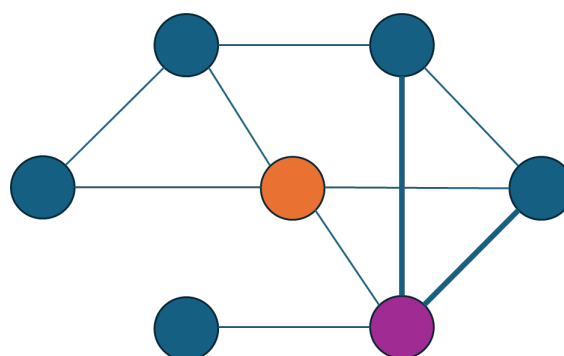
Figure 2. Degree centrality and contagion in a hypothetical network



Source: author.

Similarly, higher values of strength, which considers the size of the connections, could be associated to a node that can transmit a shock through the network. In Figure 3, the potential capacity of the purple node to act as transmitter of a shock would be higher than the capacity of the orange node, despite having both four connections, as it has larger connections to other nodes in the network.

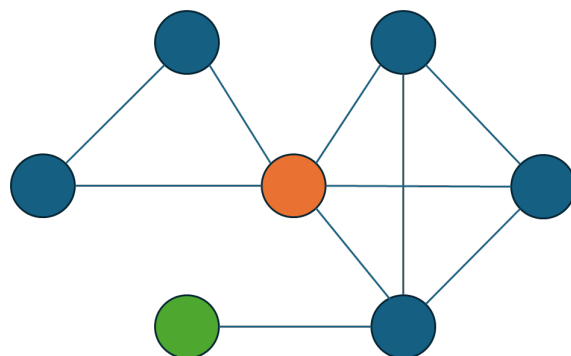
Figure 3. Strength and contagion in a hypothetical network



Source: author. Note: the thickness of the links between nodes represents the size of those links.

Betweenness and closeness can also provide interesting insights on how contagion may work in a given network. In Figure 4, the orange node, which has high values of betweenness, can be expected to play a key role in the transmission of a shock in the network, as it links the right and the left part of the network. On the other side, the green node should have a low value of betweenness and should not be seen as the node with the highest probability of transmitting shocks to other parts of the network.

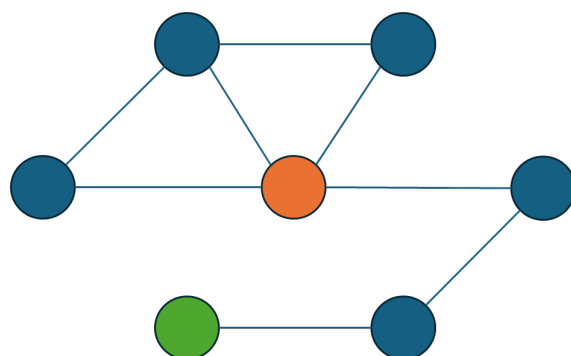
Figure 4. Betweenness and contagion in a hypothetical network



Source: author.

In terms of closeness, the green node in Figure 5 occupies a marginal position in the network (i.e., should have low values of closeness) and, as such, should have a more limited role as transmitter of a shock. The orange node, on the contrary, should have high closeness, as it is not far from any blue node, and could play a key role in the transmission of a hypothetical shock.

Figure 5. Closeness and contagion in a hypothetical network



Source: author.

Regarding other network metrics and indicators, the intuitions for eigenvalue centrality, page rank, authority score and hub score are similar to that of strength. The definition of global efficiency is close to the concepts of closeness and betweenness, and so is also the interpretation of values of global efficiency in the transmission of shocks.

5. Measures of centrality in the networks

Network analysis focuses on the links between different components of a system (usually called nodes), which, in this case, are sectors of activity. One key question in network analysis refers to the identification of the most important (or central) nodes, as their failure could have

catastrophic effects for the complete network. While there is no unique way to measure the centrality of nodes in network theory, the previous section has briefly described several indicators of centrality in a network.

First, degree centrality simply counts the number of connections that a node has. As it merely counts connections, a node with many small connections would appear more central than a node with few larger connections. Table 2 shows the degree centrality of each sector in the financial system of the twenty euro area countries. While there is certain cross-country heterogeneity, it is also possible to find some common features: banks tend to be the most central sector according to this measure and, on the other side, money-market funds and pension funds tend to be the less central sectors, even in countries where there are known to be important participants of the financial system, such as the Netherlands (pension funds) or Luxembourg (money-market funds). Households appear to have a constant number of connections across all countries. Other financial institutions, non-financial corporations, investment funds and the government also show large degree centrality. Insurance corporations display more cross-country heterogeneity, being quite central in some countries, like Belgium, Germany or Italy, and not in others, like Latvia, Estonia or Slovakia.

Table 2. Degree centrality across euro area financial systems, Q4-2024

	AT	BE	CY	DE	EE	ES	FI	FR	GR	HR	IE	IT	LT	LU	LV	MT	NL	PT	SI	SK
Banks	17	19	17	19	15	19	18	19	18	16	18	19	16	18	16	15	17	17	19	16
Gov	15	16	12	16	11	15	15	16	15	14	15	16	12	13	12	14	13	14	16	12
HH	11	11	11	11	10	11	11	11	11	10	11	11	11	11	11	11	11	11	11	11
IF	15	15	14	15	13	15	15	15	15	15	15	15	13	13	13	15	14	15	15	13
Insurance	15	16	10	16	7	14	15	15	11	12	9	16	8	10	6	11	11	15	16	8
MMF	1	7	2	8	1	8	6	8	8	1	7	8	1	6	1	2	4	2	8	1
NFC	15	15	15	16	13	15	16	15	16	14	13	16	14	14	14	15	13	15	16	14
OFI	15	16	14	16	13	16	16	16	16	11	14	16	15	15	13	15	14	16	16	14
Pensions	5	9	8	9	1	9	9	9	8	8	7	9	7	4	8	7	8	9	9	7
RoW	11	14	11	14	10	14	13	14	14	11	13	14	11	14	12	11	13	12	14	10

Source: ECB and author's calculations. Notes: RoW stands for rest of the world, OFI for other financial institutions, NFC for non-financial corporations, MMF for money market funds, IF for investment funds, HH for households and Gov for government. Green cells show the highest 10% values and the yellow cells the bottom 10% values.

As a summary of the information in Table 2, centralisation calculates a graph-level centrality score based on the degree centrality of each node. The highest values (implying a more

centralised network) are associated with Luxembourg and Ireland, while Portugal and Malta display the lowest values (Table 3).

Table 3. Centralisation across euro area financial systems, Q4-2024

	AT	BE	CY	DE	EE	ES	FI	FR	GR	HR	IE	IT	LT	LU	LV	MT	NL	PT	SI	SK
Centralisation	0.31	0.32	0.35	0.31	0.35	0.33	0.28	0.32	0.30	0.30	0.36	0.31	0.32	0.41	0.33	0.21	0.32	0.27	0.31	0.33

Source: ECB and author's calculations. Notes: Green cells show the highest 10% values and the yellow cells the bottom 10% values.

A second indicator of centrality is betweenness, which measures whether a node is important in the flow of the network. The underlying idea is that if node C is between the shortest path from node A to node B, then node C is important for the network. Betweenness counts how many shortest paths each node has: the higher a node's betweenness, the more important it is for the efficient flow in the network. These nodes would be like transport hubs, where, for example, highways or trains converge in a given city and have a high volume of traffic. Table 4 shows the betweenness across euro area countries. Insurance and other financial institutions tend to show high scores according to this measure, with rather low scores for the rest of the world, pension funds, non-financial corporations and investment funds. Banks are also among the least central sectors according to this measure, despite having high degree centrality. Sectors with high betweenness can be seen as those that, depending upon the structure and existing vulnerabilities of their balance sheet, could potentially transmit shocks originating in other sectors throughout the system. That would be the case, for example, of insurance corporations in Finland, which have a relatively high value of betweenness compared to other sectors, and which could, in principle, be expected to act as transmitters of a shock originated elsewhere in the Finnish economy. For that to occur, the balance sheet of Finnish insurance corporations should be vulnerable to shocks, through, for example, fire sales or large margin calls. The high value of betweenness of insurance corporations in Finland stems from the large exposure to households to them (in the form of assets of households, and liability of insurance corporations) and the broad exposures of insurance corporations with all other sectors of activity, except households and pension funds. On the other side, the position of pensions funds or the rest of the world in the network of Finland suggests that they are unlikely to transmit shocks to other parts of the economies.

Table 4. Betweenness across euro area financial systems, Q4-2024

	AT	BE	CY	DE	EE	ES	FI	FR	GR	HR	IE	IT	LT	LU	LV	MT	NL	PT	SI	SK
Banks	8	38	0	11	1	10	29	0	25	0	25	0	13	11	3	6	22	0	15	0
Gov	38	36	8	32	0	42	8	61	18	31	57	17	0	49	39	14	39	10	46	40
HH	18	11	10	11	22	11	21	11	11	19	21	11	32	21	29	36	11	19	11	36
IF	0	8	8	0	14	0	28	0	28	25	10	21	56	0	36	11	24	0	6	18
Insurance	40	13	50	31	14	35	61	11	40	32	36	44	11	51	0	43	32	57	15	11
MMF	0	35	0	54	0	44	26	17	24	0	0	58	0	0	0	0	4	0	32	0
NFC	3	0	36	0	10	0	0	0	0	0	10	0	0	22	7	0	15	0	0	3
OFI	49	31	22	31	22	19	29	46	51	42	0	21	32	49	33	33	28	60	43	57
Pensions	0	0	0	0	0	0	11	0	0	11	0	0	0	0	11	38	0	0	0	0
RoW	0	0	0	0	1	29	0	39	18	35	21	24	35	0	40	0	11	0	36	0

Source: ECB and author's calculations. Notes: RoW stands for rest of the world, OFI for other financial institutions, NFC for non-financial corporations, MMF for money market funds, IF for investment funds, HH for households and Gov for government. Green cells show the highest 10% values and the yellow cells the bottom 10% values.

Next, closeness is based on the shortest paths between nodes. In this case, low values mean that a node is more central than those nodes with higher values. As observed in Table 5, Estonia, Malta, Greece and Slovenia report higher values of closeness than other countries, implying that some parts of their financial system require long interactions to reach other sectors. There are several other euro area countries showing limited heterogeneity in closeness across sectors (with the recurrent exception of pension funds), such as Belgium, Germany, Spain or Netherlands. At sectoral level, pensions report the highest values of closeness in most countries, suggesting that they may be the last sector to be affected by a shock going through the whole financial system. On the other side, sectors exhibiting low values for closeness, such as money market funds in Luxembourg or other financial institutions in Ireland, could be seen as those that could more easily act as transmitters of a shock to other parts of the financial system. That would be the case, for instance, if they were particularly sensitive to sudden margin calls or operate under a business model based on short-termed assets and liabilities. In this case, the low values of closeness are linked to the existence of many connections with domestic sectors and, at the same time, very high exposures to the rest of the world that the other sectors do not exhibit. For the rest of the world, having low values of closeness when compared to other sectors (for example, in Austria, Cyprus, Malta or Portugal) could imply larger vulnerabilities of these countries to shocks originated abroad.

