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Commercial real estate debt financing in Europe: evidence from a network analysis

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Abstract

The commercial real estate (CRE) sector is a source of financial stability risk, yet its financing structures remain poorly understood because of complex corporate group structures and data limitations. This paper investigates the financing networks of the 100 largest CRE groups in the euro area, constructing two distinct networks: one for loan financing and one for bond issuance. The loan network exhibits strong regional clustering, a pronounced home bias and a core-periphery structure. Regional differences in loan financing patterns give rise to geographically concentrated communities of CRE entities with similar characteristics. The backbone of the loan market shows limited overlap among banks, both in the set of CRE borrowers they serve and in the size and composition of their loan portfolios, pointing to segmented lending relationships. By contrast, the bond network displays greater interconnectedness, is largely free of home bias and allows access to a diversified investor base. Financial stability implications are assessed through the structural properties of the networks and the identification of systemic nodes. In the loan network, regional clustering may amplify cross-border contagion, while highly central CRE groups in both networks could generate spillovers in distress, shaping credit allocation and systemic risk in the euro area.

JEL codes: G21, G28, R31, D85, C63

Keywords: commercial real estate, network analysis, systemic risk, interconnectedness, euro area

Non-Technical Summary

The commercial real estate (CRE) sector is of great importance for financial stability within the euro area, given its size and high degree of interconnectedness with the financial system. Analysis of this sector is complicated by opaque corporate structures and limited availability of granular data. This paper addresses these challenges, by providing a first comprehensive assessment of the financing networks of the largest 100 CRE groups in the euro area.

The analysis is conducted against the backdrop of a pronounced downturn in the European CRE market, driven by both cyclical and structural factors that have placed significant strain on CRE companies. In recent years, the largest CRE groups exhibited an increase in leverage ratios and weaker balance sheet positions, stemming from higher financing costs and declining asset valuations. New borrowing has been increasingly directed towards short-term liquidity needs rather than investment, while credit risk associated with CRE exposures has risen.

The paper analyses the financing structures of large CRE groups in the euro area by distinguishing between bank lending and bond market financing. A central finding of the paper is that financing structures differ markedly across instruments, with important implications for the concentration of risk and the transmission of shocks.

Bank-based financing of CRE groups is regionally concentrated and characterised by a pronounced home bias. CRE groups typically rely on a limited number of banking relationships, which are often not widely shared across banks. Cross-country differences emerge: in Germany, Austria and Luxembourg, CRE groups tend to borrow smaller amounts from a more diversified set of banks, while in other euro area countries they rely on larger credit relationships from fewer lenders. As a result, bank lending relationships form geographically concentrated communities with limited overlap among key lenders. These structural differences have important financial stability implications. The loan network is characterised by regional clustering and pockets of high interconnectedness, implying that stress originating in local CRE markets could spread within geographically defined clusters. While smaller shocks are likely to remain contained at the regional level, larger disruptions could propagate more widely through entities that link separate clusters. From a systemic risk perspective, a limited number of large and highly interconnected CRE groups are identified, whose distress could affect multiple counterparties simultaneously. At the same time, the relatively small proportion of CRE loans in banks' overall portfolios suggests that the risks to broader financial stability remain manageable under current conditions. Between 2021 and 2023, bank lending expanded in both volume and number of relationships, reflecting increased credit activity, while bond market activity contracted, indicating weaker issuance.

Bond market financing displays markedly different features. In contrast to bank

lending, the network of bond holdings exhibits absence of a home bias, higher interconnectedness, and limited regional concentration. Furthermore, the largest CRE groups tend to borrow from a broad and overlapping set of investors, while smaller groups maintain fewer connections in bond markets. Taken together, these observations underscore that bank-based and market-based financing channels contribute differently to the build-up and transmission of systemic risk associated in the CRE sector.

Overall, the findings underline the importance of monitoring not only the size of CRE exposures, but also the structure of financing relationships. Differences between bank-based and market-based financing channels influence how stress may propagate through the financial system and are therefore directly relevant for financial stability considerations.

1 Introduction

The commercial real estate (CRE) sector is of great importance for financial stability within the euro area, given its size and high degree of interconnectedness with the financial system. Vulnerabilities within the sector can be amplified via cross-border and institutional interlinkages, with adverse shocks potentially propagating through the broader financial system. Historically, the accumulation of risks in the CRE sector has been a notable driver of several financial crises (ESRB, 2015). Recently, vulnerabilities have resurfaced, necessitating policy responses. In January 2023, the ESRB published a report on CRE vulnerabilities (ESRB, 2023) alongside a Recommendation[1] urging EU and national authorities to strengthen systemic risk monitoring, promote sound financing practices and institutional resilience, and establish a consistent macroprudential framework across financial institutions. This Recommendation was issued in light of elevated cyclical pressures, including high inflation, tighter financing conditions and weaker economic growth, combined with structural challenges, such as changes in climate policy and building standards, the rise of e-commerce, and the transition toward remote working arrangements. These factors pose risks of systemic transmission via banks' loan-to-value exposures, liquidity mismatches in open-ended real estate funds, and cross-border spillovers.

The CRE sector exhibits a complex financing structure, requiring a bottom-up approach to assess which lenders are exposed and through which instruments, thereby identifying risks and potential contagion channels. Understanding the intricate corporate structures and diverse funding sources of CRE groups is essential, as illustrated by the default of the Austrian CRE group Signa.

Despite this recognised complexity, empirical evidence identifying the financiers of CRE in the euro area remains scarce. Daly et al. (2024) provide a comprehensive macro-network analysis of the CRE sector, examining ownership of physical CRE assets in the euro area and the institutions financing these owners. Their findings indicate that CRE companies are the largest asset owners, followed by real estate investment funds and trusts, with the euro area bank providing the majority of financing. While EBA (2024) and ESMA (2024) published information on CRE exposures, these analyses are limited to country-level data and do not construct networks of exposures.

Network theory has emerged as a prominent framework for studying interconnectedness in financial markets, particularly following the Global Financial Crisis (GFC), when institutional interlinkages were central to crisis propagation and contagion. In recent years the literature linking network structure to systemic risk and stability has expanded significantly, as surveyed by Iori and Mantegna (2018), Neveu (2018) and Jackson and Pernaud (2021), with a specific focus on resilience to shocks within financial networks.

[1] Recommendation of the European Systemic Risk Board of 1 December 2022 on vulnerabilities in the commercial real estate sector in the European Economic Area (ESRB/2022/9)

Resilience to shocks within financial networks was one of the highlights of this literature. Allen and Gale (2000) provide a seminal analysis of financial contagion, demonstrating that complete network structures are more resilient to liquidity shocks than incomplete ones. However, post-GFC research increasingly questions whether high interconnectedness necessarily mitigates systemic risk. Battiston et al. (2012a) argue that beyond a certain threshold, high connectivity in credit networks amplifies both individual and systemic default risks. Elliot et al. (2014) find that mid-level integration and diversification in cross-equity networks drive cascading defaults. Acemoglu et al. (2015) show that while fully connected networks can withstand small shocks, high interconnectedness worsens systemic instability under large shocks due to counterparty risk contagion. Further studies highlight the role of shock distribution in determining optimal network structures. Cabrales et al. (2017) argue that optimal bank network configurations depend on the distribution of default shocks, while Huang et al. (2016) show that highly interconnected financial institutions significantly contribute to systemic risk. Lux (2016) models a bank–firm credit network to show how structural connections can trigger, or contain, systemic financial crises, highlighting that joint exposure to shared, risky firms is a more significant, non-linear channel for contagion than direct interbank lending.

Several studies construct financial networks to analyse interconnections across the euro area. Andersen and Sánchez-Serrano (2024) develop a macro-network of the euro area financial system, highlighting its predominantly bank-centric structure prior to the GFC and the increasing role of investment funds, government debt and central banks thereafter. Sánchez-Serrano (2025) extends this framework with more granular data also to incorporate international investment positions and to capture cross-border relationships. Similar methodologies are applied by Mouakil et al. (2025) and Saldías (2025) to national financial systems. Castren and Rancan (2015) show that a more central position of the banking sector heightens the likelihood of banking crises, while Alves et al. (2015) examine the systemic importance of highly interconnected insurance groups.

Empirical studies using interbank loan data document heterogeneous euro area credit network structures at the national level, including evidence for Germany (Craig and von Peter, 2014), Italy (Finger et al., 2013), the Netherlands (Propper et al., 2013), Austria (Puhr et al., 2012), Belgium (Degryse and Nguyen, 2007) and Portugal (Cocco et al., 2013). In addition to the research focusing on interbank networks, a related strand of literature explored the the connection between the financial sector and the real economy, typically through the construction of bipartite network representations. For example, De Masi and Gallegati (2012) studied Italy's 2003 corporate credit network, identifying hierarchical structures where small firms relied on small lenders, while large firms maintained multiple credit relationships. Studies on non-European countries include De Masi et al. (2011) who examine Japanese credit relationships in 2004, finding that large banks occupy central roles, favour long-term lending, and exhibit geographical variation in credit demand across sectors. Marotta et al. (2015) and Marotta et al. (2016) tracked 32 years of Japanese bank-firm network evolution, noting persistent communities and slow changes in network attributes, and linking the credit market's backbone to economic events. Shen and Lee (2020) explored China's credit market, identifying a hierarchical core-margin structure with state-owned banks as key nodes. Silva et al. (2018) highlighted how shocks originating from companies in Brazil propagate through interbank networks.

Our paper contributes to this strand of research in several aspects. First, we employ a pan-European dataset rather than focusing on individual countries, reflecting the increasingly cross-border nature of financial systems. Second, we narrow our focus to a specific subsector of the economy: the commercial real estate sector, comprising both developers and landlords. This focus is particularly relevant given the high degree of heterogeneity across sectors, as analysing aggregated dynamics may hide critical differences and unique challenges tied to specific business models. Third, we construct networks of both loans and bonds issued, documenting sizeable differences between the two financing options. Fourth, we combine a static description of the network in 2023 with an analysis of its evolution over a three-year period marked by significant shocks that contributed to the sector's downturn.

Using detailed micro-level data, we focus on the 100 largest groups in the euro area, ensuring that intra-sector heterogeneity is not obscured by sector-level data. Additionally, we do not aggregate euro area countries, allowing for a granular analysis of the geographic distribution of major CRE groups and lenders, as well as the strength of cross-country links. We construct networks of country-sectors exposed to the largest CRE groups through financing instruments, illustrating the financing environment and the interconnections between them. For banks, we conduct an in-depth analysis of firm-bank relationships. For bonds, we construct a network of holdings at institutional sector level. The resulting networks serve as both an analytical and monitoring tool, providing a foundation for case studies and potentially simulations of shocks and spillovers during periods of financial stress.

Our analysis of granular CRE lending relationships shows: i) national differences in financing patterns, ii) evidence of regional clustering and home bias, iii) the presence of a core-periphery structure of the network, iv) the existence of critical network nodes. These findings carry important implications for financial stability. Regional clustering suggests that shocks may propagate locally, amplifying vulnerabilities within specific areas. Moreover, the failure of critical nodes within the network could disrupt specialized lenders with concentrated portfolios, potentially exacerbating systemic risks.

By contrast, the network of bonds holdings reveals i) the absence of home bias, ii) higher interconnectedness, iii) no evidence of regional clusters. Larger CRE groups borrow from a broader and overlapping set of investors, while smaller groups maintain fewer connections. Over the period from 2021 to 2023, the loan network expanded while the bond network contracted, pointing to differences in how bank-based and market-based financing reacted to a period of stress.

The remainder of the paper is structured as follows: Section 2 describes the dataset on CRE groups, Section 3 presents stylised facts about the CRE groups, Section 4 analyses loan and bond financing networks, Section 5 discusses financial stability implications, and Section 6 concludes.

2 Data on CRE groups

The CRE sector is characterised by considerable heterogeneity. The size and form of CRE firms can vary significantly, as can their debt funding. To build a granular understanding of how CRE firms are financed and map out a detailed network, it is critical to focus on a selected consistent subset of firms. From a financial stability perspective, the most relevant CRE companies to monitor are those that are large and take on relatively high levels of risk.

This paper focuses on a sample of the 100 largest CRE groups in the euro area.[2] The size of a CRE group is measured by its total assets, which account for investment properties as well as other holdings, such as joint ventures and equity stakes in listed companies. Several granular data sources are combined to identify CRE groups, applying a consistent set of criteria related to sector and purpose, as illustrated above. First, the 100 largest euro area CRE groups are identified using the S&P Capital IQ database, based on the total assets. The initial list is cross-checked against the European Public Real Estate Association (EPRA) database, which provides information on listed real estate companies in Europe, and Moody's list rated of real estate companies. This process ensures a comprehensive and accurate representation of the largest CRE groups in the euro area. [3]

Beyond size, factors like ownership and business purpose are indicators of a CRE group's risk to the financial system. Groups owned by municipalities or public entities are assumed to operate more cautiously and typically have greater financial backing, enabling them to manage refinancing issues or equity injections when needed. Similarly, groups providing social housing[4] are considered lower risk, as their primary aim is to offer housing at capped rents rather than maximize profits. Additionally, the operational focus is relevant: groups owning properties for their own use, such as manufacturing firms with warehouses, are not categorised as CRE groups. For this paper, CRE groups are defined as those primarily involved in letting, buying, or developing properties. Those firms

[2] The list consists of both listed and not listed ("private") companies.

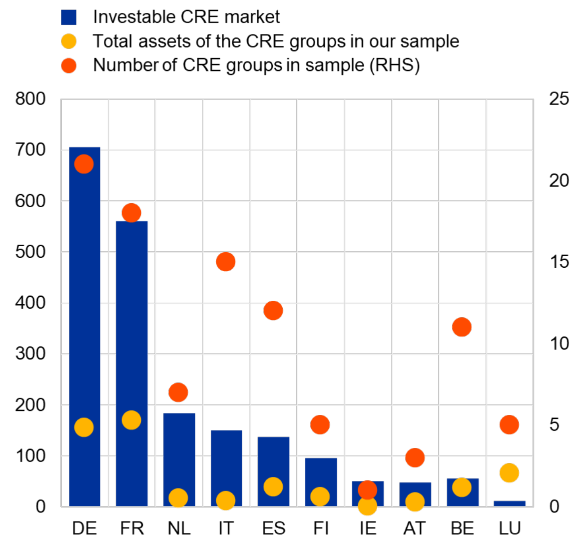
[3] For data confidentiality reasons, we cannot display the names of the companies that make up our sample. See Table A2 for a geographical breakdown of the sample.

[4] E.g. in France companies that provide social housing are given benefits such as low interest rate loans whilst having restrictions in terms of remunerations and dividends.

tend to be more leveraged than firms focused on other sectors. Against this background, the groups deemed most relevant from an euro area financial stability perspective - and thus the focus of this paper - should have private owners, be profit maximising, operate independently as real estate companies and be affiliated in the euro area.[5]

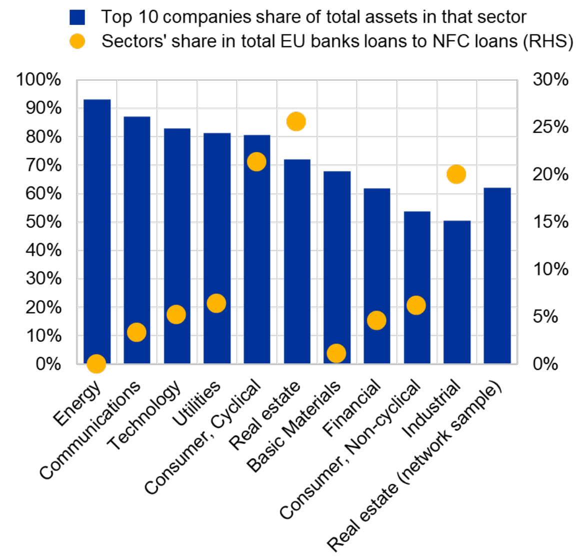
Figure 1: CRE market size and concentration

(a) Size of CRE market in countries represented in the sample (EUR billion)



Source: S&P Capital IQ, EPRA, Moody's.
Note: Listed CRE market, which is estimated by EPRA, is assumed to be part of the professional investable CRE market. Investable CRE market is defined by MSCI and covers e.g. leased office and retail properties while it excludes small private landlords. More info on the definition here. Companies in the sample have EUR 522 billion in assets. The investable CRE market is EUR 2,000 billion. Country is based on the jurisdiction of the parent company; subsidiaries can be located elsewhere. Size of CRE market in MT and GR is not available via MSCI.

(b) Concentration comparison of different sectors



Source: S&P Capital IQ, EBA.
Note: The concentration analysis compares companies listed in the EURO STOXX Index. The sectoral shares in total NFC loans are computed by aggregating different NACE codes from the EBA Risk Dashboard.

From a financial stability perspective, these groups are likely to have the largest impact, as they represent a significant share of euro area CRE companies, covering approximately a quarter of investable CRE in the region.[6] Germany accounts for the most significant share of total CRE assets (over EUR 600 billion), followed by France

[5]Exceptions to the criteria of private owners include if the company is listed and among its owners has public pension funds that make up one out of several owners. Real estate investment trusts (REIT) are also included in the sample.
[6]According to MSCI estimation, total investable market in the euro area amounts to 2 trillion euro. See Daly et al. (2025) for a comprehensive review of the owners of CRE in the euro area.

with its firms holding about EUR 500 billion of assets (Figure 1a).[7] These two countries provide the largest number of CRE groups in our sample. However, we include CRE groups from various other euro area countries, such as the Netherlands, Italy, Spain, Finland, Ireland, Austria, Belgium, Luxembourg, Malta and Greece.[8]

The CRE market is highly concentrated in terms of assets, with a substantial share of the portfolio (62% of total assets in our sample) held by the top largest 10 firms (Figure 1b). Comparing the CRE sector against other sectors that make up the European stock market suggests that it does not rank among the most concentrated sectors. However, the CRE sector is the most important in terms of bank lending to NFCs, attracting more than 25% of the banks' exposure.

While our sample includes 100 CRE groups, its actual scope is much broader, amounting to roughly 2,000 entities and spanning groups with multiple subsidiaries operating across the euro area. Specifically, we reconstruct the group structures of the largest CRE groups and their consolidated balance sheets by combining data from commercial providers, such as GLEIF and Orbis shareholdings database. By cross-referencing these sources and integrating them with the ECB's internal Register of Institutions Affiliates (RIAD) to retrieve internal company identifiers, we achieve a comprehensive mapping and facilitate integration with the ECB's internal loan and security register databases.

Granular firm and financing data are integrated to map dynamic connections between credit providers and CRE groups for the construction of a network representation of CRE financing relationships. Data for the largest CRE groups are linked to harmonised credit data at the euro area level using company identifiers. Specifically, we use the loan-level registry database from AnaCredit to analyse bank loans provided by euro area banks to CRE groups, alongside the matched Centralised Securities Issue Database (CSDB) - Securities Holdings Statistics (SHS) database to examine security-level debt and equity financing from global sectors to CRE groups. Focusing on euro area bank lending remains robust in scope, representativeness, and comprehensiveness, as CRE lending is predominantly domestic or euro area oriented.

Gasiorowski et al. (2026) estimate that EU banks' total loan exposures to real estate NFCs amount to approximately EUR 1.4 trillion in Q2 2025, while CRE loan exposures by insurance corporations and pension funds are around EUR 44 billion and EUR 31 billion, respectively, as of Q1 2025. Bond financing is estimated at EUR 0.5–1.0 trillion in October 2023, and CRE loans by Alternative Investment Funds (AIFs) have an upper limit of EUR 406 billion in Q4 2023. ESMA (2024) examines the ownership structure of investors in real

[7] The smaller size of Luxembourg's investable CRE market relative to the total assets of the CRE groups in our sample may result from the data sources and market definition applied by MSCI.

[8] Cross-country comparisons should take into account the distinct characteristics of real estate markets in those countries belonging to the sample. For example, the French market features a regime for social housing which implies subsidised loans for companies involved in providing social housing. In parts of Germany, large property portfolios were sold by the government after the reunification, which laid the ground for the emergence of large companies owning rental housing.

estate AIFs, finding that pension funds investing in these AIFs are primarily located in the Netherlands, Luxembourg, and Germany, insurance corporations in France, Germany, and Luxembourg, and households in Germany. These estimates, alongside the diversity of market actors, highlight the challenges in identifying vulnerabilities and underscore the importance of granular exposure analysis, as proposed in our network chapter.

Regarding non-bank financing of CRE firms, despite significant data gaps, Daly et al. (2024) find that bond financing amounts to roughly one-quarter of equity financing of CRE firms, with equity slightly exceeding loans to CRE firms. This is largely because real investment funds are the second-largest holders of physical CRE assets, after real estate companies. Bond financing is particularly prominent among larger firms which can better support the costs of issuing debt instruments.

To summarize, our data retrieval scheme proceeds as follows:

- Identify the biggest CRE groups in the eurozone using balance sheet data from S&P Capital IQ, cross checked with EPRA and Moody's.
- Retrieve the group structure of the CRE groups, using GLEIF and Orbis, cross checked with RIAD.
- Gather the loan data for each firm within the group using AnaCredit.
- Aggregate the loan data at CRE group level and highest bank consolidation level.
- Gather the bond holdings of each firm withing group using CSDB and SHSS.
- Aggregate the bond data at CRE group level and holder sector level.

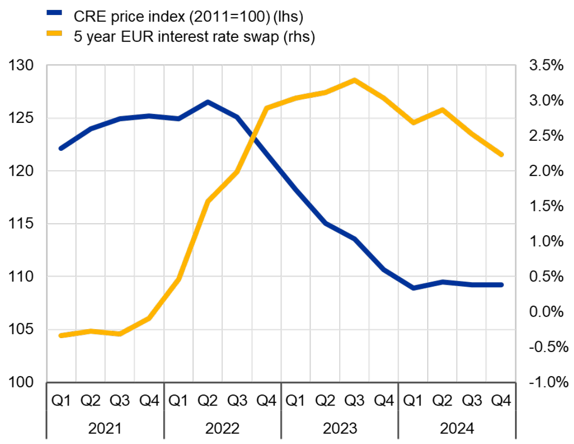
3 Stylised facts of the CRE groups

The downturn in the European CRE market given by the sharp decline in property prices alongside the steep rise in interest rates (Figure 2a), represented a combination that directly tightened financing conditions and eroded collateral values, which put CRE companies in financial strain. The largest listed CRE groups faced declining EBITDAs and rising leverage ratios (Figure 2b), which could reflect a shifting reliance on debt in their financial structure over the years, emerging in 2019 and easing in 2024. At the same time, declining property values have also contributed to higher leverage ratios in the sample. While these changes remain moderate, the upward trend of leverage ratios points to increased vulnerability to adverse economic conditions, particularly during the period of monetary policy tightening. This could increase exposure to risks stemming from falling property values, rising borrowing costs, and pressures on debt servicing capacity.

CRE companies operate with a significantly higher leverage than firms in other sectors (ESMA, 2024). Debt is essential for CRE companies as they operate a capital intense business in which they need to acquire, develop and maintain properties. While high leverage can deliver yields attractive to owners, it also entails elevated financial risk. From a financial stability perspective, this underscores the importance of examining not only the level of indebtedness, but also the structure of lenders and the quality of debt, particularly for larger CRE companies.

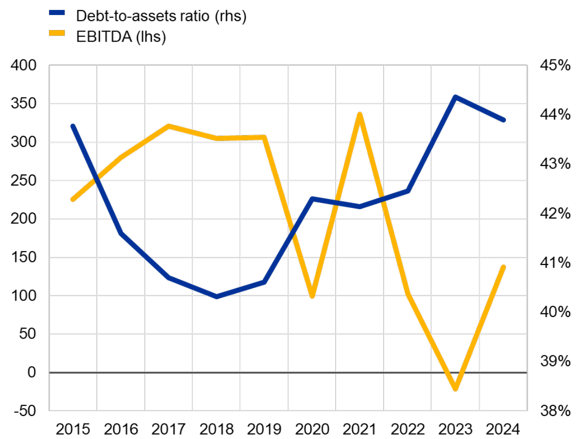
Figure 2: CRE market size and concentration

(a) CRE prices and interest rates evolution



Source: ECB, Bloomberg.
Note: Commercial property price indicator for euro area-19.

(b) CRE groups' EBITDA and leverage ratios



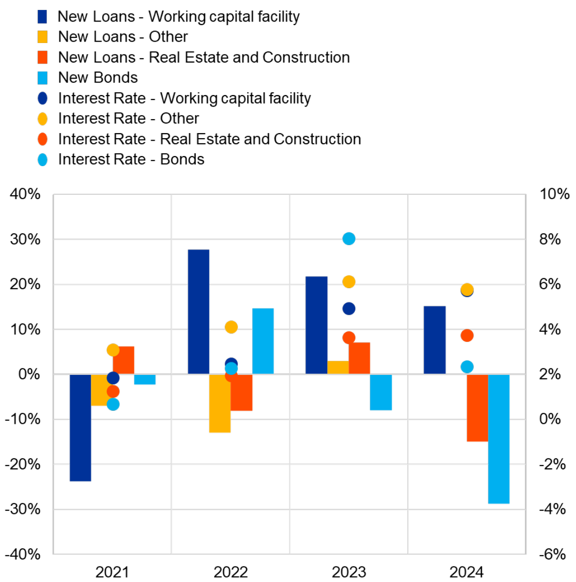
Source: S&P Capital IQ.
Note: The chart displays the average EBITDA (expressed in million euro) and the weighted average of the debt-to-assets ratio of the CRE groups in the sample.

Between 2021 and 2024, new bonds displayed pronounced volatility, as the volumes of issuance declined overall, and bond prices were initially low and then increased. During the monetary policy tightening phase, bond prices rose sharply, reflecting higher yields, but this increase was quickly reversed as market conditions normalised. The correction in bond prices, coupled with reduced issuance, highlights the market's sensitivity to shifting financial conditions. Despite the interest rate increase, firms relied on external financing to sustain operations amid rising costs and heightened uncertainty, particularly through working-capital facilities (Figure 3a). These loans provide short-term financing to cover day-to-day expenses and manage cash flows. By contrast, appetite for capital expenditure remained subdued, leading to negative growth in longer-term loans in 2021 and 2022, a brief recovery in 2023 and stagnation in 2024. This pattern shows that firms prioritised financing operational needs over investing in new properties. Tighter financial conditions and sector-specific corrections resulted in volatile growth in real estate and construction lending from 2021 to 2023, followed by a decline in 2024. The sharp increase in interest rates, particularly for working-capital loans, highlights the impact of monetary tightening on credit conditions. Although easing conditions have provided some relief more recently, refinancing remained challenging through the impact of higher interest rates on fixed-rate contracts on existing loan stocks. Market pricing for both new financing and refinancing remained significantly higher, posing challenges particularly for firms with weaker credit profiles or large volumes of maturing loans contracted previously at low interest rates.

The credit risk among CRE companies changed markedly over the period. The ratio of stage 2 loans steeply increased in the third and fourth quarters of 2023 before easing slightly thereafter, while the ratio of stage 3 loans began to rise from historically low levels in the third quarter of 2023 (Figure 3b). Early arrears, despite some volatility, broadly align with these trends.

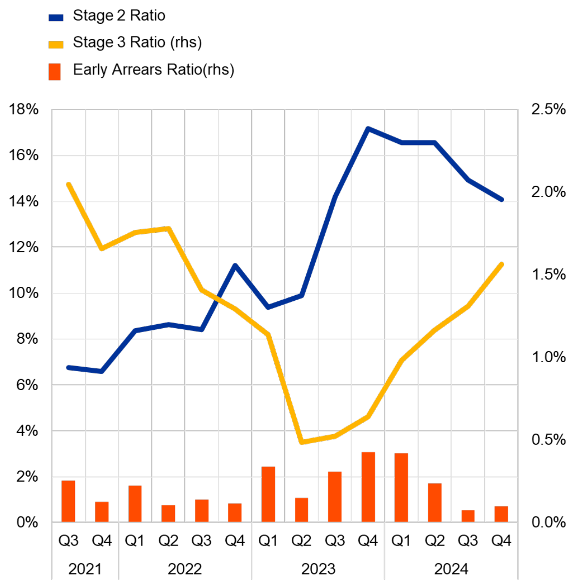
Figure 3: Credit metrics evolution of the CRE groups

(a) New funds: volumes and prices, by purpose



Source: S&P Capital IQ, AnaCredit.
Note: New loans, computed according to MIR statistics, capture loans with inception date in the relevant reference date. Breakdown by purpose of new loans, with RE and Construction covering financing of real estate property and construction, Working Capital facility covering the firms' cash flow management financing, and non-specified purposes in Other. Weighted average interest rate.

(b) IFRS9 Stage 2 and 3 ratios, Early Arrears ratio



Source: S&P Capital IQ, AnaCredit.
Note: Stage 3 (2) ratio is computed as total outstanding amount subject to impairment stage 3 (2) under IFRS9 over total IFRS9 compliant outstanding amount. Early arrears ratio presents early arrears (with 5-90 days past due) divided by total stock (all performing). Stages are based on the attribute Impairment amount under IFRS9: S2 signals a loan not impaired but with significant increase in credit risks; S3 signals an impaired loan under AnaCredit reporting.

4 Building a network of CRE financing

4.1 Bank-firm loan relationships

This chapter provides a deep dive into bank loans to CRE groups, exploiting the granularity of AnaCredit data. The lending relationship between a bank group and a CRE group is represented by a bipartite network, where each node corresponds to either a bank or a CRE group, and an edge denotes the presence of an active credit relationship at the end of 2023. Bipartite networks are commonly used to study a wide range of phenomena beyond lending contracts, for example in co-authorship, board membership or film actors' networks (Newman, 2018). In the present context, the bipartite structure captures only direct lending relationships between banks and CRE groups, abstracting from any indirect connections, for example through interbank loans. Similarly, CRE groups are not directly connected to one another, for example through common suppliers or production inputs,[9] However, for certain parts of the analysis, we extend the bipartite network by introducing links between lenders or CRE groups based on shared counterparts.

4.1.1 Overview

The structure of the CRE loan network can be analysed visually through a graphical representation. Figure 4 depicts the bipartite network in aggregated form, with banking groups being depicted as circles, hexagons or squares, depending on their size, and CRE groups represented as diamonds. Nodes are coloured according to the country of residence of the top shareholder, and their size is proportional to the total volume of loans given or received. [10]

The network is visibly dominated by German entities, with the German CRE group node and large German banks occupying a central position and maintaining the thickest lending connections. Banks from France, Italy, Spain, the Netherlands and Belgium, while fewer in number, also occupy central positions and exhibit broad connectivity, indicating diversified lending across multiple CRE groups. Lending from countries outside these core regions remains limited, consistent with the geographic concentration of CRE activity and the domestic orientation of bank lending practices.

The lending relationships tend to be spatially grouped by region, confirming that banks are more likely to lend to domestically headquartered CRE groups. Nevertheless, the network forms a almost a single connected component. [11] This implies that, while

[9] See Elliot and Golub (2022) for a review of models in which companies can be directly interconnected.

[10] We group banks according to their size for visualisation and confidentiality purposes. Figure 4 provides a summary, while the detailed micro-level dynamics discussed in the text are derived from individual-node analyses tailored to the granular dataset. These analyses capture individual bank and CRE-group behaviors, as well as specific statistical indicators representing micro-level patterns.

[11] Only one isolated component is observed, corresponding to a CRE group that exclusively borrows from local banks. However, in the aggregated visualisation this cannot be observed.

domestic banks maintain more relationships with local CRE groups, cross-border lending relationships are also important.[12] The layout reveals a clear core-periphery structure. Large and medium-sized banks tend to cluster near the centre, reflecting their involvement in multiple markets and their larger total exposures. Small banks are positioned at the periphery with fewer and thinner connections, indicating limited cross-border activity. This pattern may reflect the expansion strategies of many CRE groups, which often grow by acquiring companies owning properties while retaining existing credit relationships. This outcome may also be linked to the nature of CRE financing, in which banks typically provide loans to finance specific projects, leading companies to borrow from different banks for multiple projects in parallel. While stable client relationships are important, diversified sourcing of credit help reduce refinancing risks for CRE companies.

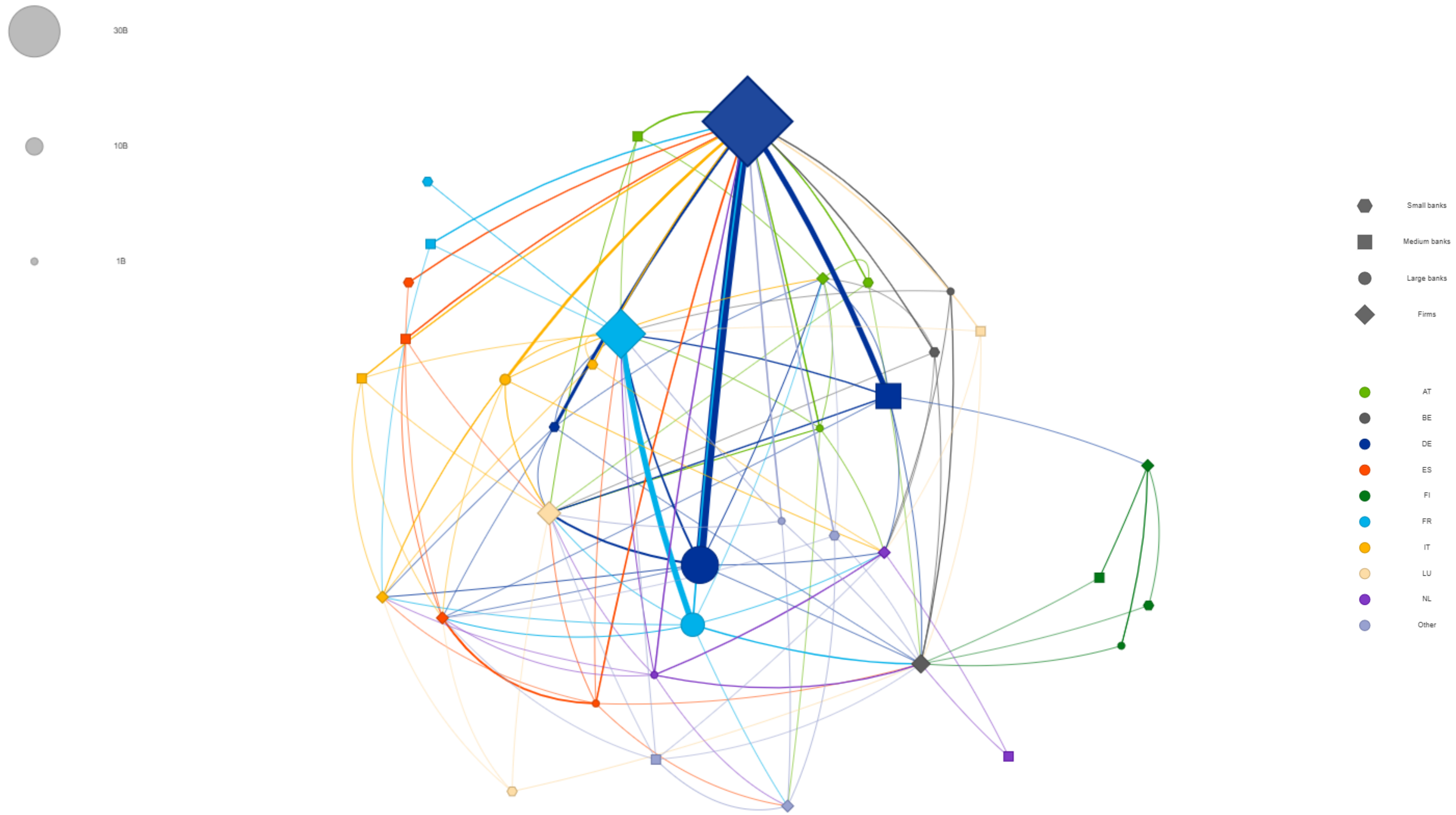
The network exhibits moderate density at the aggregate level, though underlying micro-level statistics reveal that connections are concentrated among a small number of large players. In the CRE network of 2023, the average bank lends to 3 different CRE groups, and the average CRE group borrows from 15.9 banks (Table A1).[13] When weighing the degree of a node by the loan amount it received/lent, the average degree rises to 34.9, with the average bank degree jumping to 16.6 and the average CRE group degree to 53.1. This large discrepancy between the unweighted and weighted average degree measures indicates that exposures are not uniformly distributed and are concentrated in fewer but larger players.