Table 5. Closeness across euro area financial systems, Q4-2024

	AT	BE	CY	DE	EE	ES	FI	FR	GR	HR	IE	IT	LT	LU	LV	MT	NL	PT	SI	SK
Banks	12	4.8	61	0.7	140	4.3	28	1.3	80	19	6.3	2.5	65	36	47	183	0.5	28	131	28
Gov	11	4.7	42	0.6	72	4.4	29	2.0	75	19	6.7	2.5	61	39	45	207	0.5	28	131	27
HH	10	6.7	77	0.6	311	3.5	45	2.3	49	16	6.4	2.0	70	51	50	250	0.6	49	143	31
IF	13	4.6	60	0.7	133	4.2	30	1.6	132	19	6.5	2.2	64	34	47	203	0.5	28	132	27
Insurance	11	4.5	61	0.6	465	4.1	29	1.3	128	19	6.3	2.2	89	37	51	201	0.5	28	131	37
MMF		4.8		0.7		4.3	26	1.9	83		5.8	2.6		5			0.3		132	
NFC	11	4.7	59	0.6	102	3.6	31	2.2	138	19	6.8	2.4	62	41	47	199	0.5	28	122	27
OFI	11	4.7	46	0.6	132	4.1	29	2.0	159	19	4.4	2.1	62	38	47	197	0.5	28	130	27
Pensions	124	23.6	157	4.3		33.9	170	9.7	1186	1068	56.6	57.6	188	50	471	263	3.8	107	857	72
RoW	3	4.7	29	0.7	338	4.3	42	1.8	85	19	5.6	2.6	63	21	45	82	0.3	9	133	31

Source: ECB and author's calculations. Notes: RoW stands for rest of the world, OFI for other financial institutions, NFC for non-financial corporations, MMF for money market funds, IF for investment funds, HH for households and Gov for government. Green cells show the bottom values for each country (signalling higher centrality) and the yellow cells the highest value for each country.

These three indicators (degree centrality, betweenness and closeness) offer only a partial view on centrality, as they do not take into account the size of the interconnections. To that purpose, strength refers to the sum of all the direct connections of a node to another nodes. Table 6 shows the value of the strength indicator for each sector in euro area countries, normalised to the value for banks. Banks tend to report the highest values, with the exceptions of Cyprus, Ireland, Luxembourg and Malta, indicating that in- and out-bound connections to them are the largest and, as such, they occupy a place at the core of the networks. The rest of the world and households also show high values across countries. These could be seen as the three most interconnected sectors in the networks. Individual high values can be observed for other financial institutions in Cyprus and Malta, and for investment funds in Ireland and Luxembourg. At the other end, money-market funds, pension funds and insurance corporations tend to show the lowest values for strength, implying that they have relatively small connections to other sectors.

Table 6. Strength across euro area financial systems, Q4-2024

	AT	BE	CY	DE	EE	ES	FI	FR	GR	HR	IE	IT	LT	LU	LV	MT	NL	PT	SI	SK
Banks	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Gov	0.30	0.28	0.14	0.18	0.14	0.43	0.32	0.16	0.47	0.37	0.14	0.37	0.22	0.05	0.46	0.20	0.18	0.30	0.42	0.48
HH	0.56	0.74	0.71	0.70	0.57	0.60	0.57	0.36	0.68	0.65	0.58	0.75	0.53	0.12	0.71	0.56	0.98	0.62	0.78	0.72
IF	0.29	0.26	0.11	0.38	0.22	0.19	0.45	0.16	0.07	0.05	7.72	0.13	0.04	9.92	0.02	0.56	0.41	0.09	0.16	0.09
Insurance	0.10	0.20	0.07	0.20	0.02	0.10	0.17	0.23	0.06	0.05	0.45	0.28	0.04	0.18	0.05	0.16	0.10	0.11	0.15	0.04
MMF	0.00	0.00	0.01	0.00	0.00	0.02	0.00	0.03	0.01	0.00	1.46	0.00	0.00	0.83	0.00	0.01	0.01	0.00	0.00	0.00
NFC	0.34	0.40	0.62	0.33	0.57	0.42	0.48	0.30	0.45	0.44	0.61	0.33	0.37	0.23	0.49	0.31	0.41	0.33	0.48	0.38
OFI	0.09	0.25	2.35	0.10	0.33	0.09	0.07	0.07	0.06	0.03	1.63	0.18	0.10	2.25	0.24	3.98	0.72	0.06	0.08	0.07
Pensions	0.06	0.08	0.09	0.13	0.00	0.07	0.01	0.02	0.02	0.30	0.17	0.08	0.17	0.00	0.41	0.05	0.88	0.04	0.11	0.19
RoW	0.58	0.97	2.89	0.62	0.56	0.50	0.80	0.43	0.45	0.27	10.14	0.53	0.58	11.39	0.86	4.90	1.42	0.36	0.64	0.55

Source: ECB and author's calculations. Notes: RoW stands for rest of the world, OFI for other financial institutions, NFC for non-financial corporations, MMF for money market funds, IF for investment funds, HH for households and Gov for government. Green cells show the highest 10% values and the yellow cells the bottom 10% values.

Eigenvalue centrality is another centrality indicator that takes into account the size of the connection each node has, by looking at the connections of the counterparts. It looks at nodes that are connected to nodes that are important and, hence, become themselves important. Table 7 shows the values of the eigenvalue centrality, normalised to a value of 1 for the sector with the highest value in each country. With only four exceptions (Ireland, Luxembourg, Malta and Netherlands), banks take the highest value. Investment funds get the highest score for Ireland (practically tied with the rest of the world) and Luxembourg, while the rest of the world takes the highest value for Malta and Netherlands. With limited exceptions, pension funds, other financial institutions, money-market funds, insurance corporations and investment funds tend to have low values of this indicator, pointing to their non-central place in national networks. The rest of the world tends to show quite a central position for many countries, particularly for Ireland, Lithuania, Luxembourg, Malta and the Netherlands.

Table 7. Eigenvalue centrality across euro area financial systems, Q4-2024

	AT	BE	CY	DE	EE	ES	FI	FR	GR	HR	IE	IT	LT	LU	LV	MT	NL	PT	SI	SK
Banks	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.01	1.00	1.00	0.05	1.00	0.64	0.79	1.00	1.00	1.00
Gov	0.47	0.52	0.28	0.31	0.18	0.71	0.38	0.21	0.86	0.50	0.02	0.82	0.52	0.00	0.81	0.26	0.34	0.54	0.63	0.61
HH	0.46	0.48	0.48	0.50	0.64	0.53	0.63	0.30	0.44	0.50	0.00	0.43	0.54	0.00	0.48	0.26	0.54	0.58	0.55	0.84
IF	0.16	0.19	0.12	0.22	0.24	0.17	0.31	0.08	0.06	0.04	1.00	0.13	0.06	1.00	0.02	0.78	0.35	0.09	0.11	0.12
Insurance	0.07	0.12	0.04	0.16	0.01	0.07	0.14	0.11	0.04	0.03	0.00	0.22	0.02	0.00	0.04	0.03	0.04	0.10	0.10	0.05
MMF	0.00	0.00	0.00	0.00	0.00	0.03	0.00	0.04	0.01	0.00	0.16	0.01	0.00	0.06	0.00	0.00	0.02	0.00	0.01	0.00
NFC	0.68	0.60	0.88	0.50	0.81	0.65	0.71	0.41	0.83	0.51	0.09	0.61	0.63	0.03	0.75	0.34	0.60	0.48	0.69	0.54
OFI	0.03	0.20	0.03	0.06	0.27	0.10	0.04	0.08	0.08	0.01	0.01	0.18	0.06	0.02	0.16	0.04	0.13	0.04	0.08	0.06
Pensions	0.07	0.09	0.08	0.15	0.00	0.08	0.02	0.01	0.02	0.25	0.00	0.09	0.17	0.00	0.32	0.00	0.66	0.04	0.12	0.27
RoW	0.49	0.61	0.67	0.52	0.42	0.40	0.50	0.34	0.36	0.18	1.00	0.60	0.78	0.86	0.62	1.00	1.00	0.25	0.36	0.37

Source: ECB and author's calculations. Notes: RoW stands for rest of the world, OFI for other financial institutions, NFC for non-financial corporations, MMF for money market funds, IF for investment funds, HH for households and Gov for government. Green cells show the highest 10% values and the yellow cells the bottom 10% values.

Next, the page rank indicator is based on the algorithms of Internet search engines, looking at the importance of the nodes to which a node is linked. According to the results in Table 8, banks tend to be the most central sector according to this metric for all countries, except Spain, Ireland, Luxembourg, Portugal and Slovakia. The government is the most central sector in Spain, Portugal and in Slovakia, while the rest of the world is in Ireland and Luxembourg. In general, the rest of the world and non-financial corporations have increased their centrality in a homogenous way when using this indicator. On the other side, the values for pension funds, other financial institutions, money-market funds and insurance corporations remain low, as has been the case of other indicators.

Table 8. Page rank across euro area financial systems, Q4-2024

	AT	BE	CY	DE	EE	ES	FI	FR	GR	HR	IE	IT	LT	LU	LV	MT	NL	PT	SI	SK
Banks	0.24	0.24	0.29	0.25	0.29	0.21	0.26	0.30	0.26	0.33	0.09	0.26	0.30	0.10	0.26	0.26	0.23	0.22	0.26	0.24
Gov	0.20	0.15	0.08	0.13	0.07	0.34	0.08	0.11	0.26	0.15	0.05	0.20	0.12	0.02	0.22	0.09	0.09	0.36	0.15	0.25
HH	0.07	0.08	0.11	0.08	0.11	0.07	0.10	0.06	0.09	0.11	0.03	0.07	0.09	0.02	0.09	0.09	0.11	0.08	0.10	0.11
IF	0.09	0.05	0.05	0.10	0.06	0.04	0.11	0.07	0.03	0.02	0.29	0.03	0.05	0.34	0.02	0.14	0.07	0.04	0.04	0.03
Insurance	0.02	0.03	0.02	0.03	0.02	0.02	0.03	0.04	0.02	0.02	0.02	0.03	0.02	0.02	0.02	0.02	0.02	0.02	0.04	0.02
MMF	0.02	0.02	0.02	0.02	0.03	0.02	0.02	0.03	0.02	0.02	0.06	0.02	0.02	0.04	0.02	0.02	0.02	0.02	0.02	0.02
NFC	0.17	0.18	0.20	0.18	0.20	0.14	0.19	0.21	0.18	0.21	0.05	0.20	0.17	0.03	0.15	0.11	0.15	0.13	0.20	0.15
OFI	0.02	0.05	0.02	0.02	0.06	0.03	0.02	0.03	0.03	0.02	0.03	0.04	0.03	0.05	0.04	0.03	0.04	0.02	0.03	0.03
Pensions	0.02	0.02	0.03	0.03	0.02	0.02	0.02	0.02	0.02	0.04	0.02	0.02	0.03	0.02	0.04	0.02	0.07	0.02	0.02	0.04
RoW	0.14	0.17	0.19	0.16	0.14	0.11	0.17	0.13	0.11	0.07	0.36	0.12	0.17	0.37	0.14	0.23	0.20	0.09	0.13	0.11

Source: ECB and author's calculations. Notes: RoW stands for rest of the world, OFI for other financial institutions, NFC for non-financial corporations, MMF for money market funds, IF for investment funds, HH for households and Gov for government. Green cells show the highest 10% values and the yellow cells the bottom 10% values.