Looking at more complex indicators provide additional insights into how the network is shaped. The average degree centrality is 0.0323, meaning that the average node is connected to just 3.23% of the other nodes in the network, consistent with a relatively sparse network. The average eigenvector centrality is slightly lower, at 0.0258, showing that even highly connected nodes exert limited overall influence. The average betweenness centrality is also low, at 0.0044, suggesting only a few nodes serve as key intermediaries. The clustering coefficient of 0.3027 point to a moderate overlap in credit relationships, reflecting banks that are connected to similar sets of CRE groups or vice versa. Country assortativity is positive (0.5289), indicating that lending relationships are more likely to occur between banks and CRE groups located in the same country. This likely reflects local bank relations and lower transaction costs associated with the geographic proximity between lender and property. The negative degree assortativity of -0.3647 indicates that high-degree nodes are more likely to be connected to low-degree nodes, meaning that multiple banks engage in a lending relationship to only a few CRE groups. The different indicators computed provide strong evidence in favour of the network being characterized by a core-periphery structure.

[12] Cross-border relationships can occur not only with loans to foreign entities, but when the local bank giving the loan is part of a foreign banking group, or when the local company receiving the loan is part of a foreign CRE group.

[13] The definitions used for the calculation of the indicators can be found in Annex 2.

Figure 4: Network representation of the loans of CRE groups



Source: Author's calculation based on AnaCredit data.

Note: Banks were aggregated using their asset value at end 2023, using the following thresholds: <10bln - small, between 10 and 100 bln - medium, >100 bln - large. The following mapping applies: CRE group- diamond; Small bank – hexagon; Medium sized bank - square; Large bank - circle. Size of the node is proportional to the total amount of loans given/received. Top left legend presents reference points of the size of 30 bln, 10 bln and 1 bln. The network representation was created using the ForceAtlas 2 algorithm which arranges nodes near each other when they are strongly connected through exposures relative to their total activity. Nodes of the same type appear close when they interact with similar counterparties.

4.1.2 Borrowers analysis

This section analyses the network characteristics of the CRE group nodes. The degree of a node measures the number of connections a CRE group has with different banks, thus effectively quantifying the number of banks from which it obtains loans. CRE groups in Austria, Luxembourg and Germany exhibit a stronger tendency to form multiple credit relationships, showing the highest median degree (Figure A1a). In Germany, three large groups stand out with exceptionally high connectivity. Groups domiciled in Luxembourg are more likely to obtain credit from foreign banks, suggesting a higher degree of cross-border activity among Luxembourg domiciled CRE groups. Conversely, in the rest of the countries in the sample, the number of CRE lending relationships is smaller and more homogeneous across groups, with only a few outliers present in France and Spain.

Degree centrality exhibits an almost linear relationship with the total loan amount of the group, indicating that groups with larger loan financing tend to borrow from multiple sources, thus connecting with a larger part of the network. Notably, the distribution of degree centrality and eigenvector centrality for the CRE groups are very close, with the correlation coefficient between them at 97.7%. This strong correlation indicates that nodes with a large number of connections tend to be connected to other structurally important nodes with a similarly high degree of connections. Eigenvector centrality correlates with the betweenness centrality of nodes , suggesting an alignment between influence and intermediation. In particular, there are CRE group nodes with an outlier level of centrality that also act as hubs that interlink multiple parts of the network. These groups are systemic as a shock affecting them could disrupt the connectivity of the network and fragment it in multiple parts.

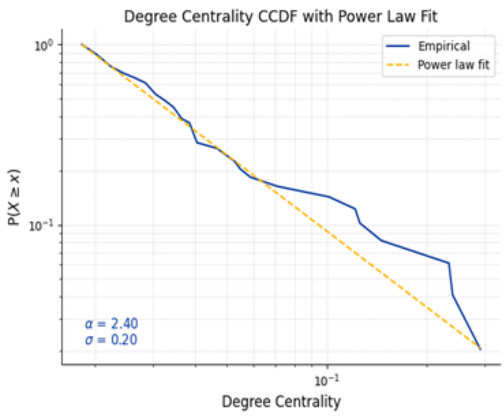
The presence of outlier groups forming high degree nodes indicates that the overall distribution of the degree centrality follows a power law pattern. This phenomenon is observed across many types of networks. To study the presence of power laws, we follow the methodology of Clauset et al. (2009), which proposes that the probability of a node having degree centrality (k) follows a power-law distribution:

$$P(k) = k^{-\alpha} \tag{1}$$

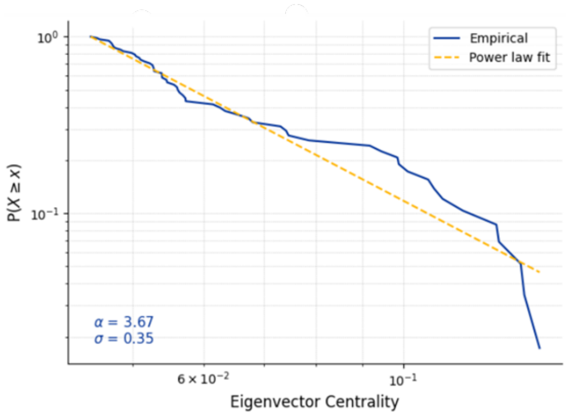
where α is the scaling exponent. Hence, as the number of connections increases, the probability of finding nodes with degree centrality k decreases. Figure 5a displays the cumulative distribution of degree centrality. The empirical data, marked by the blue line, closely align to a theoretical power law distribution drawn with the yellow dashed line, with an alpha coefficient of 2.4. Applying a log-likelihood test confirms that the empirical distribution is statistically likely to follow a power-law pattern, highlighting the significance of this network structure. Similar conclusions hold for the eigenvector centrality measure as well, which follows a power law with an alpha coefficient of 2.36. This result suggests the presence of a core-periphery structure (Newman, 2018), where the large and important nodes, often referred to as hubs, are interconnected. In the context of the CRE network, this means that the most important CRE groups tend to borrow from a larger number of lenders, and these lenders frequently coincide for the most connected groups. In contrast, smaller CRE groups have fewer connections to banks. Such networks are typically robust against failures due to the low connectivity of smaller nodes but are highly vulnerable to disruptions involving the hubs.

Figure 5: Power law simulations for the loan network

(a) Power law fit and degree centrality distribution of CRE groups in the loan network



(b) Power law fit and eigenvector centrality distribution of banks in the loan network



Source: Authors' calculation based on AnaCredit data.

Note: α displays the estimation for the scaling exponent, σ displays the standard error of its estimation.

Regional differences can be better understood by detecting communities of CRE groups. Starting from a network structure, specific algorithms can be applied to identify nodes that follow similar patterns. Because this technique cannot be applied directly to bipartite network structures, we use network projections to establish the network communities. In this context, CRE groups form a connection with each other for every common lender they share.[14]

To obtain the community structure, we employ the widely used Louvain algorithm, first introduced by Blondel et al. (2008). The algorithm is based on partitioning the network to maximise the modularity indicator, which measures how well nodes in the network are grouped with each other. The main drawback of the Louvain algorithm is its reliance on random initiation, which can lead to different community allocations across different runs. To overcome this challenge, we run the algorithm from 100 different initialisations and then compute the consensus result across all runs. The algorithm is

[14]See Annex 2 for more details about the community finding algorithm.

applied in an unweighted form.

The community detection algorithm partitions the CRE groups into five different communities with pronounced regional disparities. Figure 6a plots the community structure based on the country of residence of the CRE group.

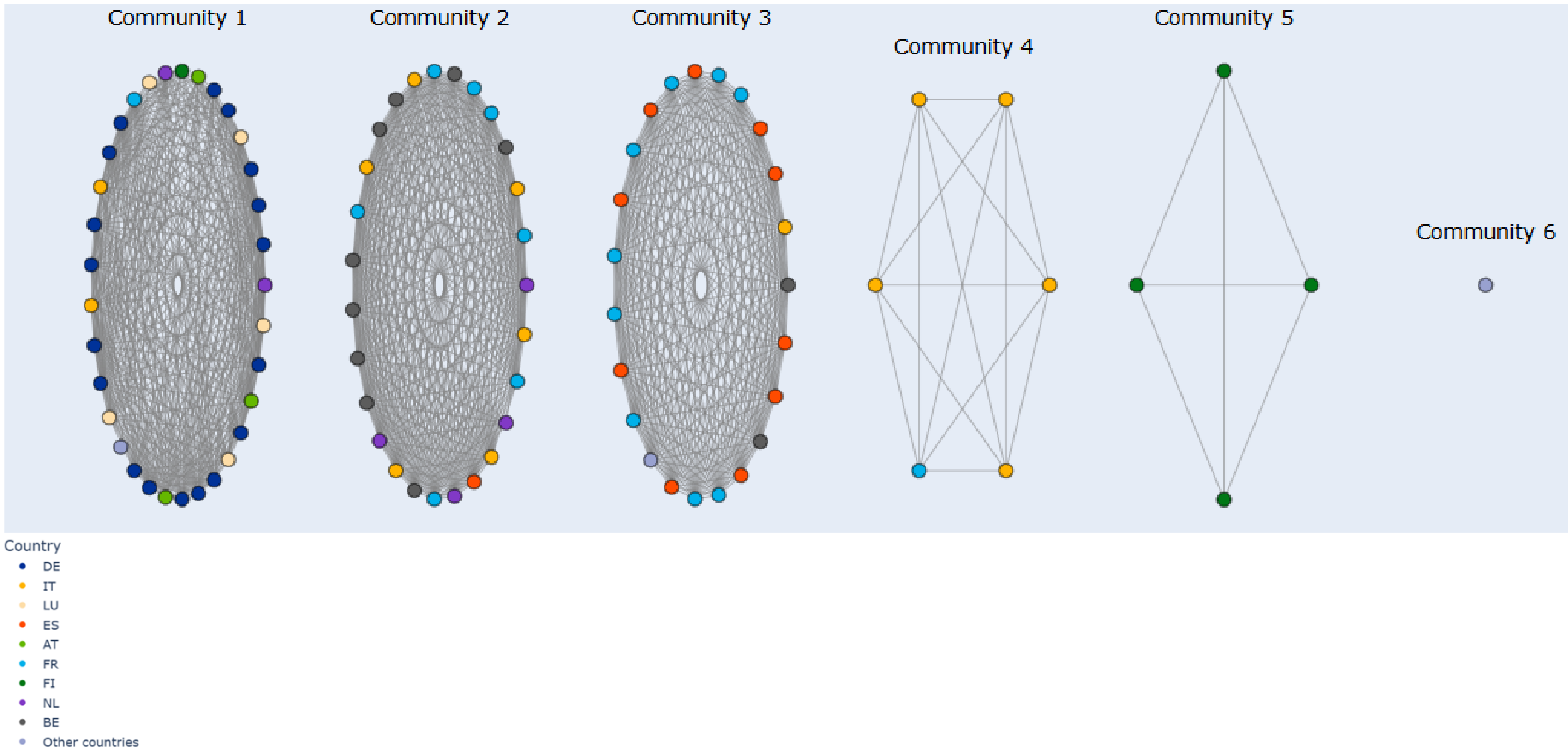
Three of the five communities are formed by CRE groups from different countries, with the largest and most connected one being comprised of groups primarily located in Germany Austria and Luxembourg. The second largest community is also very well connected and consists of groups primarily located in Belgium, France,Italy and the Netherlands. The third is more sparsely connected is mainly formed by Spanish and French groups. The other two communities are formed by groups concentrated within a single country with one being comprised of only Finnish companies and another being all Italian with a French addition. Finally, there is a community represented by the isolated node in our sample.

The geographical grouping present in these communities confirms the existence of differences in the regional lending patterns and reflects a tendency for companies to secure financing from banks located in their country of residence. Another notable characteristic of the network is that, in most cases, the communities comprise countries that are geographically close to one another. Taking the home-bias in financing into account, we are not surprised by the geographical vicinity of groups that form a community as CRE activities often involve physical operations, such as construction and building maintenance, for which establishing cross-border financing relations is costly.

Despite the pronounced regional clustering of communities, the modularity of the CRE group projection network remains relatively low (0.1364), indicating only moderate separation between communities and substantial overlap in lender relationships across regions as a result of several banks lending to CRE groups of different communities. The projected network visualization (Figure 6b) reinforces this result. While the delimitation of community boundaries is discernible, many nodes in the centre of the network form connections with nodes outside their immediate community. This suggests that, although the community structure is well defined, some companies operate beyond regional dynamics and secure financing in multiple markets. Moreover, the division of groups from France, Italy and the Netherlands into multiple communities signals a higher complexity of cross-border activities in these countries.

Figure 6: Communities of the CRE groups

(a) Communities formation of CRE groups in the loan network



Source: Authors' calculation using the Louvain algorithm.

(b) Inter-communities relationships of CRE groups in the loan network

Source: Authors' calculation using the Louvain algorithm.

4.1.3 Lenders analysis

Regional variations also emerge in the behaviour of CRE bank lenders. In France, the Netherlands, and Belgium, the median bank lends to more than five CRE groups, whereas in Germany, Italy, Luxembourg, Spain and Austria, the median bank lends to fewer CRE groups (Figure A1b). However, there are also outlier creditors in these latter countries that are specialised in CRE lending and provide credit to a wider variety of CRE groups. Consequently, banks from France, the Netherlands and Belgium typically hold larger CRE credit portfolios compared to banks in other eurozone countries, although specialised lenders in Germany, Italy, Austria and Spain also maintain significant portfolios.

The correlation between degree centrality and eigenvector centrality is weaker for banks (75.7%) compared to CRE groups (97.7%). This indicates that certain bank nodes are connected to high degree nodes but have relatively low degrees themselves. In the context of bank lending, this implies that certain banks lend to only to a few CRE groups, which are themselves highly influential. This phenomenon is also evident in the overall network structure, where large CRE groups draw loans from multiple smaller banks. In practical terms, certain lenders achieve structural importance not through broad diversification across borrowers, but being linked to a small number of influential counterparties. This divergence underscores the importance of analysing eigenvector centrality over degree centrality for banks, as it identifies lenders that finance the most central CRE groups.

Similarly to the company case, the eigenvector centrality of banks correlates with the loan amount and the betweenness centrality. This suggests that the most influential lenders in the network are also the biggest, and that they act as bridges between multiple parts of the network. This relationship is primarily influenced by the largest banks in the sample, which finance multiple CRE groups. On the other hand, there are multitudes of banks with small CRE portfolios that finance only a small number of CRE groups (often just one) and do not connect very well with the rest of the network. The eigenvector centrality distribution follows a power law, with an alpha value of 3.67 (Figure 5b). The larger scaling component provides evidence that the centre-periphery structure is more pronounced for the bank nodes than for the company ones.

Due to the large number of banks and credit relationships in the network, visualising how banks are connected based on the similarity in the CRE portfolio is relatively complex. To achieve a simplified visualisation we compute a minimum spanning tree (MST), which reduces the bank network to its fundamental relationships, often referred to as the "backbone of the network". Similar to the approach for CRE groups, the MST is applied to the projected network, connecting banks through shared CRE group debtors.

The MST is a concept from graph theory that represents the simplest structure connecting all nodes in a system through a path of minimal length. More specifically, the MST identifies a subset of edges that connect all nodes without forming any cycles, while minimising the total edge weight across the edges. A key methodological choice in MST construction is the definition of edge distances or weights. In this paper, we consider three alternative specifications: (i) an unweighted MST based solely on network topology, (ii) a loan-amount weighted MST, where lending exposures are transformed into edge distances, and (iii) a Jaccard-based MST capturing similarity in counterparties between nodes. This study provides a more comprehensive comparison than previous works, such as De Masi et al. (2011), which examined MST using only one type of weight.

In the unweighted MST (Figure 7a), nodes with a large number of connections to other well-connected nodes take central importance. This MST minimises the number of shared connections, without considering their importance. The resulting structures reveal three main hubs, primarily composed of German banks. The central nodes within these hubs are only connected to CRE nodes that are themselves central, suggesting that, under this weighing, the more central a bank is, the more it prioritises lending to important CRE groups.

In the MST weighted by loan amounts (Figure 7b), nodes with larger CRE loan portfolios become central. This MST is obtained by minimizing the largest shared exposures rather than merely the number of shared CRE groups. Consequently, most nodes connect to the largest lender, forming a big central hub, while smaller hubs reside on the periphery. These hubs represent clusters of banks that are more interconnected through shared exposures than by the rest of the network. In this representation, one German bank is a central hub, primarily composed of German banks. In addition to three somewhat smaller German hubs, there are two Austrian banks which form further relatively large hubs.

Under the weighting method with the Jaccard coefficient as edge weight (Figure 7c), the number of shared CRE groups is divided by the number of total CRE groups connected to the two nodes. Therefore, banks sharing some CRE groups receive a low similarity score if each lends to many other different CRE groups. This weighting leads to a structure in which banks with greater overlap in their CRE exposures are central. The resulting graph is more dispersed and is characterised by nine smaller hubs. The size of these hubs is less pronounced compared the other two MSTs, indicating reduced similarity in lending strategies or structural dependencies.

The MST framework applied to banking networks is a valuable tool to detect central nodes whose failure could trigger contagion, potentially leading to a systemic event. However, the substantial structural differences among the three MSTs makes it challenging to consistently point to nodes that are central under all aspects.[15] In the unweighted

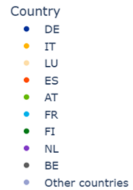
[15] For instance, the Jaccard similarity index computes the proportion of edges shared between the trees, revealing that the three MSTs have a low degree of similarity. This conclusion is further supported by the correlation of node degrees across the three structures: the unweighted MST and the Jaccard MST have a 25.5% correlation, while the Jaccard and loan weighted MSTs exhibit a correlation of only 8%.

MST structure, central nodes are predominantly banks that exclusively lend to major CRE groups. However, their absence as central nodes under the amount weighted MST shows that these banks do not lend large amounts, suggesting that if one or several of them should fail it would be relatively easy to substitute loans provided by them. The central nodes in the loan weighted MST are banks that give out the largest loans. Their failure poses greater systemic risks and financing problems for some CRE companies, as the financing gaps created by their absence may be less easily filled by other financing sources. Under the Jaccard weighed MST, central hubs represent banks with a similar CRE portfolio, meaning that they can be subject to heightened contagion risk if the shared CRE groups experience default. The sparser aspect of this MST signals that fewer banks have similar portfolios.

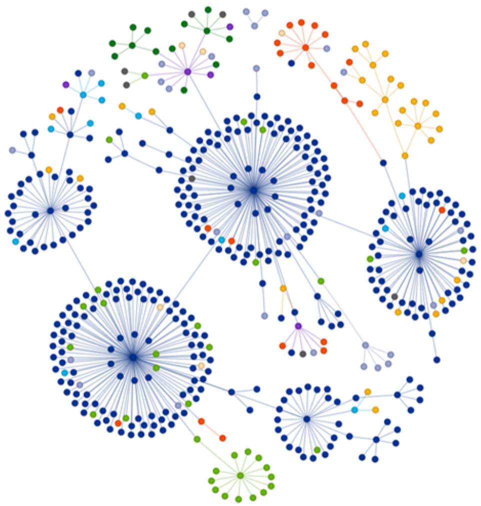
Another notable characteristic of the three MSTs is the regional clustering of hubs and connections. Similarly to the CRE groups observed in the community analysis, banks from the same countries tend to cluster within the same hubs, reflecting shared borrower characteristics or regional economic factors. German, Italian, Spanish, Austrian and Finnish banks consistently form distinct hubs across all MST structures. Interestingly, the French and Dutch banks, alongside those from less represented countries, tend to integrate into preexisting hubs rather forming separate structures on their own, highlighting potential differences in their lending patterns or borrower diversity.

This signals a major difference in the roles banks play as connectors depending on the weighing methods used. Additionally, the top ten nodes among the three methods are also almost completely different, with the unweighted MST and Jaccard sharing only two central nodes, while no overlaps exist between other combinations. The Jaccard-based structure is proven analytically to be dispersed, as evidenced by its large diameter coefficient, while the diameters of the other structures are over three times smaller. Similarly, the average path length of the Jaccard MST is the highest, exceeding that of the other methods by a factor of more than four, further highlighting its distinctive network properties.

Figure 7: Minimum spanning tree of the bank network

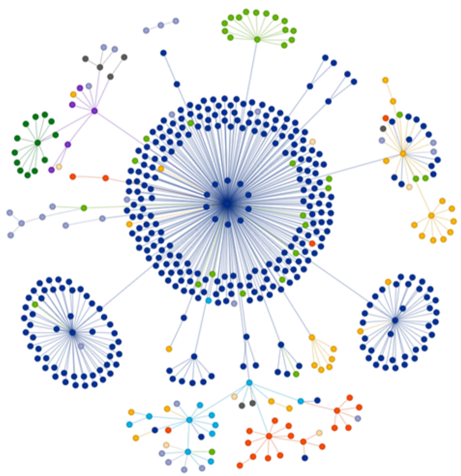


(a) Unweighted MST



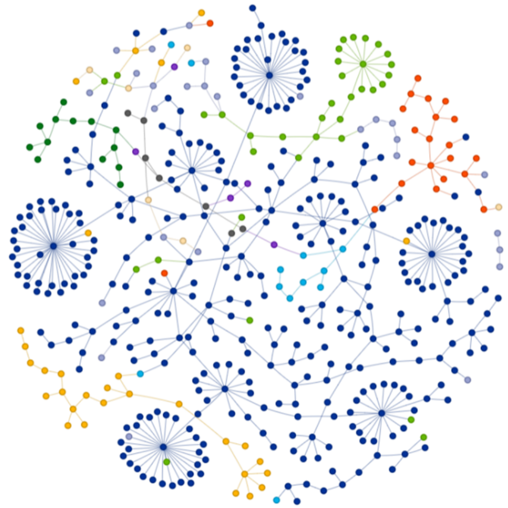
Source: Authors' calculation based on AnaCredit data.

(b) MST weighted by loan amount



Source: Authors' calculation based on AnaCredit data.

(c) Jaccard weighted MST



Source: Authors' calculation based on AnaCredit data.

4.1.4 Loan network evolution over time

The period analysed represents a tumultuous time for the CRE market in Europe, marked by a substantial decline in commercial property prices and a drop in transaction volumes (ESRB, 2024). In light of this turbulence, we examine whether CRE groups changed their behaviour, such as altering their borrowing patterns. In this subsection, we compare the main network indicators from 2021 to 2023 (Figure A2).[16]

The number of loan relationships (edges) increased significantly over the time period. Coupled with an increase of the nodes, this led to a higher average degree, as companies established more connections per node. The weighted average degree also increased, signalling that the largest new connections were mainly formed by already large nodes. After a slight decline in 2022, the average loan amount increased by 6.7% in 2023, indicating that not only were more credit relationships formed, but these also involved larger exposures.

Focusing on the network indicators we find that in 2023 average degree centrality, average eigenvector centrality, betweenness centrality and the clustering coefficient all declined relative to 2021. This serves as an indication that both the network became more sparse and that the overlap in credit relationships decreased during this time period. Moreover, the decrease in country assortativity points to a stronger preference for cross-border lending relationships, without necessarily implying a higher overall volume of cross-border lending.

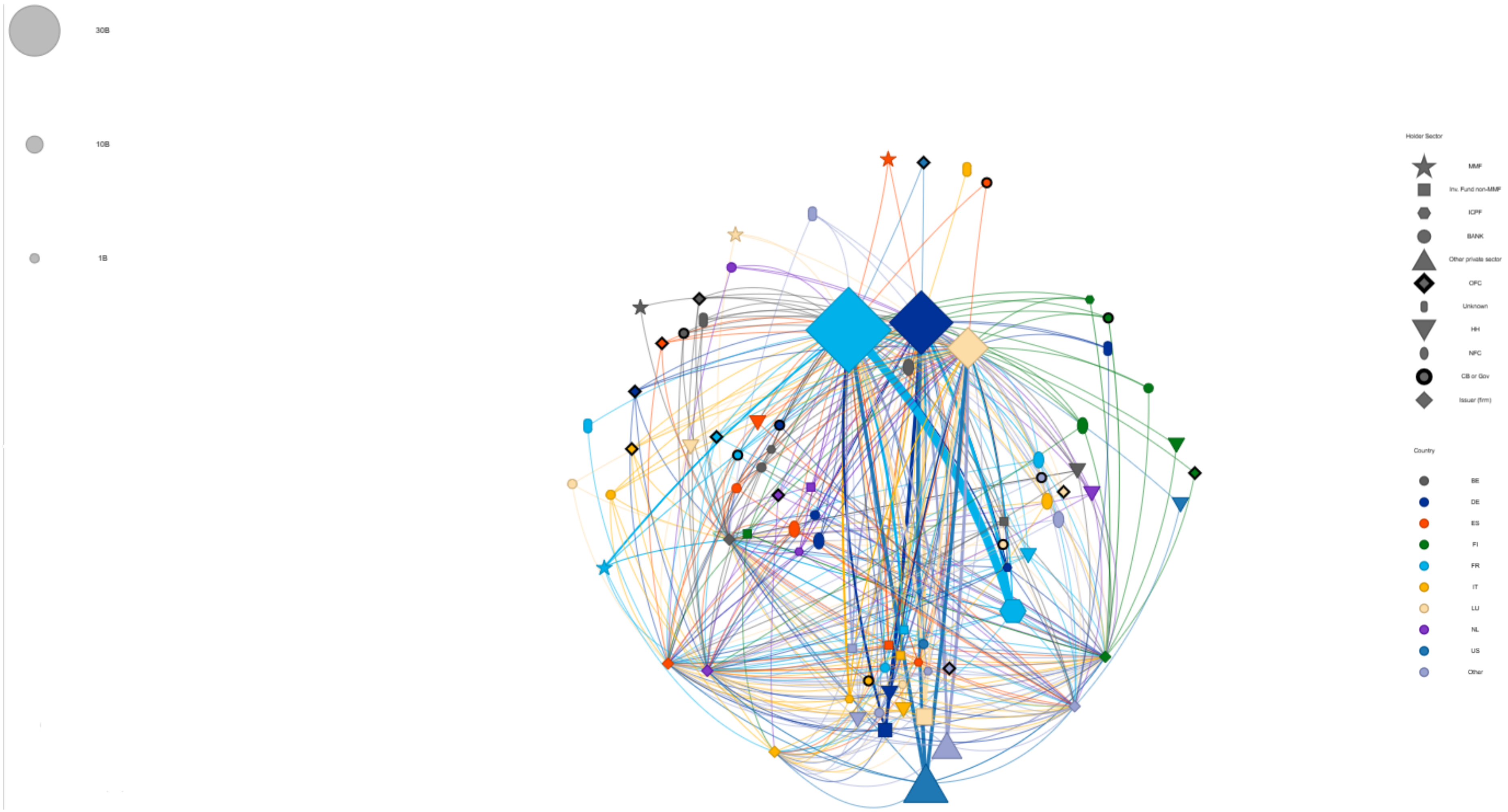
Overall, the CRE network expanded from 2021 to 2023 both in the number of credit relationships and in exposure size. Through new lending relationships, smaller company nodes increased their importance in the network, although this was partly offset by a decline in the centrality of some previously central nodes. The new lending patterns were also more geographically diverse.

4.2 Sector-firm bond financing linkages

This section constructs a macro-level network of the key financial relationships of the bond holdings of the largest CRE groups. This is essential for understanding how shocks originating in the CRE sector may affect the broader global financial system, and vice versa.

[16]Throughout this section we assume that both the bank and the CRE group structure remained the same as in 2023.

Figure 8: Network representation of the bond holdings of CRE groups



Source: Author's calculation based on SHSS data.

Note: The following mapping applies: CRE group- diamond; MMF- star, Investment Funds – square, ICPF – hexagon, Bank-circle, Other private sector – triangle, OFC – ellipse, HH- triangle inverted, NFC- circle open, Central Bank or Government – dot, Unknown – box. Size of the node is proportional to the total amount of bonds issued/held. Top left legend present points of the size of 30 bln, 10 bln and 1 bln. The ForceAtlas 2 algorithm arranges nodes near each other when they are strongly connected through exposures relative to their total activity. Nodes of the same type appear close when they interact with similar counterparties. For visualisation purposes, we aggregate all the countries/regions under "Other" into a single set of sector nodes.

4.2.1 Overview

Using the SHSS database, we construct a network of bond holdings for the CRE groups included in our sample at end 2023. However, there are notable differences in terms of coverage compared with the bank network. On the one hand, while the bond data encompasses all countries globally, the loan data is limited to the euro area.[17] On the other hand, a key limitation of the bond data is its lower level of granularity regarding holders: it only allows us to track the sectors holding the debt rather than the individual entities within those sectors that are exposed to the bonds (Figure A3).[18] To address this, we define holders by combining sector and geographical area, resulting in a total of 210 distinct entities.[19] On the issuer side, our sample includes 51 CRE groups that issued bonds in 2023. Notably, almost half of the largest 100 CRE companies in the EA do not issue bonds, highlighting that this market is primarily accessible to the largest players. Therefore, our sample likely provides high coverage of all CRE-backed bonds issued in the EU, ensuring a robust representation of this segment of the market.

Figure 8 presents the bond holdings network in country aggregated form, with the CRE groups represented with diamonds and the various holder-country combinations as other symbols.[20] Node size is proportional to the total volume of bonds issued or held, and colour indicates the country of the top shareholder.

The main takeaway from the bond network is that, in contrast to the loan network, we find a high degree of cross-border and cross-sector interconnectedness. The layout lacks the pronounced regional clustering observed in bank lending, with nodes of different countries spread out throughout the graph.[21] At the centre of the network, the largest CRE group nodes from Germany, France and Luxembourg are positioned close together, indicating a similar structure of bond holders across these issuers. Surrounding them, a diverse range of holder types maintains broad connectivity. Toward the periphery, particularly at the bottom of the chart, a distinct cluster of holders emerges, composed primarily of investment funds, ICPFs, households, banks and other private sector entities

[17]We keep as individual countries the EEA countries and the US, UK, Japan, China, Canada and Switzerland. All the other foreign countries are aggregated into regional categories (e.g.: South America), but these exposures remain limited.

[18]We define a total of 10 sectors: Investment Funds non-MMF, Insurance Corporation and Pension Funds (ICPF), Banks, Money Market Funds (MMF), Households, Non-Financial Corporations, Central bank or Government, Other Financial Corporations (OFC). There is one category that comprises the sectors that we know are private companies but cannot tell of each type, we named it Other private sector. There is also an Unknown sector which comprises the residual remaining sum that cannot be attached to any sector. Disclaimer: to study the relative composition of holdings, we include only the issuances for which holdings are found in the database. This approach may lead to an understatement of the total issuance value and the corresponding holdings by foreign sectors.

[19]For example, a MMF in France would fall in the category MMF-FR. A MMF in Brazil would fall under MMF-South America.

[20]In the main analysis, we use each CRE company as a separate node. Additionally, we include more sector-country combinations. For data confidentiality reasons, in this visualisation we aggregate some of the results.

[21]The international nature of bond debt is documented also in BIS (2025)

from outside Europe, reflecting a shared portfolio composition oriented toward similar issuer countries.

A series of indicators highlight a significant degree of interconnectedness within the extended bond network (Table A1). Despite the high aggregation of holders, the number of issuer-holder connections totals 2339 – substantially larger than in the loan network, despite having a 1 to 4 company-to-holder ratio, compared with a 1 to 5 in the banking network. The average node degree is 17.9, with issuers connecting, on average, to 45.9 types of holders, and sectors holding bonds from an average of 11.1 CRE groups. The degree weighted by the amount issued/held is notably higher, reaching on average 50.2 nodes, with issuers averaging 72.4 and holders averaging 28.2. The divergence between unweighted and weighted measures underscores that the largest issuers and holders are more interconnected compared to the entities with lower debt issuances, reinforcing their central role in the network structure.

An average node connects to 21.8% of the network. In contrast, the average eigenvector centrality is significantly lower at 4.6%. This disparity suggests that interconnectedness remains high regardless of a node's importance within the network. This result can be associated with the negative degree assortativity of -0.59, which indicates a preference for mixing high degree nodes with low degree ones. Average clustering is moderately high at 0.22. Betweenness centrality is low at 0.05 with only a few nodes acting as intermediaries in the network. Country assortativity is close to zero, showcasing neutral mixing by country and the absence of home-bias or cross-border preference. Bonds are held in an equal degree in the home country or in a foreign one. This result strongly contrasts with the bank lending network, in which companies and lenders showed stronger local mixing.