Two additional metrics are hub and authority scores, as initially developed by Kleinberg (1999). In a nutshell, nodes with high authority scores have many inbound links while nodes with high hub scores have many outbound links. Table 9 shows the authority scores across the twenty euro area countries, finding that banks report the highest score and money-market funds the lowest. The rest of the world gets the highest authority score in Cyprus, Ireland, Malta and Netherlands, while investment funds do in Luxembourg and households in Slovakia. Looking at households and non-financial corporations, their scores move along a relatively large range, with high values in Estonia, Finland and Slovakia, and low values in Netherlands, Ireland and Cyprus. Similarly, the government sector scores high in Spain, Finland, Italy and Latvia, but rather low in Germany, Ireland and the Netherlands. In average terms, banks dominate, followed by the rest of the world, non-financial corporations and households. In a network of financial exposures,

this indicates that banks issue liabilities (i.e., deposits) that are largely used by other sectors of the economy.

Table 9. Authority scores across euro area financial systems, Q4-2024

	AT	BE	CY	DE	EE	ES	FI	FR	GR	HR	IE	IT	LT	LU	LV	MT	NL	PT	SI	SK
Banks	1.00	1.00	0.03	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.01	1.00	1.00	0.05	1.00	0.01	0.19	1.00	1.00	0.70
Gov	0.27	0.44	0.00	0.18	0.21	0.46	0.50	0.22	0.24	0.31	0.01	0.51	0.33	0.00	0.50	0.00	0.08	0.45	0.24	0.63
HH	0.35	0.27	0.02	0.33	0.78	0.39	0.71	0.29	0.16	0.28	0.01	0.25	0.49	0.00	0.17	0.00	0.19	0.43	0.13	1.00
IF	0.16	0.25	0.01	0.21	0.28	0.23	0.33	0.08	0.08	0.06	0.43	0.16	0.05	1.00	0.01	0.00	0.12	0.10	0.14	0.08
Insurance	0.11	0.19	0.00	0.27	0.01	0.11	0.13	0.15	0.07	0.04	0.00	0.41	0.03	0.00	0.08	0.00	0.01	0.13	0.12	0.03
MMF	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.04	0.00	0.00	0.06	0.00	0.00	0.06	0.00	0.00	0.01	0.00	0.00	0.00
NFC	0.48	0.45	0.04	0.33	0.97	0.48	0.78	0.37	0.31	0.31	0.05	0.32	0.51	0.03	0.38	0.01	0.18	0.37	0.27	0.62
OFI	0.03	0.12	0.00	0.05	0.31	0.08	0.04	0.07	0.03	0.00	0.01	0.10	0.05	0.02	0.05	0.00	0.07	0.03	0.02	0.05
Pensions	0.12	0.15	0.00	0.25	0.00	0.12	0.02	0.02	0.03	0.43	0.00	0.17	0.26	0.00	0.57	0.00	0.24	0.06	0.17	0.18
RoW	0.49	0.56	1.00	0.52	0.56	0.36	0.50	0.33	0.21	0.11	1.00	0.61	0.74	0.47	0.35	1.00	1.00	0.22	0.22	0.34

Source: ECB and author's calculations. Notes: RoW stands for rest of the world, OFI for other financial institutions, NFC for non-financial corporations, MMF for money market funds, IF for investment funds, HH for households and Gov for government. Green cells show the highest 10% values and the yellow cells the bottom 10% values.

Hub scores identify sectors that are more connected to central sectors. As seen in Table 10, households and banks report the maximum value for nine and six countries, respectively. Other financial institutions get the highest value in Cyprus, Malta and Netherlands, investment funds in Ireland and the rest of the world in Luxembourg. At the other end, lowest values are usually associated with money-market funds, and in some instances also for governments (Cyprus, Ireland, Malta), non-financial corporations (Luxembourg and Malta), pensions (Estonia and Luxembourg) and the rest of the world (Malta). Several sectors show very low scores across countries, such as the government, insurance, money-market funds and pensions. Households and banks would then be the sectors that invest the most in liabilities of other sectors, in the form of mainly deposits and loans. The low scores of the government imply a limited role in investing in other financial instruments and contrasts with the higher values in the authority scores, which signal the large issuance of debt securities to fund their activities.

Table 10. Hub scores across euro area financial systems, Q4-2024

	AT	BE	CY	DE	EE	ES	FI	FR	GR	HR	IE	IT	LT	LU	LV	MT	NL	PT	SI	SK
Banks	1.00	0.67	0.06	0.80	1.00	0.93	1.00	1.00	0.38	0.67	0.04	0.67	1.00	0.02	0.36	0.03	0.43	0.94	0.30	1.00
Gov	0.10	0.04	0.00	0.04	0.09	0.18	0.22	0.03	0.15	0.14	0.00	0.03	0.09	0.00	0.14	0.00	0.00	0.05	0.07	0.19
HH	0.96	1.00	0.04	1.00	0.64	1.00	0.53	0.43	1.00	1.00	0.01	1.00	0.89	0.00	1.00	0.02	0.35	1.00	1.00	0.48
IF	0.23	0.21	0.02	0.27	0.15	0.14	0.27	0.08	0.03	0.02	1.00	0.08	0.02	0.52	0.01	0.05	0.30	0.04	0.05	0.04
Insurance	0.07	0.19	0.02	0.12	0.02	0.09	0.10	0.12	0.02	0.02	0.08	0.21	0.06	0.02	0.02	0.03	0.09	0.05	0.05	0.03
MMF	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.02	0.00	0.00	0.23	0.00	0.00	0.05	0.00	0.00	0.00	0.00	0.00	0.00
NFC	0.25	0.24	0.00	0.22	0.46	0.39	0.19	0.20	0.31	0.34	0.00	0.22	0.36	0.00	0.41	0.00	0.04	0.32	0.34	0.17
OFI	0.14	0.24	1.00	0.13	0.43	0.16	0.08	0.08	0.07	0.04	0.33	0.21	0.16	0.18	0.21	1.00	1.00	0.09	0.03	0.06
Pensions	0.01	0.03	0.01	0.03	0.00	0.04	0.00	0.01	0.00	0.11	0.01	0.03	0.19	0.00	0.19	0.01	0.45	0.02	0.03	0.08
RoW	0.34	0.84	0.01	0.31	0.44	0.47	0.68	0.38	0.24	0.14	0.43	0.23	0.42	1.00	0.58	0.00	0.13	0.31	0.25	0.46

Source: ECB and author's calculations. Notes: RoW stands for rest of the world, OFI for other financial institutions, NFC for non-financial corporations, MMF for money market funds, IF for investment funds, HH for households and Gov for government. Green cells show the highest 10% values and the yellow cells the bottom 10% values.

To sum up, through the computation of various indicators of centrality, it is possible to identify certain patterns across euro area countries. The banking sector dominates in the majority of euro area economies and only in four countries banks are not the most central sector in the economy. This finding seems to confirm that Europe continues to be overbanked, as identified by Pagano et al. (2014). However, beyond this high-level finding, other indicators provide also useful insights in terms of which sectors (i) could potentially act as transmitters of shocks, as seen from the scores in betweenness and closeness, (ii) have large exposures to other sectors, as observed in eigenvalue, strength and page rank, and (iii) issue liabilities that are key for the system, as shown by authority and hub scores.

6. Further characterisation of the networks

Identifying the most central nodes in a network is important but it does not represent everything that can be analysed in a network. In this section I look at other indicators, which can provide interesting insights on the structure of the financial system of the twenty euro area economies.

A first indicator is edge density, which computes the share of connections over the total potential connections in a network. Table 11 shows that highest edge densities are found in Belgium, Germany, Spain, Finland, France, Italy and Slovenia. At the other end, Estonia, Latvia and Slovakia display the less dense networks.

Table 11. Edge density across euro area financial systems, Q4-2024

	AT	BE	CY	DE	EE	ES	FI	FR	GR	HR	IE	IT	LT	LU	LV	MT	NL	PT	SI	SK
Edge density	0.60	0.69	0.57	0.70	0.47	0.68	0.67	0.69	0.66	0.56	0.61	0.70	0.54	0.57	0.53	0.58	0.59	0.63	0.70	0.53

Source: ECB and author's calculations. Notes: Green cells show the highest 10% values and the yellow cells the bottom 10% values.

A second indicator on the density of a network is the clustering coefficient (also known as transitivity). It measures the number of times that a tri-lateral relation between three nodes is closed. For example, given A, B and C nodes, and if A is connected to B and C, the density of the network is different whether B is connected to C or not. This is what the clustering coefficient measures. Table 12 shows the highest value for Estonia (it has few connections but closed), with Ireland and Luxembourg at the other side of the distribution. The latter is somehow a logic result given the structure of their financial system, with massive bilateral connections between other financial institutions, investment funds and the rest of the world, which remain less connected to the other domestic sectors. Germany, Spain, France, Croatia, Italy, Portugal, Slovenia and Slovakia also show relatively high values of the clustering coefficient. In general, the high values of the clustering coefficient, above 0.8, point to very dense networks across the twenty euro area countries.

Table 12. Clustering coefficient across euro area financial systems, Q4-2024

	AT	BE	CY	DE	EE	ES	FI	FR	GR	HR	IE	IT	LT	LU	LV	MT	NL	PT	SI	SK
Clustering coefficient	0.90	0.93	0.91	0.94	1.00	0.94	0.93	0.94	0.91	0.94	0.82	0.94	0.91	0.87	0.88	0.89	0.90	0.95	0.94	0.94

Source: ECB and author's calculations. Notes: Green cells show the highest 10% values and the yellow cells the bottom 10% values.

Computing edge density and the clustering coefficient tries to measure the density of a network but says nothing about how similar a particular network (i.e., country) is to the others. This can be assessed using the cosine similarity, as shown in Table 13. Higher values signal larger similarities between two networks. In this case, there are almost identical networks between several pairs of countries, such as Cyprus and Malta, or Luxembourg and Ireland. Other networks with remarkably high similarity are those, for instance, between Spain and Austria, Austria and Germany, Spain and Portugal, and Spain and Slovenia. It is also worth noting that the networks of Ireland, Luxembourg and Malta are remarkably different to the networks of Greece, Croatia, Lithuania, Portugal, Slovenia and Slovakia.

Table 14, Slovakia, Portugal, Estonia and Latvia report high values of global efficiency, signalling their potential vulnerability to quick contagion from a shock.² At the other extreme, France, Germany, Italy, Netherlands and Spain report the lowest values for global efficiency, so they could be, in principle, less vulnerable to contagion from a shock affecting the domestic financial system. Interestingly, these are the five largest economies in the euro area.

Table 14. Global efficiency across euro area financial systems, Q4-2024

	AT	BE	CY	DE	EE	ES	FI	FR	GR	HR	IE	IT	LT	LU	LV	MT	NL	PT	SI	SK
Global efficiency	0.0102	0.0046	0.2585	0.0003	1.2249	0.0032	0.0410	0.0001	0.5650	0.1028	0.0131	0.0010	0.0416	0.0050	1.2145	0.1781	0.0022	2.7591	0.1112	3.7298

Source: ECB and author's calculations. Notes: Green cells show the lowest 10% values and the yellow cells the highest 10% values.

To recap the findings in this section, I have looked at the density of each network and at similarities across them. On the latter, there is a substantial degree of homogeneity in the networks of sixteen euro area countries (excluding Cyprus, Malta, Ireland and Luxembourg, which are, in turn, very similar between them).

7. Identifying communities in the networks

An interesting exercise to better understand the structure of the networks across the twenty euro area countries is to identify communities. The underlying idea is that some sectors in a network may be tightly interconnected among them and less connected with others. There are several methods to identify communities in the related literature, based on different algorithms (for further details, see Hernández-García et al., 2024, and the references therein). The most used algorithm is the Louvain algorithm, developed by Blondel et al. (2008), which has two relevant limitations: it requires the network to be undirected, and it does not allow a node to be in more than one community.