Overall, the bond network presents a markedly different topology from the loan network: it is denser, more internationally diversified, and lacks the domestic orientation that characterises bank lending relationships. This reflects the inherently cross-border nature of capital markets, where institutional investors hold diversified portfolios regardless of issuer domicile.

4.2.2 Bond issuers

The largest bond-issuing companies in our sample are primarily based in Luxembourg and France, with one notable outlier in Germany. These issuers also exhibit the highest node degree, indicating their bonds are held by a wider range of sectors in different countries (Figure A4a). However, there is no well-defined linear relationship between the bond amount issued and the node centrality.[22] The relationship is driven by a few outliers corresponding to the largest issuing companies, but for the rest of the nodes it remains flat. This implies that holders do not systematically prefer large issuers, and that even

[22]We refer here only to degree centrality, but an eigenvector centrality analysis is similar, as these measures have an almost linear relationship and a correlation of 97%.

smaller companies' debt can be held in many countries by various types of entities. The outliers also push the relationship of degree centrality and betweenness, with the most connected and influential nodes also being the most likely connectors of CRE groups across sectors.

Another interesting aspect is the relationship between the clustering coefficient and degree centrality, which follows a logarithmic distribution.[23] For the part of the nodes with degree centrality between 0 and 0.3, the clustering coefficient rises sharply, while for the rest of the companies the clustering coefficient is more similar, even decreasing. This result is coupled with a flat relationship between clustering and the issuing amount, excepting the outliers. This pattern happens as the CRE groups with a lower number of connections have a higher chance to match with a sector that holds the debt of another firm. As the centrality grows, the nodes get connected to sectors which are already holding bonds of other CRE groups, forming bipartite clusters. However, after a certain threshold the relationship flattens out as the extra sectors that the most central nodes connect to do not hold the debt of other CRE groups in the sample.

The issuers in the bond network exhibit a looser core-periphery structure, outlined by the power law fit of both the degree centrality and eigenvector centrality (Figure 9a). The α coefficient of the power law is 5.16, which is almost double that of the banking network. This means that the disparity between the most central nodes and the others is even more accentuated in the bond network compared with the loan network. However, this disparity is driven mainly by three outlier CRE groups that have a large issuance with a large investor base. The rest of the bond network is less dominated by high-degree hubs compared with the bank-firm loan network. This likely reflects the more standardised and open access nature of investor participation in the bond market.

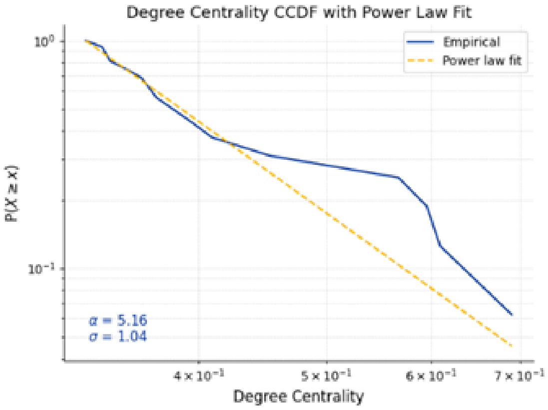
The lack of a regional dimension in the bond network becomes evident when applying a community detection algorithm to the CRE groups. Using the same methods as applied to the loan network, only two communities emerge (Figure 5a). With a modularity score almost null at 0.0163, the community structure is effectively negligible, indicating significant interaction between CRE groups across the two communities. The first community is highly interconnected, composed of 37 CRE groups that are central to the bond network. This group includes both core nodes and certain peripheral nodes that share common characteristics in their debt holders (Figure A5b). The second community comprises 14 companies that are more peripheral in the network, characterised by lower interconnectedness. Half of these companies are based in Belgium, with three from Germany and two from the Netherlands. Their clustering in the bond network reflects a reliance on Belgian debt holders, supplemented by institutional investors from Luxembourg and Switzerland. However, in the loan network they belong to different communities,

[23] This contrasts the loan network where there isn't any discernible relationship between clustering and degree centrality, for either CRE groups or banks.

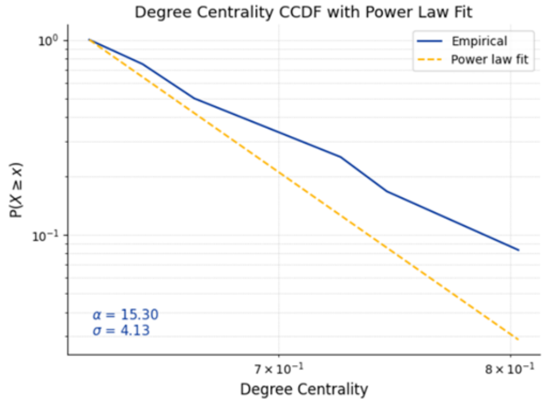
highlighting different financing patterns between the instruments.

Figure 9: Power law simulations for the bond network

(a) Power law fit and degree centrality distribution of issuers in bond network



(b) Power law fit and degree centrality distribution of holders in bond network



Source: Authors' calculation based on AnaCredit data.

Note: α displays the estimation for the scaling exponent, σ displays the standard error of its estimation.

4.2.3 Bond holders

Bond investors can be categorized by sector and country. The most diversified investors include investment funds, OFCs, the public sector, and ICPFs, with the median investor in these categories holding bonds issued by over 10 companies in the sample (Figure A4b). From the country perspective, the most diversified holders are located in Ireland, France and Belgium, each holding median exposures to more than 25 companies in the sample.

Similar to the company case, no clear relationship exists between degree centrality and total bond holdings. However, certain sector-country combinations stand out as outliers, characterised by substantial holdings across a significant proportion of companies. The nodes with the largest holdings, over 10 billion, are in ICPF-France, Other private sector-US, and Investment Funds-Luxembourg, who is also among the most connected nodes in the sample. The other nodes which are connected to over 70% of the CRE groups in the sample are Bank-Switzerland and other private sector-Switzerland, but their holdings are much smaller.

Similar to the bond issuers, the holders' relationship between clustering and degree centrality[24] tend to follow a logarithmic curb, with a rapid rise in clustering for degree centrality up to 0.3, followed by a plateau and decline. For low-degree holders debt investments are typically made in CRE groups already covered by large investment sectors, so early additions quickly create clustering. High-degree holders are already active in the

[24] Same idea holds true for the eigenvector centrality, as this measures are very similar with 98% correlation.

most dense areas of the market, where additional holdings do not significantly increase their clustering. Thus, the logarithmic pattern reflects rapid early integration followed by structural saturation among diversified holders. This behaviour is not affected by the total bond holdings, although there are outliers nodes with large holdings and large clustering. The linear relationship of eigenvector centrality and betweenness is also present for the holders, meaning the most influential nodes are also more likely to be network bridges.

The core-periphery structure cannot be plausibly defined by a power law fit of the degree centrality distribution (Figure 9b). Given the sectoral aggregation of individual entities data, we cannot be certain that national hubs do not exist within the defined sector. However, this possibility is unlikely given the guidelines on risk and concentration limits these institutional sectors need to follow, which may also drive the absence of core sector nodes.

4.2.4 Bond network evolution over time

The recent downturn in the CRE market has led to a contraction in the bond network from 2021 to 2023, with the average bond issuance declining by 16.6% over this period.[25] The number of issuer-holder relationship peaked in 2022, and then decreased by 3.8% in 2023. This evolution comes despite the marked increase in the number of participating holders, shown by additional sector-country combinations. There is one CRE group which quit bond financing in 2023.

The widespread weakening of the bond network connectivity can be also testified by the drop in average degree, weighted degree, degree centrality and eigenvector centrality (Figure A6). In addition to the network becoming sparser, average betweenness centrality and the clustering coefficient decreased as well, meaning less overlapping portfolios and less connecting bridges exist. However, country assortativity indicators increased, signalling that as cross-border exposures shrank, domestic structures remained intact. The degree assortativity increased as well, indicating that marginal issuer–holder relationships disappeared first.

Over the span of three years, the CRE bond market also became less interconnected. This trend likely reflects an active process of retrenchment in bond market activity, driven by tightening financial conditions, reduced issuance, and portfolio rebalancing away from specific issuers. This finding contrasts with the loan market, which expanded over the period, suggesting that financing through loans and bonds may serve as substitute instruments for certain entities within the sample. However, the descriptive analysis presented in Section 3 offers indicative evidence of a reallocation towards specific instruments, implying that the impact of tightening conditions in bank lending may not be fully captured by aggregate volumes and relationships. Instead, these effects are likely manifested

[25] Similar to the loan network, we assume that CRE group structure has remained the same. We also use the same categorization of holder sectors throughout the years.

across various term dimensions, such as collateral requirements and pricing. Additionally, other country factors and market conditions such as bank competition may have contributed to mitigate the full transmission of tightening measures to companies. A comprehensive comparative analysis of the impact of monetary tightening falls outside the scope of this paper.

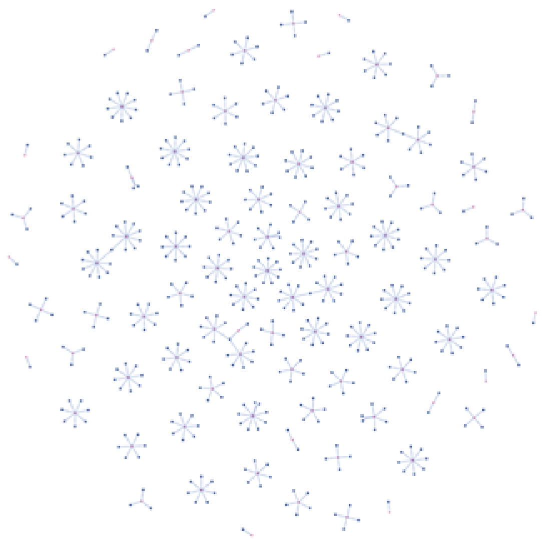
5 Financial stability implications

In this section, we analyse the financial stability implications of the CRE groups financing through two angles: the topography of the network structure and the relative importance of central nodes. A prime concern for network resilience is the degree of network connectivity and the formation of clusters. The loan network is characterised by pronounced regional clustering, as reflected in the communities formation. This clustering behaviour creates areas with a high degree of local connectivity, while cross-regional linkages remain weaker. To illustrate these features, we generate a series of random networks that replicates key properties of the observed network in various ways. Figure 10a shows a random graph that matches the number of banks and firms, as well as the average degree of the network. This network results in a structure where each company is financed by distinct banks, with no lenders in common. By contrast, Figure 10b presents a graph that also matches the total number of edges and the exact degree sequence of each node in the observed network. This results in a network with higher interconnectedness, but still lacking the clustering patterns observed in the real-world CRE network (which, for reference, is plotted in Figure 10c).

In the network in Figure 10a, risks are largely local. The failure of a single company would only affect a limited number of banks, with limited potential of risks spreading out to other lenders. Figure 10b forms an opposite scenario, where high interconnectedness allows shocks to propagate more easily, although risks are also more widely dispersed, potentially increasing overall resilience. These two configurations represent polar cases of a fully fragmented and a fully integrated, cross-border CRE credit market. The actual CRE network (Figure 10c) lies between these extremes. With its regional clustering and areas of high connectivity, the risk is neither purely local nor sufficiently dispersed to form a type of resilient network as found in the literature. Instead, the real-world network structure may exhibit fragilities: smaller shocks may propagate through nodes within regional cluster, while larger shocks may transmit outside clusters through bridge nodes connecting different parts of the network.

Figure 10: Comparison of different structures of the loan network

(a) Random loan network with low interconnectedness



Source: Authors' computation.
Note: Network is based on an algorithm that constructs a random network keeping the same number of bank and company nodes present in the real CRE network and matching the average network degree.

(b) Random loan network with high interconnectedness

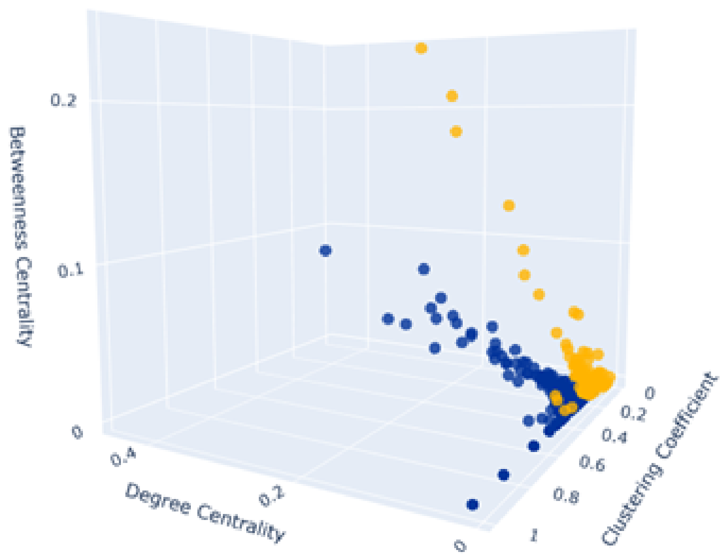
Source: Authors' computation.
Note: Network is based on an algorithm that constructs a random network that matches the number of nodes, the number of edges and the degree sequence of the real CRE network. More details about the algorithms can be found in Annex 2.

(c) Real loan network

Source: Authors' computation.
Note: Red nodes display companies and blue nodes banks. For confidentiality purposes, country attributions, or exposure values are undisclosed; nodes are uniform in size and unlabelled.

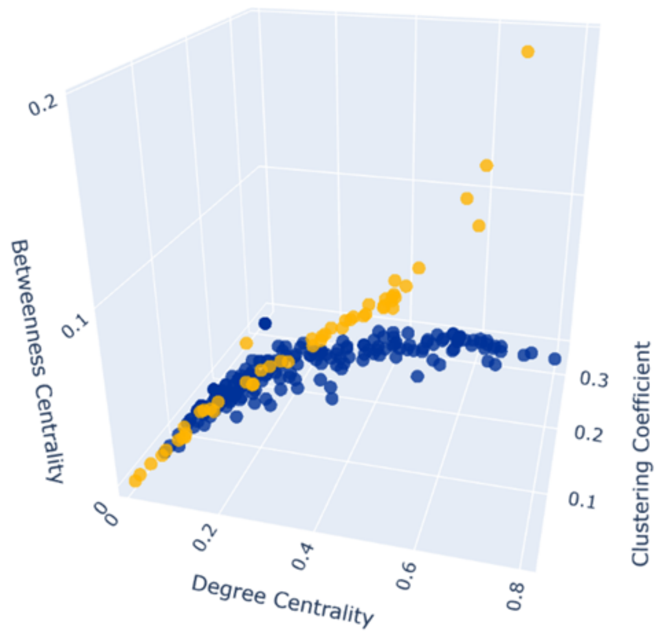
Figure 11: Important nodes identification

(a) Node characteristics in the loan network



Source: Authors' computation.

(b) Node characteristics in the bond network



Source: Authors' computation.

The recent insolvency of the Signa Holding can be viewed as a cautionary tale of such systemic vulnerabilities. Signa was one of the largest European CRE groups amassing a large portfolio of properties, mostly located in Austria and Germany.[26] Although we do not formally establish causality, we note that following the shock in Q4 2023, NPL ratios rose in Germany (+1.1 p.p.), Austria (+0.5 p.p.) and Luxembourg (+3.2 p.p.), while developments in other countries were more muted.[27] This divergence exemplifies the regional shock absorption aspect of the CRE market, although the failure of a larger or more interconnected entity could have resulted in more widespread repercussions.

Besides considerations of risk stemming from the network structure, financial stability implications also depend on the identification of central nodes, whose failure could destabilise the system. While methods such as the Debt Rank algorithm are commonly used to identify systemic nodes (Battiston et al., 2012b), developing such an approach is beyond the scope of this paper. Instead, we rely on alternative indicators of node importance. We note that the most important nodes, identified by their loan size and central position, are also the most connected nodes in the network, exhibiting highest degree centrality and eigenvector centrality. More specifically, we analyse node importance through three metrics: degree centrality, betweenness centrality and the clustering coefficient. Figure 11a shows that several nodes combine high degree centrality and betweenness centrality with a low clustering coefficient. These nodes act as bridges, connecting different parts of the network without being part of dense clusters. Since these nodes are CRE groups serving as connectors between bank clusters, their financial issues could affect a large number of banks across multiple regions. Additionally, the presence of specialised lenders can be identified by high clustering combined with low centrality, reflecting banks that lend to a small number of similar firms within localised clusters and are therefore exposed to concentration risk.

An inverse relationship emerges between the clustering coefficient and the degree centrality. The most connected CRE group nodes are located in neighbourhoods that are otherwise weakly connected with the rest of the network. This result is driven by the largest German CRE companies, which borrow from a multitude of specialised banks. There are also some CRE groups that have a low degree centrality but a high clustering coefficient. These groups borrow from banks that are key lenders in the network, forming neighbourhoods around them. Additionally, there are banks that establish cross-border credit relationships with significant CRE groups, and their international role prevents them from belonging to regional clusters. Conversely, banks with high clustering coefficients but low centrality are more localised, financing the same CRE groups within similar countries and thereby forming distinct clusters.

[26]Signa's debts amounting to approximately 5.7 bn euro at the time of its insolvency, according to https://www.financierworldwide.com/signa-files-for-insolvency

[27]Increases at end of 2024. Source for the NPL rate is the EBA Risk Dashboard.

Even if the default of an important CRE company node could disrupt the network, spillovers to broader financial stability may remain limited. For none of the banks in the sample does the CRE loan exposure exceed 8% of its total nominal loans. However, banks with lower nominal exposure often display higher relative exposure due to specialisation in CRE lending. Some of these banks maintain fewer than five loan relationships, highlighting their vulnerability to concentration risks. By contrast, the largest lenders in our sample are diversified banks, with diversified CRE client portfolios and relatively low overall CRE exposure in their total balance sheet. But, as Lux (2016) demonstrates, in a risk-propagation simulation, joint exposure to failing firms can be significant channel for contagion.

From a financial stability perspective, the bond issuance network exhibits significant differences compared with the credit network. It poses a larger degree of interconnectedness, lacks a home bias and features a higher prevalence of cross-border connections. This typically means that the bond network tends to be more resilient to shocks, as the risk is more widely distributed across different type of entities and jurisdictions. The bond market therefore resembles a more complete network in which shocks are more evenly spread out across the nodes.

Nevertheless, a few outlier nodes stand out in terms of importance (Figure 11b). On the issuer side, three CRE groups combine large issuance volumes with high centrality, with their debt held by a variety of sector and jurisdictions. On the investor side, five sector-country combinations (ICPF-France, Other private sector-US, Investment Funds-Luxembourg, Investment Funds-Germany, Other private sector-UK) account for large holdings across many issuers. However, the absence of information on the number of individual entities within these sectors limits a full assessment of the individual risk.

Overall, declining CRE markets can lead to defaults among CRE groups and rising NPLs. At the same time, falling real estate valuations may also impair asset quality of banks through its impact on collateral, creating liquidity issues and contagion effects. These risks are more pronounced in the loan network, where strong regional clustering can amplify local shocks and allow them to propagate through bridge nodes. In bond markets, risks are more widely distributed across investors, but stronger cross-border linkages may amplify international spillovers. Each financing channel has distinct financial stability implications. While the loan network may be more vulnerable to shocks, the risk is partially offset by collateralisation and the closer relationship between banks and firms. By contrast, bond financing is typically unsecured, and market liquidity may prompt investors to sell their participation at early signs of distress, even for a discount, potentially triggering destabilising dynamics.

The network analysis helps identify areas where intensified monitoring is warranted. First, large CRE groups with high connectivity act as critical connectors in the network, and their failure could affect multiple banks and regions. Second, the two most highly interconnected regional communities may amplify financial stability risks and merit closer surveillance. Third, specialised banks with concentrated exposures to a small number of CRE groups are particularly vulnerable to concentration risk. More generally, during CRE market downturns, refinancing conditions may deteriorate in bond markets due to higher risk premium, while information on firms' financial conditions may be less readily available to bond investors than within bank-based lending relationships.

6 Conclusion

In this paper we map out the network of financing of the major CRE groups in the euro area, connecting them the banks from which they borrow, and the investors holding their bonds. Focusing on bank credit, we examine the granular structure of loan relationships between banks and CRE groups by creating a bipartite network. The loan network is characterized by a strong core-periphery structure, supported by the finding that the degree centrality distribution of CRE groups and the eigenvector centrality of banks follow a power law pattern, further supporting the presence of such a structure. Our findings also point to a pronounced home bias and regional disparities in financing patterns, leading to the formation of clusters. Specifically, CRE groups located in Germany, Austria and Luxembourg tend to secure smaller loans from a broader range of banks, whereas groups in other regions establish larger credit relationships with fewer lenders. These financing patterns foster the emergence of communities of CRE groups sharing similar regional characteristics in their credit relationships. Notwithstanding these network characteristics, we observe limited overlap among key lenders in terms of the number of large CRE clients, portfolio size and portfolio composition.

Additionally, we analyse the characteristics of financing through the issuance of bonds, by investigating the sectors and countries that hold bonds issued by the largest CRE groups. While not directly comparable to the loan network due to differences in the granularity and scope of the bond-holder side, the bond network exhibits a higher degree of interconnectedness and no evidence of home bias or regional clustering. The degree centrality of issuers follows a steeper power-law distribution than the loan network, with the three largest issuers emerging as clear outliers in terms of connectivity. Nevertheless, smaller issuers also attract investors from a diverse range of sectors. Between 2021 and 2023, the bond network contracted, whereas the loan network expanded.

After the analysis of the network characteristics, which by itself reveals important implications for risk monitoring, we turn to study the financial stability implications of the network structures. Regional clustering in the loan network may limit risk sharing and reduce shock absorption, whereas the higher interconnectedness of the bond network may enhance broader loss absorption capabilities. At the same time, both networks contain a small number of highly central nodes, characterised by elevated centrality, betweenness, and clustering, whose distress could affect a large share of participants in the CRE debt market.

The scope of the analysis is constrained by current data availability and could be extended in several directions. First, the sample of CRE groups could be enlarged. Second, loan data could be enriched by incorporating loans from outside the euro area. Third, the granularity of bond holdings could be improved. Further research is required to simulate shock transmission dynamics and to identify critical nodes with greater precision. Bridging the loan and bond markets would allow for a system-wide perspective on contagion risks. Despite these limitations, our findings offer valuable insights into the financial stability implications of CRE financing and provide a basis for analysing the impact of shocks on specific entities.

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Annex 1 Additional tables and figures

Table A1: Summary of the main credit network indicators

Indicator	Loan network	Bond network
Total number of nodes	600	261
Bank / Holder nodes	500	210
Company nodes	100	51
Bipartite edges (number of relationships)	1496	2339
Average degree	5.0971	17.9234
Average bank/holder degree	3.0345	11.1381
Average company degree	15.9149	45.8627
Weighted-average degree	34.8871	50.3133
Average degree centrality	0.0323	0.2184
Weighted-average bank/holder degree	16.6236	28.2253
Weighted-average company degree	53.1506	72.4012
Assortativity by degree	−0.3647	−0.5943
Average betweenness centrality	0.0044	0.0056
Average eigenvector centrality	0.0258	0.0455
Average clustering coefficient	0.3027	0.2195
Assortativity by country	0.5289	0.0309

Source: Authors' calculation.

Note: For details about the indicators' definition, see Annex 2.

Table A2: Geographical distribution of the CRE groups sample

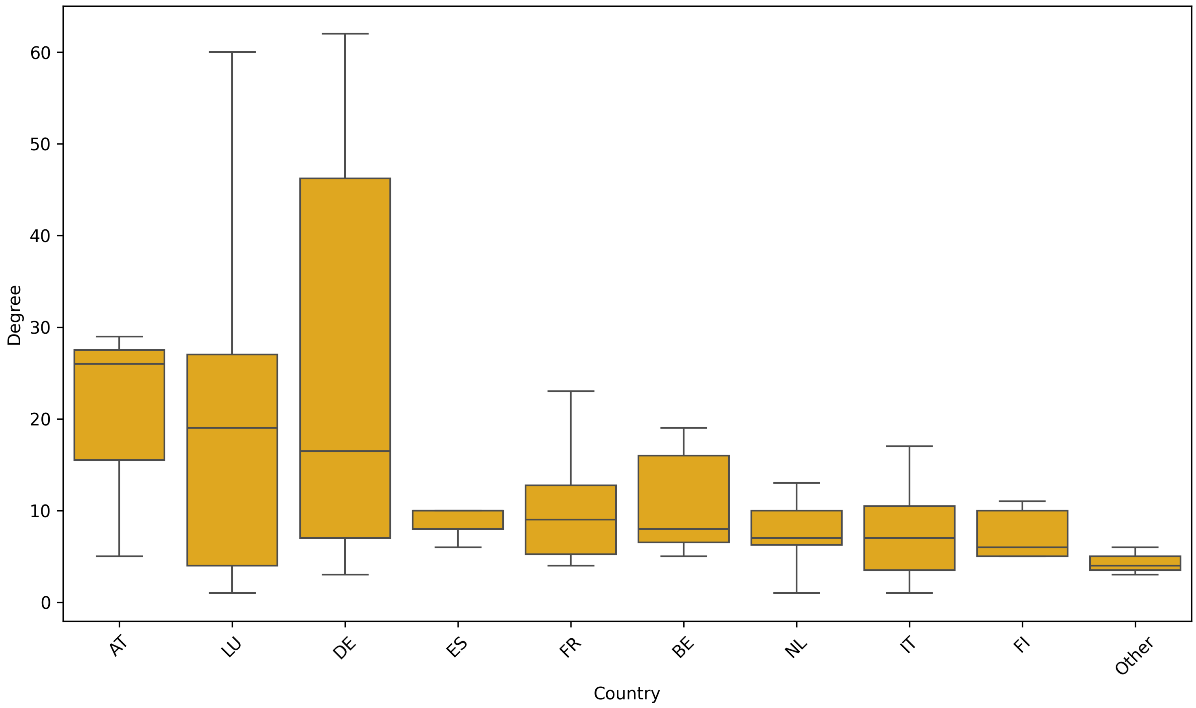
Country	**Number of CRE groups**	**Share of total assets**
Germany	21	29.3%
France	18	32.2%
Italy	15	2.1%
Spain	12	7.2%
Belgium	11	7.0%
Netherlands	7	3.2%
Luxembourg	5	12.5%
Finland	5	3.6%
Austria	3	1.6%
Other EA countries	3	1.4%
Total	100	100%

Source: Authors' calculation.

Note: Share of total assets represents the share of each country in the total assets of the 100 CRE groups at end-2023.

Figure A1: Characteristics of the loan network

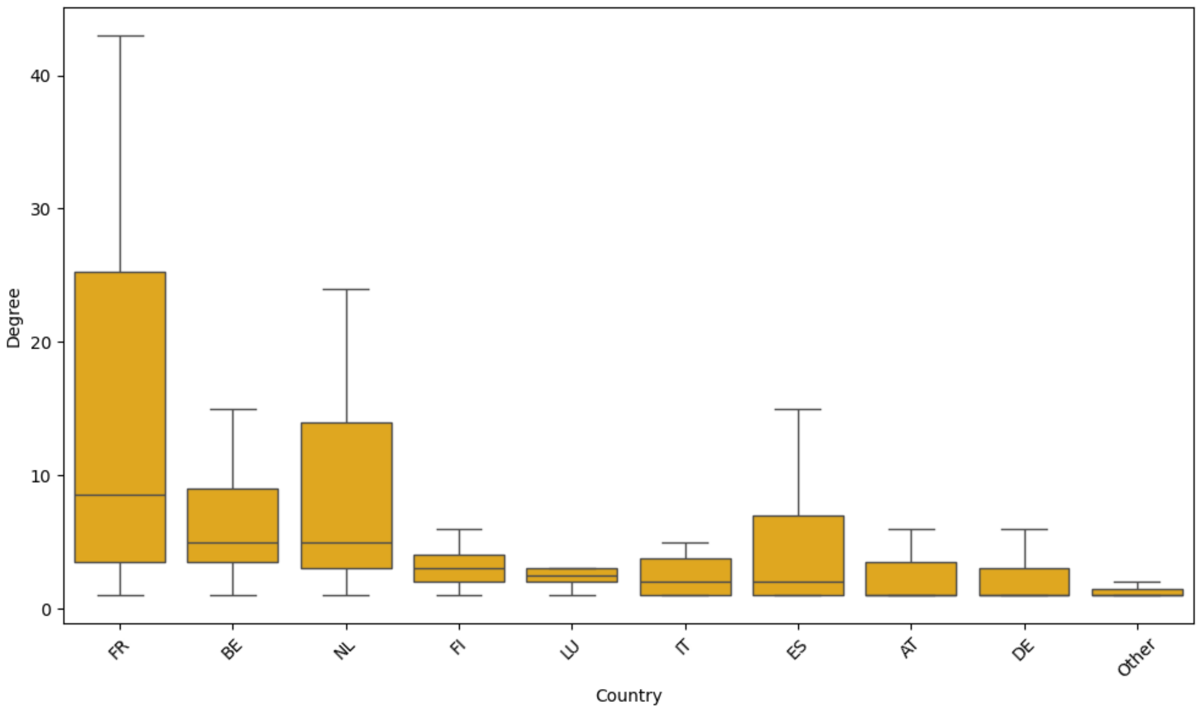
(a) Distribution of degree of CRE group nodes in the loan network



Source: Authors' computation.

Note: For confidentiality purposes, we exclude the visualization of outliers that are present for Germany (3), Spain (3) and France (1).

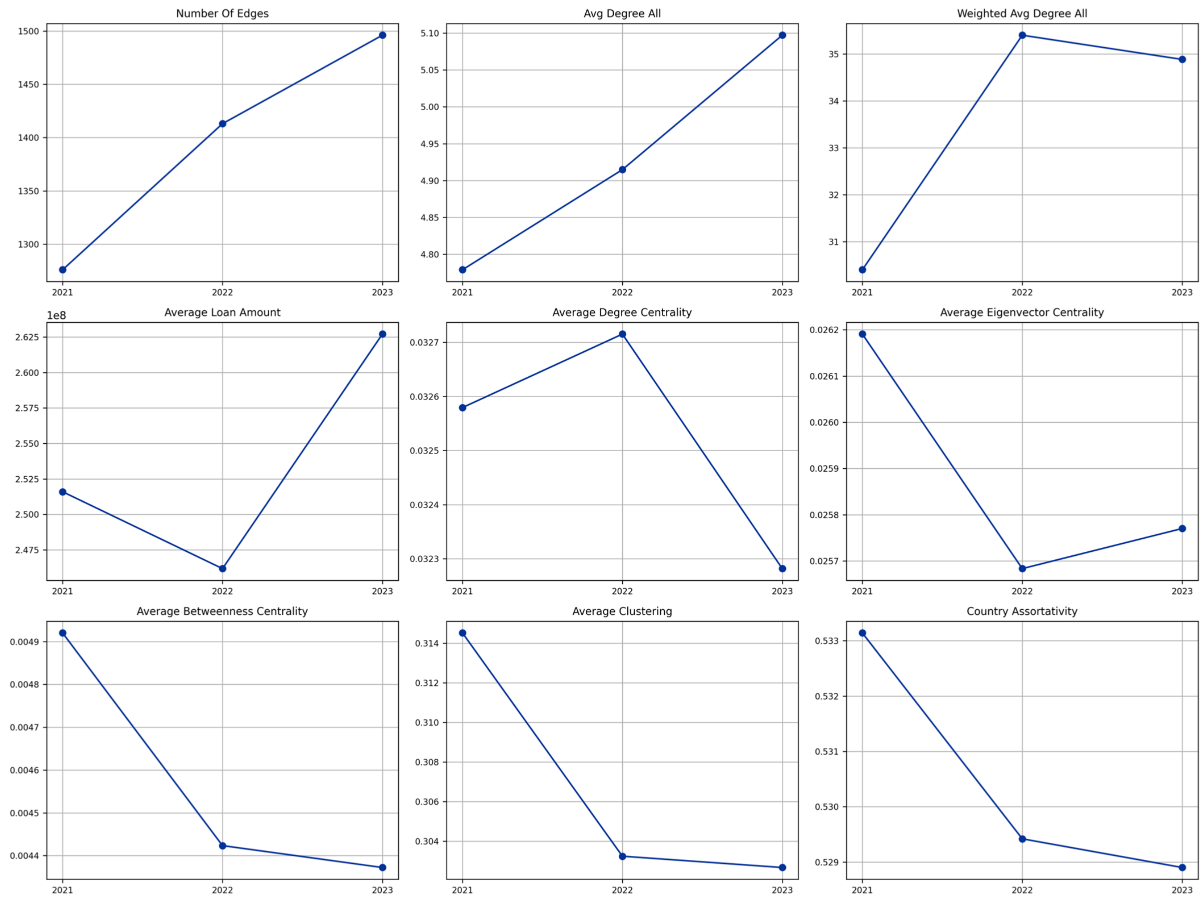
(b) Distribution of degree of bank nodes in the loan network



Source: Authors' computation.