There are several possibilities to create an undirected network from a directed network. One of them is to take the maximum exposure between two nodes i and j :

$$A_{i,j} = \max(A(i,j), A(j,i)) \tag{18}$$

where $A_{i,j}$ refers to the exposure in the undirected network between nodes i and j .

² Slovakia, Latvia and Estonia also had the lowest edge density, according to Table 10.

Table 15 shows the communities identified by the Louvain algorithm, where cross-sectoral exposures are computed according to Equation (18). The immediate result is that there are no pair of euro area countries with the same communities.

Table 15. Communities identified using the Louvain algorithm, maximum of exposures, Q4-2024

	AT	BE	CY	DE	EE	ES	FI	FR	GR	HR	IE	IT	LT	LU	LV	MT	NL	PT	SI	SK
Banks	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Gov	2	2	1	2	2	2	2	1	1	1	1	2	2	1	2	1	2	1	2	2
HH	1	1	1	1	1	1	1	2	1	1	1	2	1	1	3	1	2	1	1	1
IF	2	2	1	2	1	1	2	2	2	2	2	2	1	2	3	2	2	2	2	1
Insurance	2	2	1	1	2	2	1	2	2	2	1	2	2	1	3	1	2	2	2	2
MMF	2	2	1	1	3	2	1	1	2	1	2	2	2	1	3	1	2	2	2	2
NFC	1	3	1	2	1	2	2	1	2	2	1	1	1	1	1	1	1	2	2	2
OFI	2	3	2	2	2	1	2	1	2	2	2	1	1	2	1	2	1	2	1	2
Pensions	1	1	1	1	3	1	1	2	1	1	1	2	2	1	3	2	2	1	1	1
RoW	2	2	2	2	2	2	2	1	2	2	2	2	2	2	2	2	1	2	2	2

Source: ECB and author’s calculations. Notes: numbers 1, 2 and 3 indicate membership into a community and they are coloured for presentational reasons. RoW stands for rest of the world, OFI for other financial institutions, NFC for non-financial corporations, MMF for money market funds, IF for investment funds, HH for households and Gov for government.

While there are no countries with identical communities, there is a rather homogenous characterisation across sectors. Most countries have two communities (only Belgium, Estonia and Latvia have three communities), with similar, albeit not identical, composition. Banks, households, non-financial corporations and pensions are often included into the same community, which can be labelled as “real economy”. On the other hand, investment funds, insurance corporations, money-market funds, other financial institutions and the rest of the world tend to appear in the same community, which can be labelled “financial sector”. The consideration of the rest of the world in this second community (except for France and Netherlands) aligns with the view that cross-border financial flows are now primarily driven by finance, rather than by trade, as hinted by Maechler (2025). Finally, the government sector may appear into any of the two communities.

As stated above, there are other possibilities to make the networks undirected, before applying the Louvain algorithm. A second possibility is to use the sum of the exposures between nodes i and j :

$$A_{i,j} = A(i,j) + A(j,i) \tag{19}$$

Under this computation, the cross-country pattern of two communities, one around the real economy and the second one around non-bank financial institutions and the rest of the world, is also visible in Table 16. The composition of these communities remains broadly constant, although pension funds and other financial institutions appear now in the second community for several countries.

Table 16. Communities identified using the Louvain algorithm, sum of exposures, Q4-2024

	AT	BE	CY	DE	EE	ES	FI	FR	GR	HR	IE	IT	LT	LU	LV	MT	NL	PT	SI	SK
Banks	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Gov	2	2	1	2	2	2	2	2	1	2	1	2	2	1	2	1	2	2	2	2
HH	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	2	1	1	1
IF	2	2	2	2	2	2	2	2	2	3	2	2	1	2	2	2	3	2	2	2
Insurance	2	2	1	2	2	2	1	2	2	2	1	2	2	1	2	1	3	2	2	2
MMF	2	2	1	2	3	1	1	2	2	2	2	2	2	1	2	1	2	2	2	2
NFC	1	3	1	1	1	1	2	1	1	3	1	1	1	1	1	1	1	1	1	1
OFI	2	3	2	2	2	1	2	1	1	3	1	1	1	2	1	2	3	1	1	1
Pensions	1	1	1	1	3	1	1	1	1	2	1	1	2	1	2	2	2	2	2	2
RoW	2	2	2	2	2	2	2	2	1	3	2	2	2	2	2	2	3	2	2	2

Source: ECB and author's calculations. Notes: numbers 1, 2 and 3 indicate membership into a community and they are coloured for presentational reasons. RoW stands for rest of the world, OFI for other financial institutions, NFC for non-financial corporations, MMF for money market funds, IF for investment funds, HH for households and Gov for government.

The Louvain algorithm is the most used algorithm for the identification of communities but not the only one. One interesting alternative to the Louvain algorithm is the optimal modularity clustering, which computes the communities that maximise modularity across all potential partitions, and which results are presented below. Annex 3 presents the results of applying two other algorithms to the identification of communities in a network, walktrap and simulated annealing, which have a rather different starting point.

In formal terms, the optimal clustering b^* is found when the modularity Q is maximised across all possible partitions of the graph:

$$b^* = \operatorname{argmax}_b Q \quad (20)$$

Table 17 presents the communities identified following optimal modularity clustering. In a visual exploration, there seems to be a pattern whereby two communities are identified in each country, one comprising, among other sectors, banks, households and non-financial corporations, and a second one that includes investment funds, the rest of the world, insurance corporations and money-market funds. Results are broadly aligned with those in Table 15 and in Table 16, for the

Louvain algorithm, albeit, naturally, with differences. Among the latter, there are more countries with three communities identified with optimal modularity clustering (Belgium, Estonia, Spain, France, Croatia, Lithuania, Luxembourg and Netherland) than when identified with the Louvain algorithm. The allocation of sectors to communities tends to be rather homogenous, with eleven euro area countries having the same communities or less than two differences between Table 15 and Table 17. The largest differences between the application of the Louvain algorithm and optimal modularity clustering are found in France, Greece and Croatia.

Table 17. Communities identified using optimal modularity clustering, Q4-2024

	AT	BE	CY	DE	EE	ES	FI	FR	GR	HR	IE	IT	LT	LU	LV	MT	NL	PT	SI	SK
Banks	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Gov	2	2	1	2	2	2	2	2	2	2	1	2	2	1	2	1	2	2	2	2
HH	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	2	1	1	1
IF	2	2	2	2	2	2	2	2	1	3	2	2	3	2	2	2	3	2	2	2
Insurance	2	2	1	2	2	2	2	2	1	2	1	2	2	2	2	1	3	2	2	2
MMF	2	2	1	2	3	3	1	2	1	2	2	2	2	2	2	1	2	2	2	2
NFC	1	3	1	2	1	3	2	3	1	3	1	1	1	1	1	1	1	1	1	1
OFI	2	3	2	2	2	1	2	1	1	3	1	1	1	3	1	2	3	1	1	1
Pensions	1	1	1	1	3	1	1	1	1	2	1	1	2	1	2	2	2	2	2	2
RoW	2	2	2	2	2	2	2	2	1	3	2	2	2	2	2	2	3	2	2	2

Source: ECB and author's calculations. Notes: numbers 1, 2 and 3 indicate membership into a community and they are coloured for presentational reasons. RoW stands for rest of the world, OFI for other financial institutions, NFC for non-financial corporations, MMF for money market funds, IF for investment funds, HH for households and Gov for government.

To sum up, the application of the Louvain algorithm and optimal modularity clustering for the identification of communities leads to two communities for most euro area countries, one focused on the real economy and including banks, and a second one covering non-bank financial institutions and the rest of the world.

8. Conclusions

In this paper, I have applied network analysis to describe the cross-sectoral financial interconnections of euro area countries, using who-to-whom data from the financial accounts, at aggregated level. The methodology applied to construct these networks can be applied regularly to, among others, monitor developments in the financial system and identify pockets of vulnerabilities. While the networks have been computed aggregating the exposures through different instruments, it is possible and certainly interesting to see whether and how these networks would change when individual instruments (debt securities, investment fund shares,

listed shares, loans and deposits) are used. At instrument level, it is possible to anticipate the dominance of specific sectors: banks in loans and deposits, governments in bonds, and non-financial corporations in listed shares.

The main results are summarised in Table 18 below. In terms of centrality measures, banks find themselves at the core of the network, with just four exceptions: Cyprus, Ireland, Luxembourg and Malta. In these countries, other financial institutions and investment funds are at the core, showing also limited links to the domestic real economy and very strong ones with the rest of the world. The central role played by banks and the large interconnections with the real economy could justify the focus of prudential regulation (at both national and European level) on them, while the concentration of financial non-bank activities in just four countries with large cross-border flows could suggest the need of a certain degree of centralisation in their regulation and supervision. There are also useful insights, at country level, on which sectors could potentially transmit a shock through the whole financial system, which, when complemented with a thorough analysis of existing vulnerabilities in their balance sheet or contagion models, could also be relevant in discussions at national policy fora. These sectors acting as potential transmitters of shocks should also be under the radar of authorities, even if they may be of small size.

Table 18. Summary of main results

	Eigenvalue centrality		Authority					Communities	
	Edge density	Global efficiency	Top 3 sectors			score	Hub score	1. Real economy	2. Finance abroad
						Top sector	Top sector		
AT	0.60	0.0102	Banks	NFC	RoW	Banks	Banks	Yes	Yes
BE	0.69	0.0046	Banks	RoW	NFC	Banks	HH	Yes	Yes
CY	0.57	0.2585	Banks	NFC	RoW	RoW	OFI	Yes	No
DE	0.70	0.0003	Banks	RoW	HH	Banks	HH	Yes	Yes
EE	0.47	1.2249	Banks	NFC	HH	Banks	Banks	Yes	Yes
ES	0.68	0.0032	Banks	Gov	NFC	Banks	HH	Yes	Yes
FI	0.67	0.0410	Banks	NFC	HH	Banks	Banks	Yes	Yes
FR	0.69	0.0001	Banks	NFC	RoW	Banks	Banks	No	No
GR	0.66	0.5650	Banks	Gov	NFC	Banks	HH	Yes	Yes
HR	0.56	0.1028	Banks	NFC	Gov	Banks	HH	Yes	Yes
IE	0.61	0.0131	IF	RoW	MMF	RoW	IF	Yes	Yes
IT	0.70	0.0010	Banks	Gov	NFC	Banks	HH	No	Yes
LT	0.54	0.0416	Banks	RoW	NFC	Banks	Banks	Yes	Yes
LU	0.57	0.0050	IF	RoW	MMF	IF	RoW	Yes	Yes
LV	0.53	1.2145	Banks	Gov	NFC	Banks	HH	No	No
MT	0.58	0.1781	RoW	IF	Banks	RoW	OFI	Yes	Yes
NL	0.59	0.0022	RoW	Banks	Pensions	RoW	OFI	No	No
PT	0.63	2.7591	Banks	HH	Gov	Banks	HH	Yes	Yes
SI	0.70	0.1112	Banks	NFC	Gov	Banks	HH	Yes	Yes
SK	0.53	3.7298	Banks	HH	Gov	HH	Banks	Yes	Yes

Source: ECB and author's calculations. Notes: RoW stands for rest of the world, OFI for other financial institutions, NFC for non-financial corporations, MMF for money market funds, IF for investment funds, HH for households and Gov for government. Regarding communities, a country is considered to have the first community (real economy) when banks, households, and non-financial corporations or pension funds are included in the same community, according to Table 15. Similarly, to have the second community, the rest of the world, and insurance corporations or investment funds must belong to the same community.