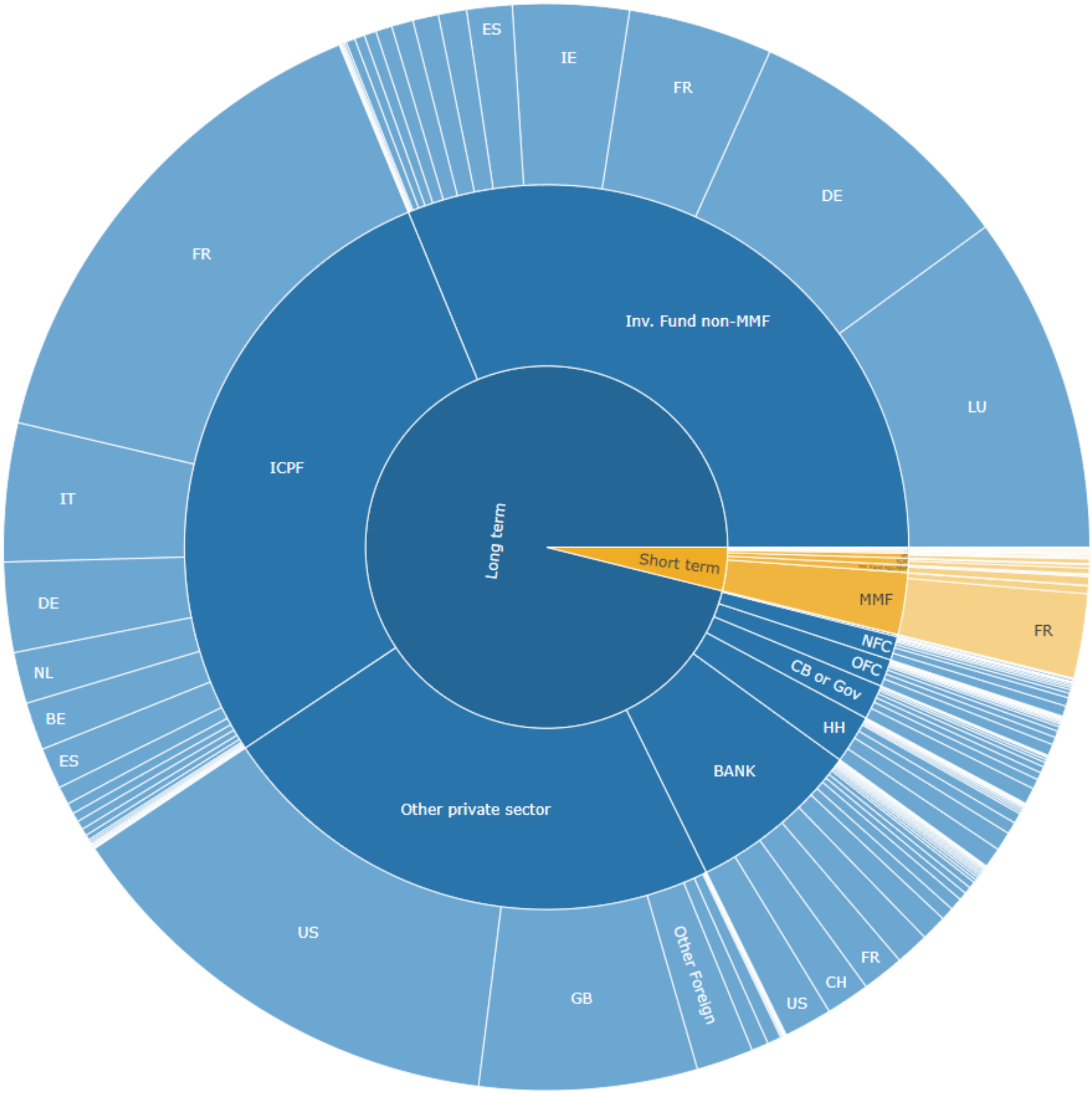
Note: For confidentiality purposes, we exclude the visualization of outliers that are present for Luxembourg (1), Italy (5), Spain (1), Austria (1), Germany (11) and Other (3).

Figure A2: Summary of the loan network indicators' time evolution



Source: Authors' computation.

Figure A3: Summary of holders of CRE groups' bond issued, end 2023

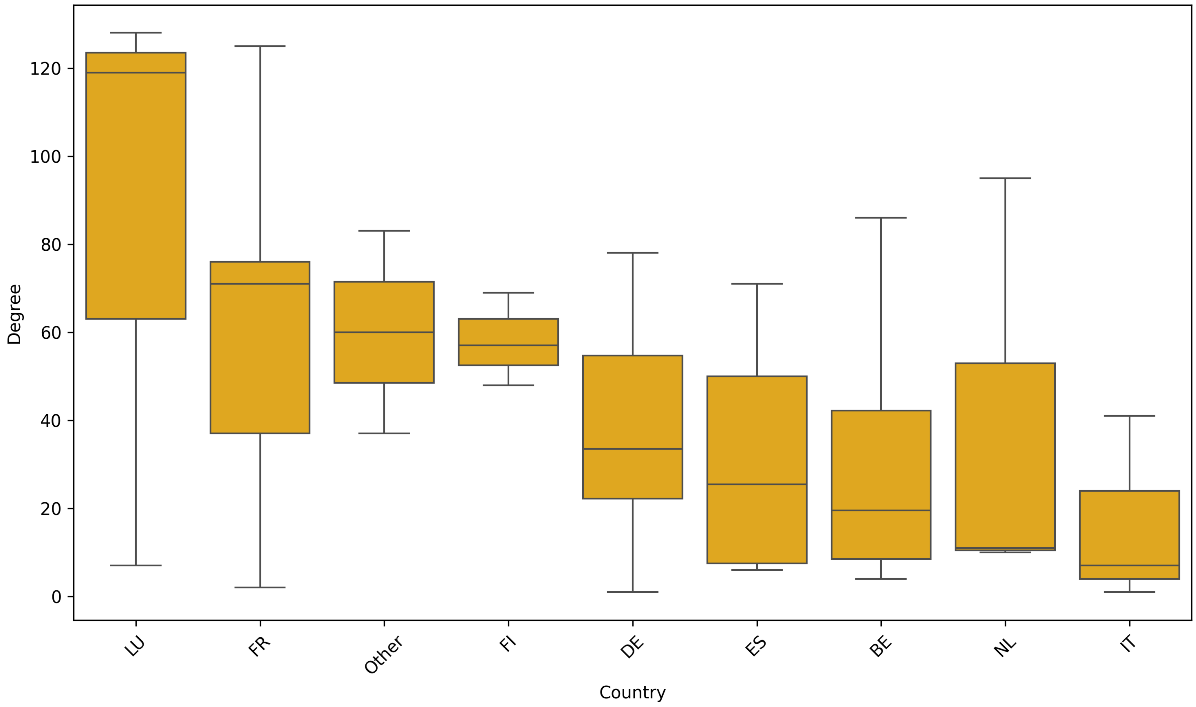


Source: Authors' computation.

Note: For visualisation purposes, we display only the countries that have an exposure larger than 1% of the total.

Figure A4: Characteristics of the bond network

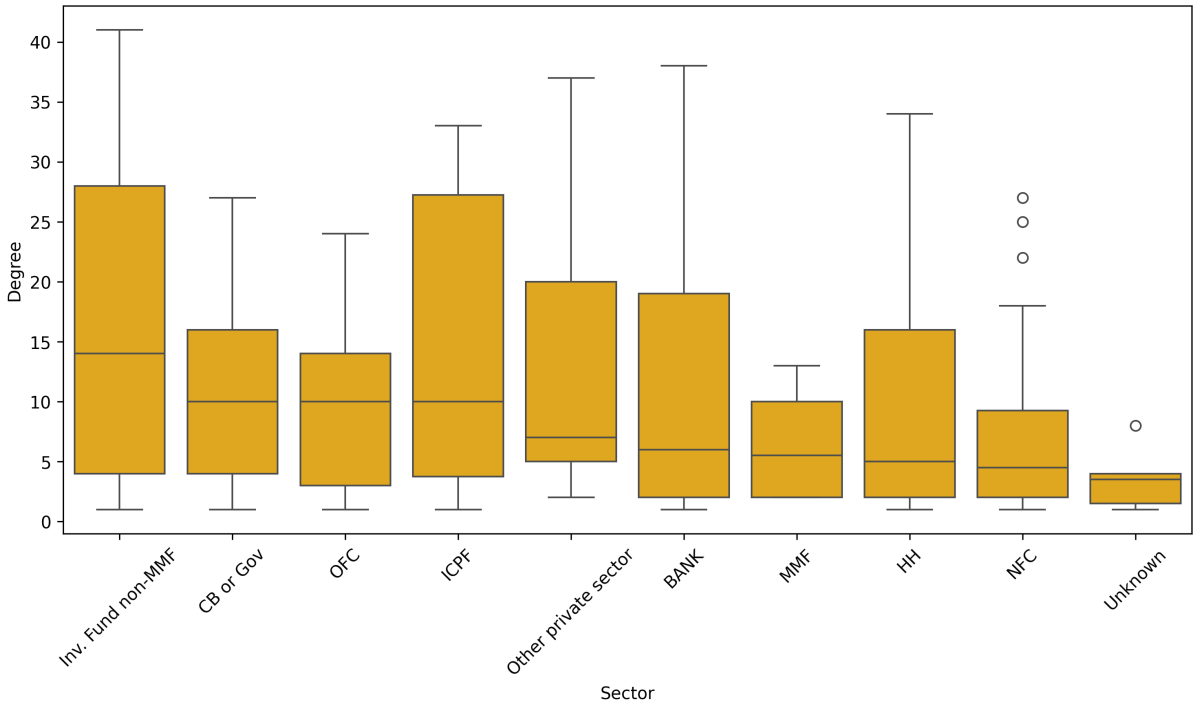
(a) Distribution of degree of CRE group nodes in the bond network



Source: Authors' computation.

Note: For confidentiality purposes, we exclude the visualization of an outlier that is present for Germany.

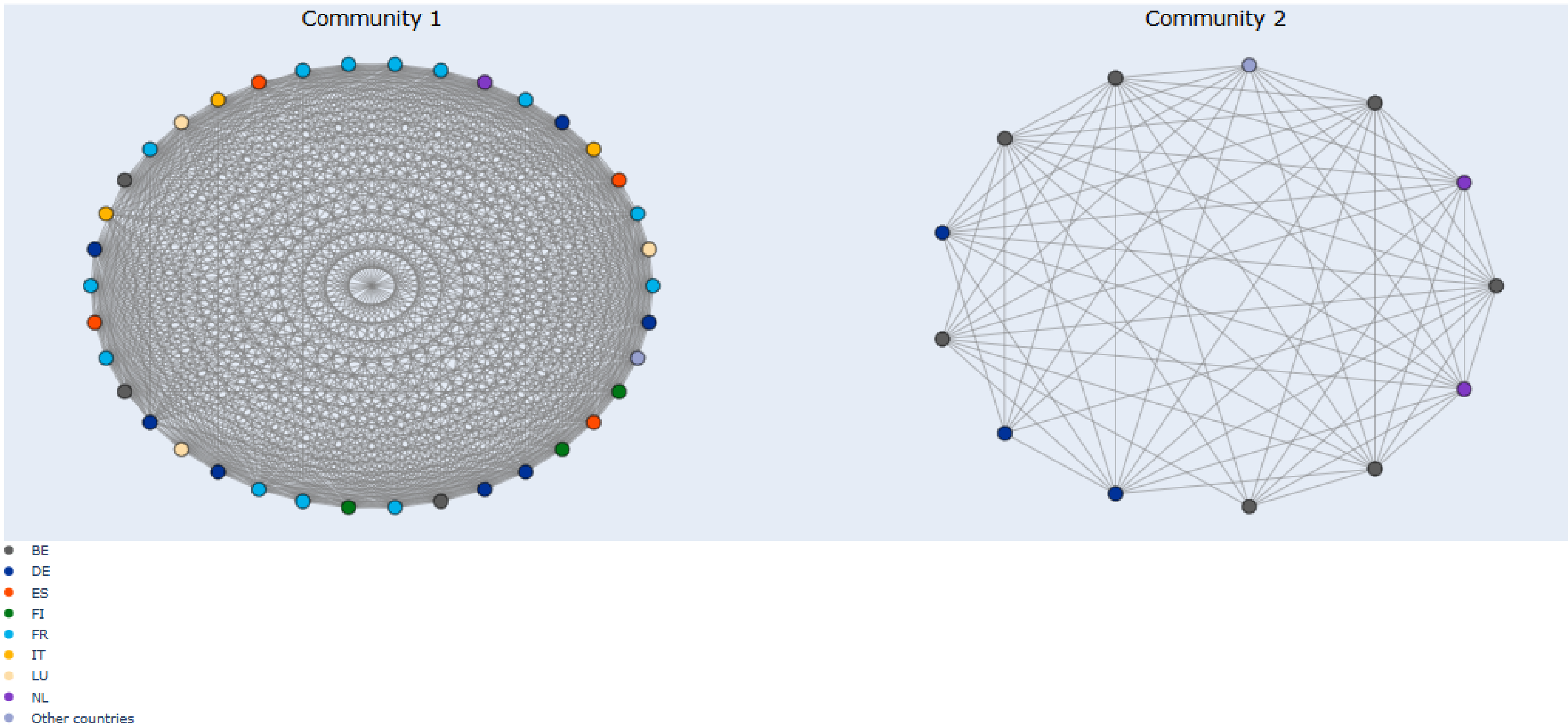
(b) Distribution of degree of holder sector nodes in the bond network



Source: Authors' computation.

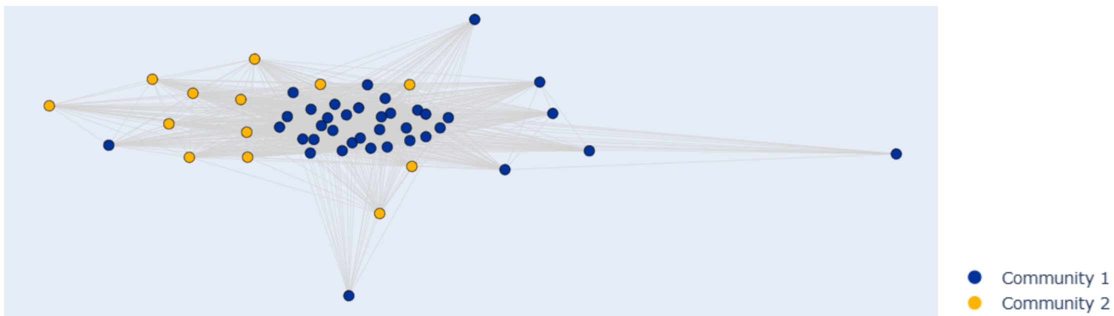
Figure A5: Communities formation in the bond network

(a) Communities formation of the CRE groups in the bond network



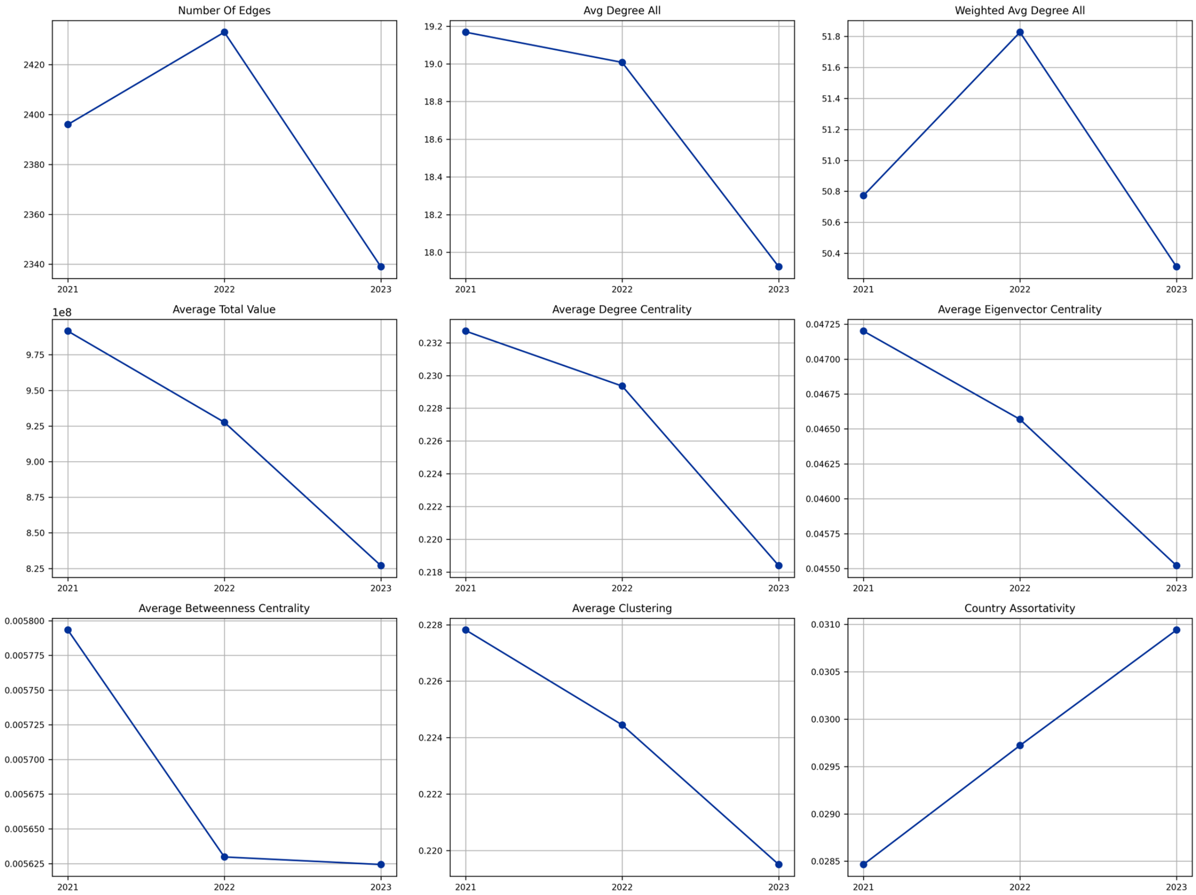
Source: Authors' computation using the Louvain algorithm.

(b) Inter-communities relationships of CRE groups in the bond network



Source: Authors' computation using the Louvain algorithm.

Figure A6: Summary of the bond network indicators' time evolution



Source: Authors' computation.

Annex 2 Technical annex

This Annex presents a technical overview of the concepts used for the network analysis in sections 5 and 6. The computations were done using the NetworkX package in Python (Hagberg et al., 2008). The technical apparatus presented in this annex is based on Newman (2018), Latapy et al. (2008) and Borgatti and Everett (1997).