Furthermore, there is a substantial degree of heterogeneity in the density of the network (higher for the largest economies) but certain homogeneity when we split countries between those where banks dominate and those where banks do not. Identifying communities using the Louvain and optimal modularity clustering algorithms tends to find a community around the real economy (including banks) and a second community comprising financial institutions other than banks and the rest of the world.

Beyond the descriptive approach presented in this paper, there are at least two areas for further research. The first one implies the definition of shocks to the system and a simulation of its transmission through the networks, following Castrén and Kavonius (2009), Kubelec and Sá (2012), Alves et al. (2013), Castrén and Rancan (2013), Peralta and Crisóstomo (2016) and Foglia

et al. (2023). An important pre-requisite for that is to obtain more granular data, at least at country level, for the rest of the world. As shown by Bijlsma (2019) and Sánchez Serrano (2025a), a possibility would be to use the country breakdown from the dataset of the international investment position. These simulations could also consider networks at the level of financial instrument (deposits, debt securities, listed shares, and investment fund shares). The second potential area for further research could focus on how these networks have changed over time and, particularly, how they behave during episodes of financial stress, such as the global financial crisis, the euro sovereign crisis, Brexit or the outbreak of the COVID-19 pandemic. Both can potentially provide interesting and policy-relevant insights to macroprudential authorities.

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Annex 1. A comparison of the networks in 2019 and 2024

The interconnections between sectors in an economy tend to change slowly over time, implying that the findings of the analysis in the main body, which refers to the fourth quarter of 2024, should be generally valid, without the need to re-run the exercise for each quarter. Saldias and Mizinski (2025) show cosine similarities above 0.9 for most financial instruments in their analysis of networks of the Portuguese financial system, in an analysis covering more than ten years, from 2014 to 2025.

To provide evidence of the persistence of network structures, I have replicated the twenty networks with data at the end of 2019 and computed the key network metrics. Before discussing the results, it is necessary to make a clarification on the data of 2019. At that date, there are several data gaps in the dataset, particularly for money-market funds, other financial institutions and pension funds, which are reported as zero. However, these zeroes do not indicate the absence of a connection, but rather the fact that there is no data to quantify that connection. Therefore, network metrics related to money market funds, other financial institutions and pension funds may change substantially between 2019 and 2024 merely due to data availability in the initial date.

An initial consideration of edge density reveals similar values in the networks at the end of 2019 and of 2024 (Table A1). There are six countries with no change at all between these five years, while in several others the change is below 0.03 in absolute terms.

Table A1. Edge density of the networks in Q4-2019 and difference with Q4-2024

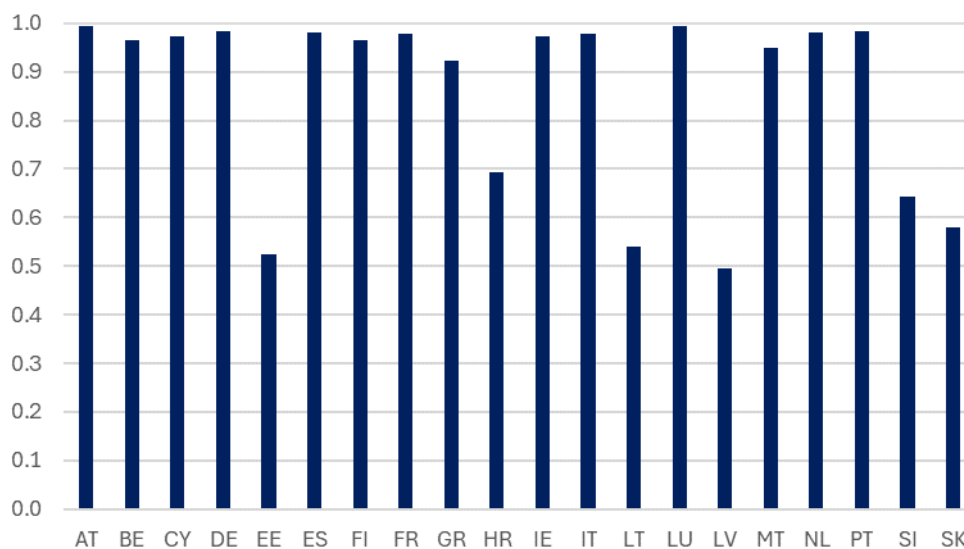
	AT	BE	CY	DE	EE	ES	FI	FR	GR	HR	IE	IT	LT	LU	LV	MT	NL	PT	SI	SK
Edge density	0.59	0.69	0.50	0.70	0.51	0.63	0.67	0.70	0.68	0.51	0.55	0.70	0.53	0.60	0.52	0.60	0.65	0.61	0.70	0.53
Difference (2024 - 2019)	0.01	0.00	0.07	0.00	-0.04	0.05	0.00	-0.01	-0.02	0.05	0.06	0.00	0.01	-0.03	0.01	-0.02	-0.06	0.02	0.00	0.00

Source: ECB and author's calculations. Notes: Green cells show the highest 10% values and the yellow cells the bottom 10% values.

A comparison of the two networks per country using the cosine similarity reveals a substantial degree of similarity for most euro area countries, which report values above 0.95 (Chart A1). The main exceptions are Estonia, Croatia, Lithuania, Latvia, Slovenia and Slovakia, with cosine similarities below 0.7. These countries, which represent around 1% of the total interconnections in the twenty networks, initiated a transition to market open economies after the fall of communism in 1989 and have adopted the euro in recent years. As a result of it, their domestic economic structures may be changing at a faster pace than in other euro area countries, which

have not been subject to comparable developments. All in all, though, values of the cosine similarity confirm, in general, that that structure of the networks exhibits large persistence over time.

Chart A1. Cosine similarity between networks in Q4-2019 and Q4-2024



Source: ECB and author's calculations.

Turning the measures of centrality, I focus on strength and eigenvalue centrality. Strength offers a quantification of the connections in and out of each sector, capturing thus not only the existence of a connection but also its size and direction. The top panel of Table A2 shows the value of strength for the different networks at the end of 2019 and the bottom panel displays the differences between the values for 2024 (Table 6) and those of 2019. Values are normalised to the strength of banks for each country. As in Table 6, banks tend to be the sector with the largest connections with others in the networks, with just few exceptions: Cyprus, Ireland, Luxembourg and Malta. Belgium has a similar value for banks and the rest of the world, while the Netherlands show several sectors of similar size (banks, pension funds, rest of the world, and households). In terms of differences between 2019 and 2024, there are countries with very limited differences (for instance, Austria, Germany, Spain, France or Italy), while other countries display several sectors with differences larger than 0.15 in absolute value (such as, Cyprus, Estonia, Ireland, Latvia or Slovakia).

Table A2. Strength across euro area financial systems, Q4-2019 and differences with Q4-2024

	Strength - 2019																			
	AT	BE	CY	DE	EE	ES	FI	FR	GR	HR	IE	IT	LT	LU	LV	MT	NL	PT	SI	SK
Banks	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Gov	0.28	0.34	0.11	0.20	0.04	0.43	0.29	0.19	0.31	0.25	0.22	0.38	0.14	0.05	0.14	0.06	0.23	0.36	0.25	0.30
HH	0.56	0.86	0.40	0.73	0.24	0.62	0.53	0.44	0.58	0.47	0.58	0.67	0.28	0.11	0.20	0.27	1.13	0.59	0.36	0.51
IF	0.29	0.24	0.04	0.42	0.02	0.17	0.34	0.18	0.02	0.04	6.53	0.10	0.02	8.54	0.01	0.23	0.62	0.06	0.05	0.07
Insurance	0.14	0.32	0.03	0.25	0.01	0.13	0.15	0.34	0.05	0.06	0.41	0.28	0.03	0.15	0.02	0.08	0.15	0.13	0.09	0.05
MMF	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.00	0.00	1.31	0.00	0.00	0.53	0.00	0.00	0.01	0.00	0.00	0.00
NFC	0.32	0.48	0.83	0.30	0.83	0.38	0.53	0.29	0.40	0.75	0.78	0.25	0.78	0.20	0.84	0.68	0.40	0.36	0.73	0.56
OFI	0.09	0.38	1.78	0.07	0.10	0.13	0.08	0.07	0.04	0.03	0.32	0.21	0.05	2.50	0.08	1.65	0.81	0.08	0.04	0.06
Pensions	0.06	0.10	0.04	0.14	0.08	0.07	0.02	0.02	0.01	0.11	0.23	0.06	0.07	0.00	0.09	0.02	1.07	0.06	0.05	0.10
RoW	0.59	1.10	2.08	0.60	0.17	0.49	0.70	0.50	0.38	0.21	8.11	0.48	0.25	9.77	0.26	2.07	1.58	0.41	0.34	0.36
	Difference (2024 - 2019)																			
	AT	BE	CY	DE	EE	ES	FI	FR	GR	HR	IE	IT	LT	LU	LV	MT	NL	PT	SI	SK
Banks	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Gov	0.02	-0.06	0.03	-0.01	0.10	0.00	0.03	-0.03	0.15	0.12	-0.08	0.00	0.08	0.01	0.32	0.14	-0.05	-0.07	0.17	0.18
HH	0.00	-0.12	0.32	-0.04	0.33	-0.03	0.04	-0.08	0.10	0.17	0.00	0.08	0.25	0.01	0.51	0.34	-0.15	0.03	0.42	0.21
IF	0.00	0.01	0.08	-0.04	0.20	0.02	0.11	-0.02	0.05	0.00	1.19	0.03	0.03	1.38	0.01	0.34	-0.21	0.03	0.11	0.03
Insurance	-0.04	-0.11	0.04	-0.05	0.01	-0.03	0.02	-0.11	0.01	0.00	0.04	0.00	0.01	0.03	0.04	0.08	-0.05	-0.02	0.06	-0.01
MMF	0.00	0.00	0.01	0.00	0.00	0.01	0.00	0.00	0.01	0.00	0.15	0.00	0.00	0.30	0.00	0.00	0.00	0.00	0.00	0.00
NFC	0.02	-0.08	-0.21	0.03	-0.26	0.04	-0.05	0.01	0.06	-0.31	-0.18	0.08	-0.41	0.03	-0.35	-0.37	0.00	-0.03	-0.24	-0.18
OFI	0.00	-0.13	0.57	0.04	0.23	-0.03	-0.01	0.00	0.03	0.01	1.31	-0.03	0.05	-0.25	0.16	2.33	-0.09	-0.01	0.04	0.01
Pensions	0.00	-0.02	0.04	-0.01	-0.08	-0.01	0.00	0.00	0.00	0.19	-0.06	0.01	0.11	0.00	0.32	0.03	-0.19	-0.01	0.06	0.10
RoW	-0.01	-0.13	0.81	0.02	0.39	0.00	0.10	-0.07	0.07	0.06	2.03	0.05	0.33	1.62	0.60	2.83	-0.16	-0.04	0.30	0.19

Source: ECB and author's calculations. Notes: RoW stands for rest of the world, OFI for other financial institutions, NFC for non-financial corporations, MMF for money market funds, IF for investment funds, HH for households and Gov for government. In the top panel, green cells show the highest 10% values and the yellow cells the bottom 10% values. In the bottom panel, yellow cells mark changes in absolute value above 0.15.

When considering eigenvalue centrality (Table A3), differences seem to be smaller. For most euro area countries, banks seem to be the most central sector, with the only exceptions of Ireland, Luxembourg and the Netherlands. In Malta, the rest of the world was the most central sector in 2024, not banks. As with the measure of strength, some countries do not report major differences in their networks between 2019 and 2024 (for example, Austria, Germany, Spain, France or Italy), while others report substantial changes in the position of some sectors in their networks (for example, Cyprus, Greece, Malta or Slovenia).

Table A3. Eigenvalue centrality across euro area financial systems, Q4-2019 and differences with Q4-2024

		Eigenvalue centrality - 2019																			
		AT	BE	CY	DE	EE	ES	FI	FR	GR	HR	IE	IT	LT	LU	LV	MT	NL	PT	SI	SK
Banks		1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.01	1.00	1.00	0.06	1.00	1.00	0.60	1.00	1.00	1.00
Gov		0.47	0.75	0.18	0.37	0.03	0.73	0.28	0.28	0.39	0.35	0.04	0.89	0.11	0.00	0.12	0.14	0.37	0.59	0.28	0.33
HH		0.50	0.52	0.34	0.55	0.35	0.67	0.66	0.37	0.63	0.42	0.00	0.45	0.35	0.00	0.22	0.24	0.45	0.59	0.33	0.65
IF		0.17	0.21	0.03	0.28	0.01	0.19	0.20	0.11	0.02	0.03	1.00	0.11	0.01	1.00	0.00	0.32	0.52	0.08	0.02	0.06
Insurance		0.11	0.22	0.02	0.23	0.01	0.13	0.13	0.19	0.05	0.03	0.00	0.25	0.01	0.00	0.01	0.03	0.05	0.13	0.04	0.05
MMF		0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.04	0.00	0.00	0.18	0.00	0.00	0.05	0.00	0.00	0.02	0.00	0.00	0.00
NFC		0.66	0.97	0.45	0.53	0.32	0.79	0.66	0.50	0.60	0.41	0.20	0.67	0.33	0.02	0.28	0.24	0.67	0.50	0.35	0.41
OFI		0.04	0.29	0.04	0.06	0.10	0.18	0.04	0.10	0.05	0.01	0.01	0.27	0.04	0.02	0.06	0.04	0.14	0.09	0.04	0.04
Pensions		0.08	0.13	0.03	0.19	0.06	0.12	0.03	0.03	0.02	0.15	0.00	0.09	0.05	0.00	0.04	0.00	0.67	0.07	0.04	0.12
RoW		0.52	0.83	0.25	0.52	0.10	0.42	0.33	0.42	0.40	0.14	0.99	0.62	0.13	0.88	0.17	0.67	1.00	0.25	0.12	0.23
		Difference (2024 - 2019)																			
		AT	BE	CY	DE	EE	ES	FI	FR	GR	HR	IE	IT	LT	LU	LV	MT	NL	PT	SI	SK
Banks		0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.01	0.00	-0.36	0.19	0.00	0.00	0.00
Gov		0.00	-0.23	0.10	-0.06	0.15	-0.02	0.10	-0.07	0.46	0.15	-0.02	-0.06	0.41	0.00	0.69	0.11	-0.03	-0.05	0.34	0.28
HH		-0.04	-0.05	0.14	-0.05	0.29	-0.15	-0.02	-0.08	-0.19	0.07	0.00	-0.02	0.19	0.00	0.26	0.02	0.09	-0.01	0.23	0.19
IF		-0.01	-0.02	0.09	-0.05	0.24	-0.02	0.11	-0.03	0.04	0.01	0.00	0.02	0.05	0.00	0.02	0.46	-0.17	0.01	0.09	0.06
Insurance		-0.04	-0.10	0.03	-0.07	0.00	-0.06	0.01	-0.08	-0.01	0.00	0.00	-0.03	0.01	0.00	0.04	0.00	-0.01	-0.04	0.07	-0.01
MMF		0.00	0.00	0.00	0.00	0.00	0.02	0.00	0.00	0.01	0.00	-0.02	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00
NFC		0.02	-0.37	0.44	-0.03	0.49	-0.14	0.05	-0.09	0.23	0.11	-0.11	-0.06	0.30	0.01	0.47	0.09	-0.07	-0.03	0.35	0.13
OFI		0.00	-0.09	-0.01	0.01	0.17	-0.08	0.00	-0.03	0.03	0.00	0.00	-0.09	0.02	0.00	0.11	0.01	-0.01	-0.05	0.04	0.02
Pensions		-0.01	-0.03	0.05	-0.04	-0.06	-0.04	-0.01	-0.01	0.00	0.10	0.00	0.00	0.12	0.00	0.27	0.00	-0.01	-0.02	0.08	0.15
RoW		-0.03	-0.21	0.42	0.00	0.33	-0.02	0.17	-0.08	-0.04	0.04	0.01	-0.02	0.65	-0.02	0.45	0.33	0.00	0.00	0.23	0.15

Source: ECB and author's calculations. Notes: RoW stands for rest of the world, OFI for other financial institutions, NFC for non-financial corporations, MMF for money market funds, IF for investment funds, HH for households and Gov for government. In the top panel, green cells show the highest 10% values and the yellow cells the bottom 10% values. In the bottom panel, yellow cells mark changes in absolute value above 0.15.

Last, I identify communities in the networks of 2019 using the Louvain algorithm, to consider whether the pattern found in 2024 (which tends to find two communities, one around the real economy and a second one on financial institutions other than banks and the rest of the world) persists. As seen in Table A4, the Louvain algorithm generates the same communities in 2019 and in 2024 in some countries: Austria, Germany, France, Italy, Luxembourg, Malta and Netherlands. In general, even if there are variations of the allocation of sectors to communities, the pattern found in 2024 persists, with banks, non-financial corporations and households generally belonging to one community, and a second community organised around investment funds and the rest of the world.

Table A4. Communities identified using the Louvain algorithm, maximum of exposures, Q4-2019 and differences with Q4-2024

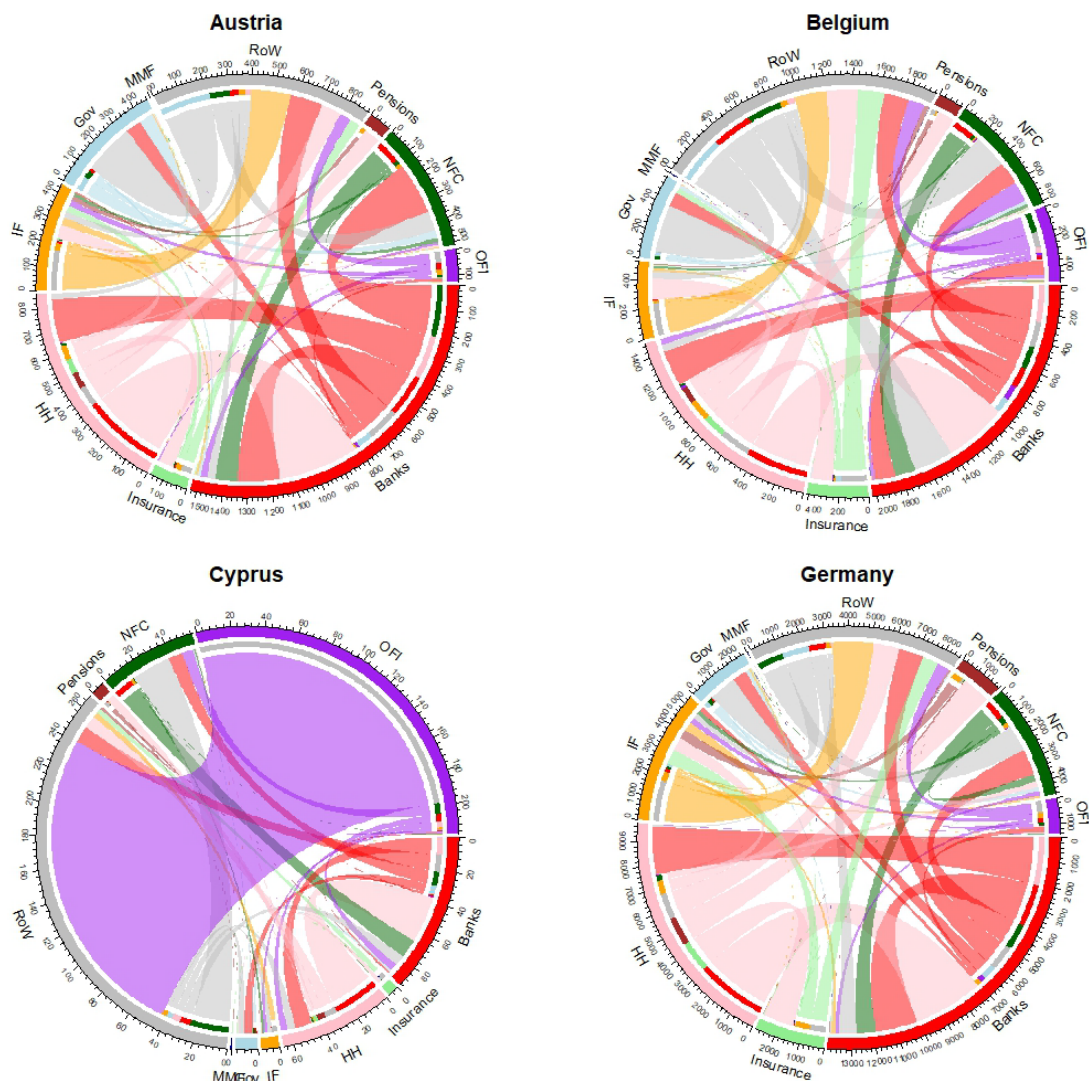
	AT	BE	CY	DE	EE	ES	FI	FR	GR	HR	IE	IT	LT	LU	LV	MT	NL	PT	SI	SK	
Banks	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	
Gov	2	2	1	2	2	2	2	1	2	1	1	2	2	1	2	1	2	2	2	2	
HH	1	1	1	1	2	1	1	2	1	2	1	2	2	1	2	1	2	1	1	3	
IF	2	2	2	2	2	2	3	2	2	2	2	2	2	2	2	2	2	1	2	3	
Insurance	2	2	1	1	2	2	3	2	2	2	1	2	2	1	2	1	2	2	2	3	
MMF	2	2	1	1	2	1	3	1	2	2	2	2	2	1	3	1	2	2	2	3	
NFC	1	2	1	2	1	1	2	1	1	1	2	1	1	1	1	1	1	1	1	1	
OFI	2	2	2	2	2	1	2	1	1	2	1	1	1	2	2	2	1	1	1	2	
Pensions	1	1	1	1	2	1	1	2	1	2	1	2	2	1	2	2	2	2	1	2	3
RoW	2	2	2	2	2	2	2	1	2	1	2	2	2	2	2	2	1	2	2	2	