Adjacency matrix for a bipartite network

Consider a bipartite graph $G = (U, V, E)$ with disjoint node sets U and V, where $|U| = n$, $|V| = m$, and edges exist only between the two sets, such that $E \subseteq U \times V$. The standard matrix representation orders vertices by listing all nodes in U first, followed by all nodes in V. Let $N = n + m$ denote the total number of nodes.

Biadjacency matrix

Define the biadjacency matrix $B = [b_{ij}]$ of dimension $n \times m$ as follows:

$$b_{ij} = \begin{cases} 1, & \text{if } (u_i, v_j) \in E \\ 0, & \text{otherwise} \end{cases} \tag{2}$$

If edges carry weights according to a weight function $w : E \to \mathbb{R}_{\geq 0}$, the matrix is given by

$$b_{ij} = \begin{cases} w(u_i, v_j), & \text{if } (u_i, v_j) \in E \\ 0, & \text{otherwise} \end{cases} \tag{3}$$

Adjacency matrix in block form

The full adjacency matrix A of the bipartite graph, of dimension $(n+m) \times (n+m)$, takes the canonical block structure

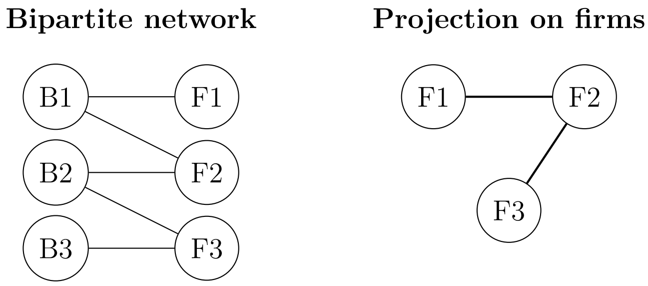
$$A = \begin{bmatrix} 0_{n\times n} & B \\ B^T & 0_{m\times m} \end{bmatrix} \tag{4}$$

One-mode projections

The one-mode projections onto U and V are given by

$$P_U = BB^T, \qquad P_V = B^T B \tag{5}$$

The figure below shows a bipartite network with three banks and three firms, followed by its projection onto firms.



In this example:

- F1 and F2 share lender B1,
- F2 and F3 share lender B2,
- F1 and F3 do not share lenders.

The projection therefore produces edges $(F1, F2)$ and $(F2, F3)$.

Indicators

Degree

The degree of a node in a bipartite graph counts the number of neighbors it has in the opposite set. For $u_i \in U$,

$$\deg(u_i) = \sum_{j=1}^{m} \mathbf{1}(b_{ij} > 0), \tag{6}$$

and for $v_j \in V$,

$$\deg(v_j) = \sum_{i=1}^{n} \mathbf{1}(b_{ij} > 0). \tag{7}$$

In vector form,

$$\mathbf{d}_U = B\mathbf{1}_m > 0, \qquad \mathbf{d}_V = B^T\mathbf{1}_n > 0, \tag{8}$$

where $\mathbf{1}_k$ is a k-dimensional vector of ones and the indicator ensures only positive-weight edges count toward degree.

Weighted degree

The weighted degree sums the weights of the adjacent edges. For $u_i \in U$,

$$\deg_w(u_i) = \sum_{j=1}^{m} b_{ij}, \tag{9}$$

and for $v_j \in V$,

$$\deg_w(v_j) = \sum_{i=1}^{n} b_{ij}. \tag{10}$$

In vector form,

$$\mathbf{d}_{w,U} = B\mathbf{1}_m, \qquad \mathbf{d}_{w,V} = B^T\mathbf{1}_n. \tag{11}$$

Thus, the unweighted degree counts the number of counterparties, while the weighted degree captures the magnitude of relationships (e.g., loan exposures).

Degree centrality

Degree centrality normalizes degree by the maximum possible degree within the opposite mode. For $u_i \in U$,

$$C_D(u_i) = \frac{\deg(u_i)}{m}, \tag{12}$$

and for $v_j \in V$,

$$C_D(v_j) = \frac{\deg(v_j)}{n}. \tag{13}$$

Weighted degree centrality follows analogously by replacing $\deg(\cdot)$ with $\deg_w(\cdot)$ when required for weighted bipartite analyses.

Average degree centrality

$$\overline{C_D} = \frac{1}{n+m} \sum_{x \in U \cup V} C_D(x). \tag{14}$$

Eigenvector centrality in bipartite networks

Eigenvector centrality assigns a positive importance score to each node proportional to the importance of its neighbors. Let $\mathbf{x}$ denote the N-dimensional vector of centrality scores, partitioned conformably as

$$\mathbf{x} = \begin{bmatrix} \mathbf{x}_U \\ \mathbf{x}_V \end{bmatrix}, \qquad \mathbf{x}_U \in \mathbb{R}^n,\ \mathbf{x}_V \in \mathbb{R}^m.$$

The eigenvector centrality vector solves the eigenvalue equation

$$A\mathbf{x} = \lambda\mathbf{x}, \tag{15}$$

where $\lambda > 0$ is the largest eigenvalue of A (Perron–Frobenius eigenvalue).

Expanding the block matrix yields the coupled bipartite relations

$$B\mathbf{x}_V = \lambda\,\mathbf{x}_U, \qquad B^T\mathbf{x}_U = \lambda\,\mathbf{x}_V. \tag{16}$$

Thus, the centrality of a node in one mode is proportional to the sum of the centralities of adjacent nodes in the other mode. NetworkX normalizes eigenvector centrality such that

$$\sum_{x\in U\cup V} x_i^2 = 1, \tag{17}$$

ensuring uniqueness of the eigenvector up to sign.

Let $C_E(x)$ denote the eigenvector centrality of node x after normalization. Then

$$\mathbf{x} = \begin{bmatrix} C_E(u_1) & \cdots & C_E(u_n) & C_E(v_1) & \cdots & C_E(v_m) \end{bmatrix}^T.$$

Average eigenvector centrality

Analogous to degree centrality, the average eigenvector centrality across all nodes is

$$\overline{C_E} = \frac{1}{N}\sum_{x\in U\cup V} C_E(x). \tag{18}$$

Betweenness centrality in bipartite networks

Betweenness centrality measures the extent to which a node lies on shortest paths between other nodes. Let σ_{st} denote the number of shortest paths between nodes s and t, and let $\sigma_{st}(x)$ denote the number of those paths that pass through a node $x \in U \cup V$.

The betweenness centrality of a node x is:

$$C_B(x) = \sum_{\substack{s\neq x\neq t \\ s\neq t}} \frac{\sigma_{st}(x)}{\sigma_{st}}. \tag{19}$$

In bipartite networks, shortest paths are constrained to alternate between the two modes U and V, and $\sigma_{st} = 0$ yields a convention of zero contribution.

NetworkX normalizes bipartite betweenness centrality by the number of unordered node pairs (s,t) excluding x, where s,t are in the *same* bipartite set as x, since geodesic paths for centrality in bipartite graphs originate and terminate in the same mode.

The normalized bipartite betweenness centrality is

$$\tilde{C}_B(x) = \begin{cases} \dfrac{2\,C_B(x)}{(n-1)(n-2)}, & x \in U, \\[2ex] \dfrac{2\,C_B(x)}{(m-1)(m-2)}, & x \in V. \end{cases} \tag{20}$$

This rescaling ensures that

$$0 \leq \tilde{C}_B(x) \leq 1,$$

with equal treatment of the two modes.

Average betweenness centrality

Let $\tilde{C}_B(x)$ denote the normalized betweenness centrality of node x. The average betweenness centrality over all nodes in G is:

$$\overline{C_B} = \frac{1}{N} \sum_{x \in U \cup V} \tilde{C}_B(x). \tag{21}$$

Bipartite clustering coefficient

In bipartite networks, classical (one-mode) clustering based on triangles is structurally impossible because edges occur only across sets U and V. Therefore, clustering in two-mode networks is measured through the density of *4-cycles* (squares), which represent the smallest closed connectivity pattern in bipartite graphs (Latapy et al., 2008). Intuitively, a 4-cycle indicates that two nodes in one mode share at least two neighbors in the opposite mode, implying redundancy in connections and local cohesion.

The number of shared neighbors of two nodes in U is given by $(BB^T)_{ij}$. Thus, for $u_i \in U$:

$$C(u_i) = \frac{\sum_{\substack{j,k=1 \\ j \neq k}}^{n} (BB^T)_{jk}}{\sum_{\substack{j,k=1 \\ j \neq k}}^{n} \left[(BB^T)_{jj} - 1 + (BB^T)_{kk} - 1\right]}. \tag{22}$$

A symmetric form holds for $v_j \in V$ using $B^T B$. These expressions measure the fraction of observed squares among all possible squares in which the node could participate. If a node has fewer than two neighbors, its clustering coefficient is set to zero.

Assortativity in bipartite networks

Assortativity measures the tendency of nodes to connect to other nodes that are similar according to a given attribute. In bipartite networks, assortativity can be computed with respect to: (i) a categorical attribute (e.g., country), and (ii) a structural attribute (e.g., degree).

Let $G = (U, V, E)$ be a bipartite graph with $|U| = n$, $|V| = m$, and total nodes $N = n + m$. Let x and y be attributes associated to the endpoints of edges in G.

Attribute mixing matrix Define the mixing matrix $M = [m_{ab}]$ for attribute classes a and b as

$$m_{ab} = \frac{1}{|E|} \sum_{(u,v)\in E} \mathbf{1}(x(u) = a, x(v) = b), \tag{23}$$

where $\mathbf{1}(\cdot)$ is the indicator function. Let

$$e_{ab} = m_{ab}, \qquad a_a = \sum_b e_{ab}, \qquad b_b = \sum_a e_{ab}.$$

Assortativity coefficient (categorical) For categorical attributes, assortativity is defined as

$$r = \frac{\sum_a e_{aa} - \sum_a a_a b_a}{1 - \sum_a a_a b_a}. \tag{24}$$

This coefficient satisfies

$$-1 \le r \le 1,$$

where $r > 0$ indicates preferential connections between similar types, and $r < 0$ indicates disassortative mixing.

Degree assortativity in bipartite networks Degree assortativity measures whether nodes tend to connect to nodes of similar degree. Let $k_u = \deg(u)$ and $k_v = \deg(v)$ for $(u, v) \in E$. NetworkX uses Pearson correlation across edges:

$$r_{deg} = \frac{\sum_{(u,v)\in E} k_u k_v - \frac{1}{|E|}\left(\sum_{(u,v)\in E} k_u\right)\left(\sum_{(u,v)\in E} k_v\right)}{\sqrt{\left[\sum_{(u,v)\in E} k_u^2 - \frac{1}{|E|}\left(\sum_{(u,v)\in E} k_u\right)^2\right]\left[\sum_{(u,v)\in E} k_v^2 - \frac{1}{|E|}\left(\sum_{(u,v)\in E} k_v\right)^2\right]}}. \tag{25}$$

In bipartite networks, this coefficient reflects whether high-degree nodes in one mode tend to connect to high-degree nodes in the opposite mode.

Community detection: Louvain algorithm and modularity

Community detection seeks to identify groups of nodes that are more densely connected to each other than to the rest of the network. A common empirical approach is to project the bipartite graph onto one partition and then apply standard community detection algorithms such as Louvain.

The Louvain algorithm detects communities by maximizing modularity, a measure of the extent to which edges fall within communities more often than would be expected under a null model. It iterates over two phases: (i) local node movements that increase modularity, and (ii) aggregation of communities into super-nodes to form a reduced network. These steps repeat until modularity converges.

Modularity objective

For a weighted network with adjacency matrix $A = [A_{ij}]$, degrees $k_i = \sum_j A_{ij}$, and total edge weight

$$2M = \sum_{i,j} A_{ij},$$

modularity for a partition c_i of nodes into communities is

$$Q = \frac{1}{2M} \sum_{i,j} \left(A_{ij} - \frac{k_i k_j}{2M} \right) \mathbf{1}(c_i = c_j). \tag{26}$$

The Louvain method seeks

$$c^\star = \arg\max_c Q(c). \tag{27}$$

Annex 2.0.1 Local improvement step

For a given node i, consider moving i from its community C to a neighboring community C'. The change in modularity is computed as

$$\Delta Q = \left[\frac{\sum_{j \in C'} A_{ij}}{M} - \frac{k_i \cdot \sum_{j \in C'} k_j}{(2M)^2} \right] - \left[\frac{\sum_{j \in C} A_{ij}}{M} - \frac{k_i \cdot \sum_{j \in C} k_j}{(2M)^2} \right]. \tag{28}$$

Node i is moved into the community that yields the largest positive ΔQ. If no positive gain exists, it remains in its current community.

Annex 2.0.2 Aggregation phase

After no further local improvement is possible, each detected community is collapsed into a single super-node, producing a smaller weighted graph. The algorithm re-applies the same process to the aggregated network. This hierarchical aggregation continues until modularity reaches a stable maximum.

Annex 2.1 Minimum spanning tree (MST) in financial bipartite networks

A Minimum Spanning Tree (MST) is a reduced network representation that connects all nodes with the minimum total edge weight while eliminating cycles. In financial network analysis, MSTs are used to extract the core structure of relationships by preserving only the most essential connections. The MST is constructed on the undirected bank co-exposure projection.

Let the projected bank network be denoted by $G_B = (U, E_B)$, where U is the set of banks and E_B contains weighted edges representing similarity or co-exposure links.

Annex 2.1.1 General definition

Given a weighted graph $G = (V, E)$ with weight function $w : E \to \mathbb{R}_+$, the MST is the spanning tree T such that

$$T = \arg\min_{T \subseteq E} \sum_{(i,j) \in T} w(i, j), \tag{29}$$

subject to T connecting all nodes and containing no cycles. Classical algorithms such as Kruskal's or Prim's algorithm are used to compute the MST.

Annex 2.1.2 Edge weighting approaches

Three weighting schemes were applied to represent different bank similarity structures:

1. Unweighted MST Edges encode whether two banks share at least one borrower. Define

$$w_{ij}^{(U)} = \begin{cases} 1, & \text{if banks } i \text{ and } j \text{ share borrowers,} \\ \infty, & \text{otherwise.} \end{cases} \tag{30}$$

This produces an MST based solely on binary co-exposure links.

2. Loan-amount weighted MST Let W_{ij} denote total shared loan exposure between banks i and j. To transform similarity into a distance measure appropriate for MST construction,

$$w_{ij}^{(L)} = \frac{1}{W_{ij} + \epsilon}, \tag{31}$$

where ϵ is a small constant for numerical stability. Higher co-exposure implies shorter distance and thus a more likely MST edge.

3. Jaccard-based MST Let S_i and S_j be the sets of firms financed by banks i and j. The Jaccard similarity is

$$J_{ij} = \frac{|S_i \cap S_j|}{|S_i \cup S_j|}. \tag{32}$$

The corresponding distance measure is

$$w_{ij}^{(J)} = 1 - J_{ij}. \tag{33}$$

This emphasizes structural similarity in portfolio composition rather than exposure size.

Annex 2.2 Random network benchmarks

Two random benchmark networks were generated in order to serve as null models to compare observed patterns against networks that lack economic structure. Both random graphs are bipartite and use Poisson degree processes, but they differ in the constraints they preserve relative to the real network.

Annex 2.2.1 Random Poisson bipartite network: size-matched only

The first null model preserves only the number of banks and firms (n, m). Edges between banks and firms are formed independently with probability p, where p is chosen exogenously rather than calibrated to match the empirical number of edges. That is,

$$(u, v) \sim \text{Bernoulli}(p), \qquad u \in U,\, v \in V$$

with no constraint on the resulting total number of edges. This produces a bipartite Erdős–Rényi random graph.

Because each node has m (for banks) or n (for firms) possible neighbors, degrees follow a Poisson distribution in the limit:

$$\mathbb{P}(\deg(u) = k) \approx \frac{\lambda^k e^{-\lambda}}{k!}, \qquad \lambda = pm$$

for banks, and analogously for firms with $\lambda = pn$.

This network acts as a baseline capturing randomness in connections without reproducing the empirical degree structure.

Annex 2.2.2 Bipartite configuration model (degree-sequence preserving)

The second null model preserves not only the number of banks and firms but also the empirical degree sequence. Let $\{d_U\} = \{\deg(u) : u \in U\}$ and $\{d_V\} = \{\deg(v) : v \in V\}$ be the observed bank and firm degree sequences. The random network is constructed such that

$$\deg_{\text{random}}(u) = \deg_{\text{real}}(u), \qquad \deg_{\text{random}}(v) = \deg_{\text{real}}(v),$$

for all $u \in U$, $v \in V$. This is achieved via a bipartite configuration model, where stub pairs are matched between banks and firms, sometimes called a degree-preserving model. Formally, if B_{random} is the biadjacency matrix of the random network, then

$$\sum_{j=1}^{m} B_{\text{random},ij} = d_U(i), \qquad \sum_{i=1}^{n} B_{\text{random},ij} = d_V(j).$$

This preserves the heterogeneity of exposures (number of links each bank and firm has) but destroys higher-order structure such as clustering or core–periphery patterns.

The two random networks serve different benchmarking roles:

- **Size-only Poisson network:** tests whether observed structures arise purely from the bipartite size.
- **Degree-matched network:** tests whether observed patterns persist after controlling for the exact connectivity level of each bank and firm.

Comparing the empirical network to these null models allows isolating structural features driven by economic behavior (such as sectoral clustering, shared-lender communities, and concentration patterns) rather than random graph mechanics.

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For specific terminology please refer to the ESRB glossary (available in English only).

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