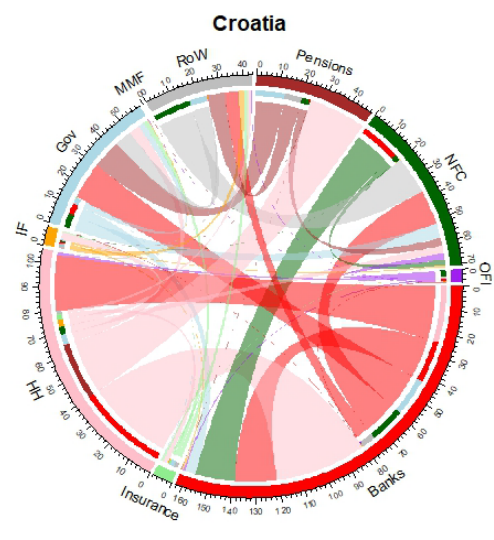
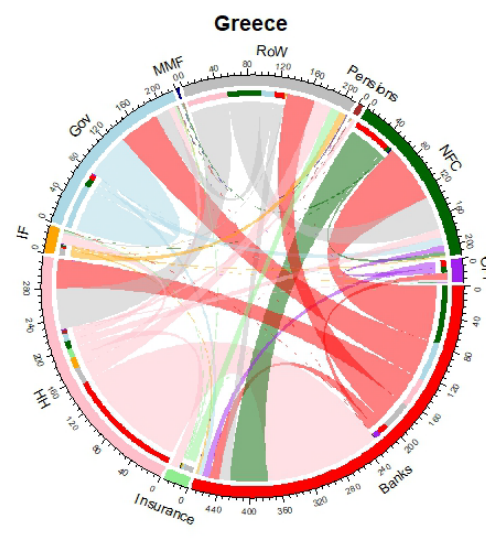
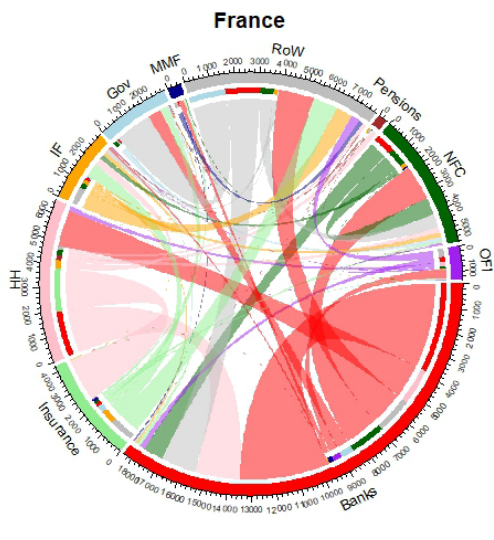
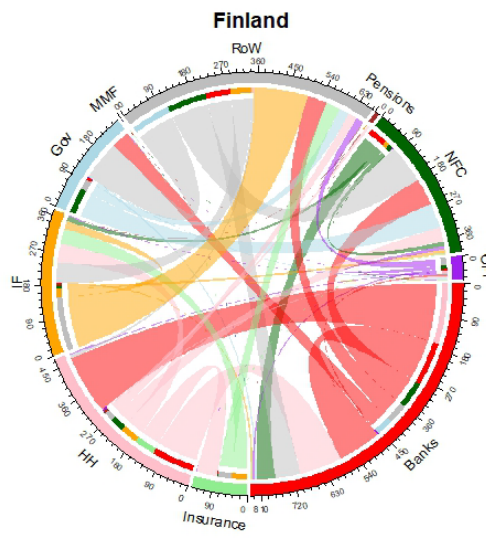
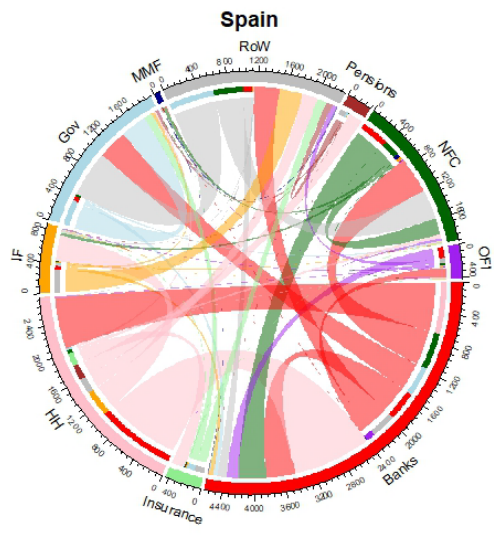
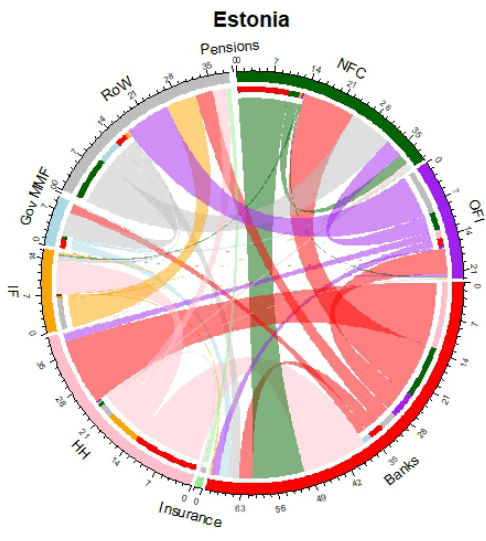
Source: ECB and author's calculations. Notes: numbers 1, 2 and 3 indicate membership into a community and they are coloured for presentational reasons. RoW stands for rest of the world, OFI for other financial institutions, NFC for non-financial corporations, MMF for money market funds, IF for investment funds, HH for households and Gov for government. Numbers in bold italic red colour indicate allocation to a different community than in 2024.

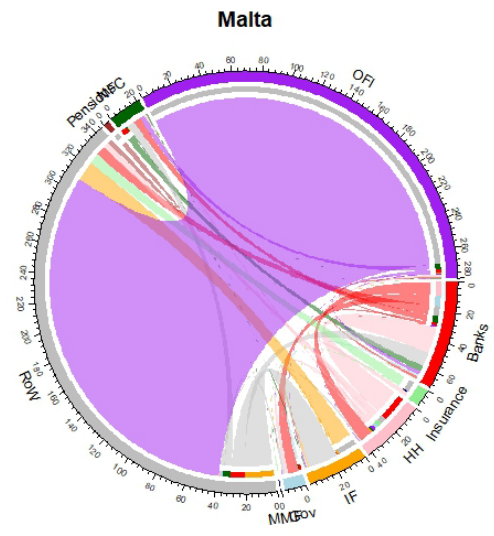
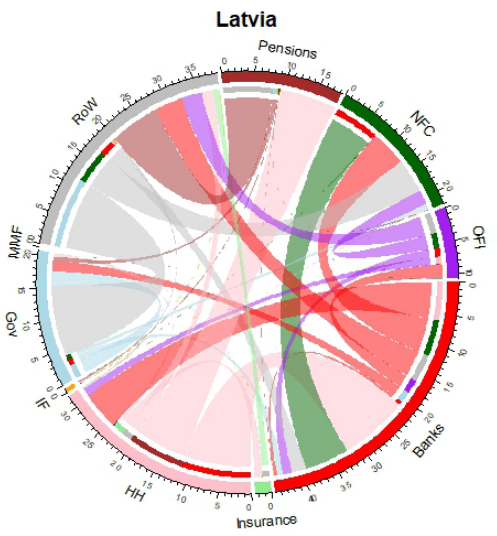
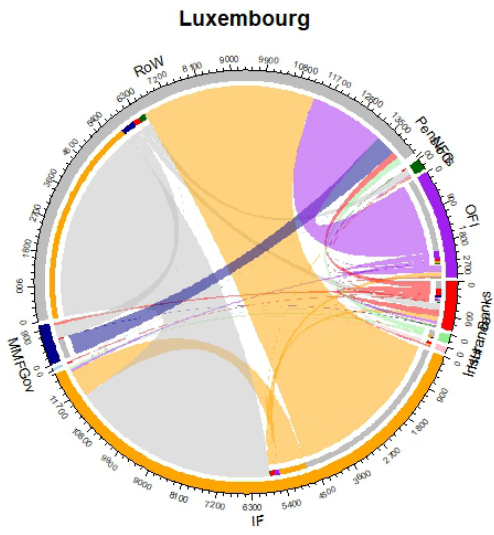
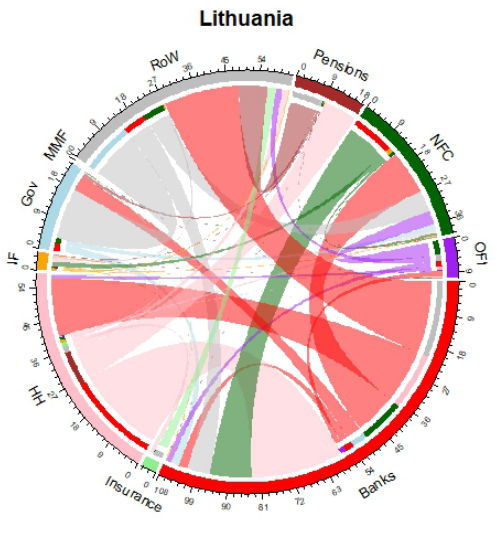
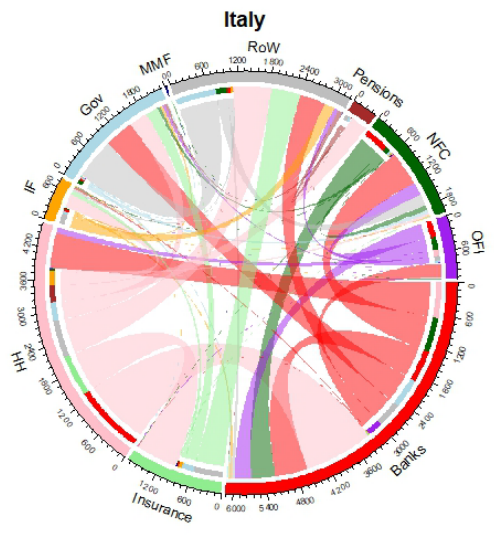
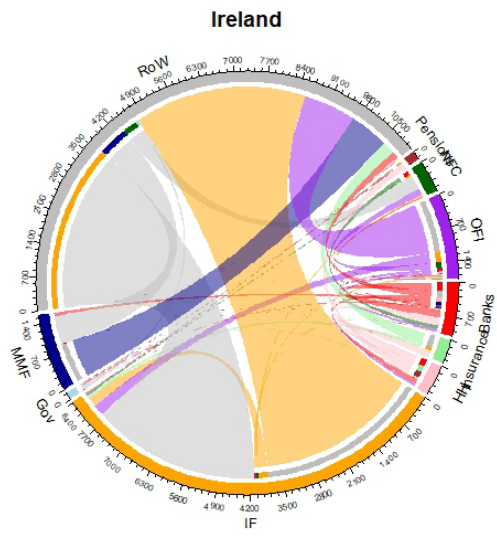
In general, the network metrics computed in this annex support the idea that there is substantial persistence and stability in the structure of the networks constructed from sectoral balance sheets for euro area economies. While finding complete identical networks is materially not possible, there is a large degree of similarity over time between the networks in terms of density, centrality and communities. As a result, the results in the main body of the paper should not be interpreted as referring only to the fourth quarter of 2024, but to having a broader temporal range.

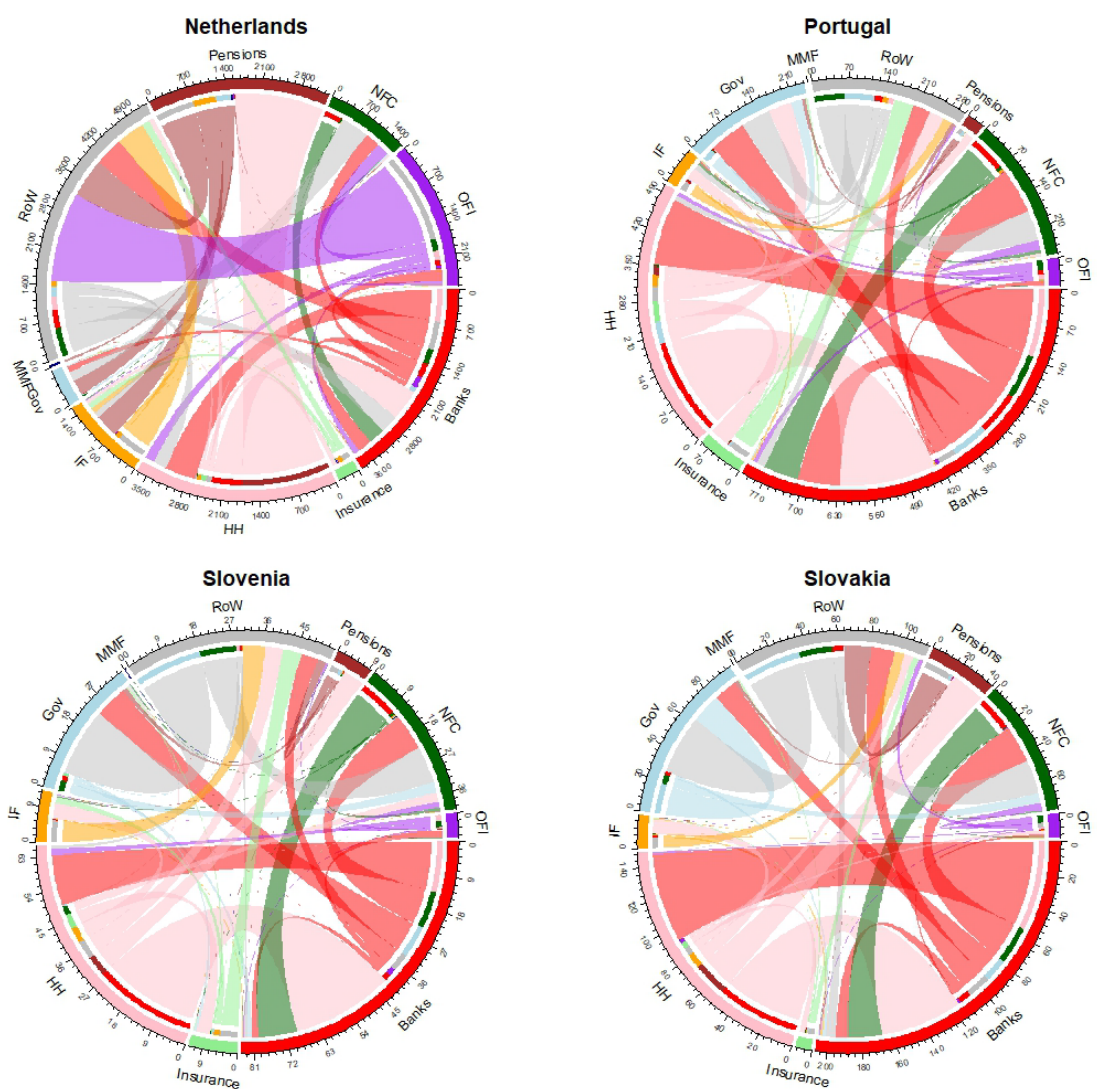
Annex 2. Chord diagrams wheels of euro area countries

Chart A2. Chord diagrams of euro area countries, Q4-2024, billion euros









Source: European Central Bank and author's calculations. Notes: HH stands for households, IF for investment funds, Gov for government, MMF for money-market funds, RoW for rest of the world, NFC for non-financial corporations, and OFI for other financial institutions.

Annex 3. Identification of communities using other algorithms

The Louvain and the optimal modularity clustering algorithms are not the only ones that can be used to identify communities in a network. As a robustness check of the findings in the main text, this annex considers two other algorithms for the identification of communities in a network:

- The walktrap algorithm, which is based on the idea that short random walks tend to remain within the same community. At the start, each node is initially treated as a separate community and the distance between all adjacent nodes, with 4 steps, is calculated. Then, two communities are merged on the basis of the reduction of the overall quality function, and distances are recalculated. This step is repeated until all nodes are in the same community and the algorithm selects the partition with the highest modularity.³
- The simulated annealing algorithm, based on the spin-glass model and simulated annealing techniques, explores the structure of the graph to identify communities. In a nutshell, simulated annealing is a probabilistic technique for approximating the global optimum of a function. Reichardt and Bornholdt (2006) describe in further detail the algorithm, which draws from the field of metallurgy.

The walktrap algorithm works with directed networks, which is one of the main shortcomings of the Louvain algorithm. Besides, while the simulated annealing algorithm works only with undirected networks, it provides good results when working with relatively simple networks.

Results from the application of the walktrap algorithm are rather disappointing, as there is one community in most euro area countries, being Austria, Estonia, Finland, Ireland and Italy the only exceptions (Table A5). The fact that the algorithm is based on random walks coupled with the relatively low number of nodes in the network (ten) may explain these results. Using the Infomap algorithm, which is similar in the underlying concept to the walktrap algorithm, also leads to the identification of one community in each euro area country.

³ For further details, see Pons and Latapy (2005).

Table A5. Communities identified using walktrap algorithm, Q4-2024

	AT	BE	CY	DE	EE	ES	FI	FR	GR	HR	IE	IT	LT	LU	LV	MT	NL	PT	SI	SK
Banks	1	1	1	1	1	1	2	1	1	1	2	2	1	1	1	1	1	1	1	1
Gov	2	1	1	1	1	1	1	1	1	1	2	1	1	1	1	1	1	1	1	1
HH	1	1	1	1	1	1	2	1	1	1	2	1	1	1	1	1	1	1	1	1
IF	2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Insurance	2	1	1	1	1	1	1	1	1	1	2	1	1	1	1	1	1	1	1	1
MMF	3	1	1	1	2	1	2	1	1	1	1	1	1	1	1	1	1	1	1	1
NFC	1	1	1	1	1	1	1	1	1	1	1	2	1	1	1	1	1	1	1	1
OFI	2	1	1	1	1	1	1	1	1	1	1	2	1	1	1	1	1	1	1	1
Pensions	1	1	1	1	2	1	2	1	1	1	2	1	1	1	1	1	1	1	1	1
RoW	2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1

Source: ECB and author's calculations. Notes: numbers 1 and 2 indicate membership into a community and they are coloured for presentational reasons. RoW stands for rest of the world, OFI for other financial institutions, NFC for non-financial corporations, MMF for money market funds, IF for investment funds, HH for households and Gov for government.

Turning to the communities identified by the simulated annealing algorithm (Table A6), more than half of the euro area countries report two communities. Austria, Germany, Spain, Finland, Lithuania, Latvia, Netherlands and Slovakia report three, while it is not possible to apply this algorithm to the data of Estonia. Looking at the composition of the communities, the trend to have banks, households and non-financial corporations in the same community is not as pronounced as when applying the Louvain algorithm or optimal modularity clustering, although it remains for some euro area countries. The rest of the world and investment funds tend to be in the same community for most euro area countries, as is the case in the communities identified via the Louvain algorithm or optimal modularity clustering.

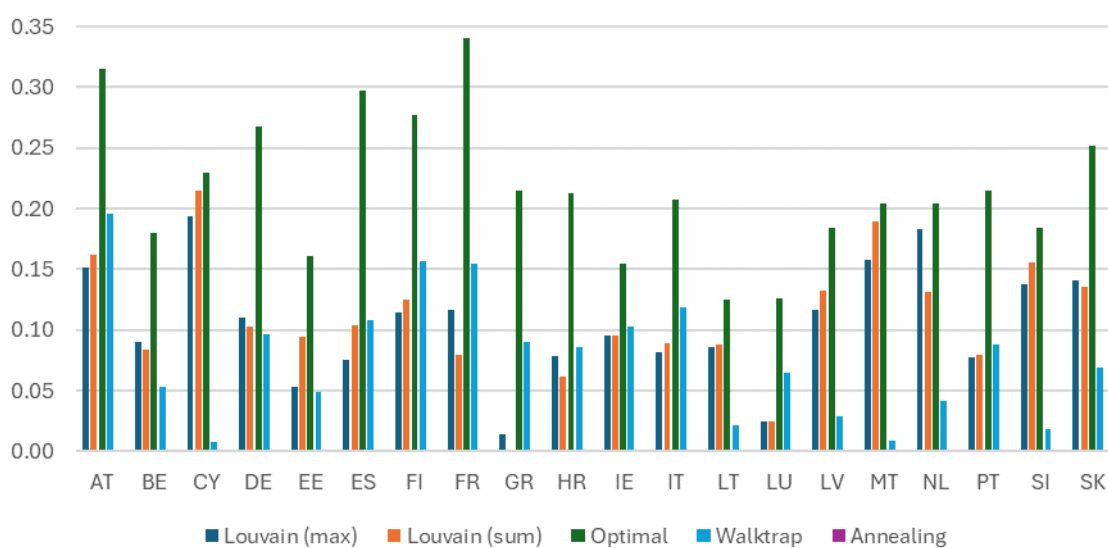
Table A6. Communities identified using the simulated annealing algorithm, Q4-2024

	AT	BE	CY	DE	EE	ES	FI	FR	GR	HR	IE	IT	LT	LU	LV	MT	NL	PT	SI	SK
Banks	1	2	1	2		1	1	1	2	1	2	2	2	2	2	2	3	2	2	3
Gov	1	2	1	2		1	3	1	2	1	2	2	3	2	2	2	2	2	2	1
HH	3	2	1	3		2	1	2	1	1	2	1	1	2	1	2	2	2	2	3
IF	2	1	1	1		2	2	1	1	2	1	1	1	1	1	1	1	1	1	3
Insurance	3	1	1	3		2	1	2	1	2	2	1	3	2	1	2	1	1	1	1
MMF	3	1	1	3		3	1	1	2	1	1	2	3	2	3	2	2	1	1	2
NFC	1	1	1	2		3	3	1	2	2	1	2	2	2	2	2	3	1	1	1
OFI	2	2	2	1		1	2	1	2	1	1	2	3	1	2	1	1	2	2	1
Pensions	3	2	1	3		2	1	2	1	1	2	1	1	2	1	1	2	2	2	3
RoW	2	1	2	1		3	2	1	1	2	1	1	3	1	2	1	1	1	1	1

Source: ECB and author's calculations. Notes: numbers 1, 2 and 3 indicate membership into a community and they are coloured for presentational reasons. RoW stands for rest of the world, OFI for other financial institutions, NFC for non-financial corporations, MMF for money market funds, IF for investment funds, HH for households and Gov for government.

While there is no single rule to use one algorithm or the other when trying to identify communities in a network, it can be useful to compare the modularity under the different algorithms used (Chart A3). In general, the optimal modularity clustering achieves the highest modularity, followed by the two approaches to the Louvain algorithm. The walktrap algorithm gets particularly high modularity for few countries, such as Austria, Finland and France. Modularity of the simulated annealing algorithm is basically zero across euro area countries.

Chart A3. Modularity under different algorithms for the identification of communities, Q4-2024



Source: ECB and author's calculations.

Therefore, modularity scores tend to confirm the convenience of using the Louvain and the optimal modularity clustering algorithms for the identification of communities.

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The views expressed in this paper are those of the author and do not necessarily represent the views of the European Systemic Risk Board (ESRB), any of its Member Institutions or the ESRB Secretariat.

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