BANCA D'ITALIA
EUROSISTEMA

Questioni di Economia e Finanza

(Occasional Papers)

Interconnectedness in the Italian financial sector: a multilayer network analysis

by Valentina Michelangeli, Silvia Sacco, Valentino Bado, Valeria De Chiara, Ginette Eramo, Francesco Ficarola, Irene Mavilia, Claudia Miani, Ivan Quaglia, Giuseppe Reale, Francesco Sciarretta, Riccardo Scimone and Laura Sigalotti

July 2026

Number 1049

BANCA D'ITALIA
EUROSISTEMA

Questioni di Economia e Finanza

(Occasional Papers)

Interconnectedness in the Italian financial sector: a multilayer network analysis

by Valentina Michelangeli, Silvia Sacco, Valentino Bado, Valeria De Chiara, Ginette Eramo, Francesco Ficarola, Irene Mavilia, Claudia Miani, Ivan Quaglia, Giuseppe Reale, Francesco Sciarretta, Riccardo Scimone and Laura Sigalotti

Number 1049 – July 2026

The series Occasional Papers *presents studies and documents on issues pertaining to the institutional tasks of Banca d'Italia and the Eurosystem. The* Occasional Papers *appear alongside the* Working Papers *series which are specifically aimed at providing original contributions to economic research.*

The Occasional Papers *include studies conducted within Banca d'Italia, sometimes in cooperation with the Eurosystem or other institutions. The views expressed in the studies are those of the authors and do not involve the responsibility of the institutions to which they belong.*

The series is available online at www.bancaditalia.it .

ISSN 1972-6643 (online)

Designed by the Printing and Publishing Division of Banca d'Italia

INTERCONNECTEDNESS IN THE ITALIAN FINANCIAL SECTOR: A MULTILAYER NETWORK ANALYSIS

by Valentina Michelangeli*, Silvia Sacco*, Valentino Bado*, Valeria De Chiara*, Ginette Eramo*, Francesco Ficarola*, Irene Mavilia*, Claudia Miani*, Ivan Quaglia*, Giuseppe Reale*, Francesco Sciarretta*, Riccardo Scimone* and Laura Sigalotti*

Abstract

We analyse the structure and evolution of the Italian financial system over the period 2019–2025 using a multilayer network framework that captures interconnections across financial institutions and instruments. The network has a bank-centred core, with insurance companies acting as intermediate connectors and investment funds forming a broad periphery. Although the overall number of institutions remains broadly stable, sectoral dynamics diverge, as consolidations among banks and insurers are offset by the expansion of the investment fund sector. While individual layers have distinct topological characteristics, cross-sector linkages account for a growing share of total connections, underscoring their increasing role in shock transmission. Despite its sparse structure, the network exhibits small-world properties, implying a rapid contagion potential. Consolidation episodes are associated with temporary but meaningful structural shifts, while the network's overall architecture remains remarkably stable over time.

JEL Classification: G21, G22, G23, G18.

Keywords: banks, insurers, investment funds, interconnections, network analysis.

DOI: 10.32057/0.QEF.2026.1049

---

* Valentina Michelangeli (Banca d'Italia, ECS-STF), Silvia Sacco (Ivass-NPV), Valentino Bado (Banca d'Italia, ECS ARET GE), Valeria De Chiara (Banca d'Italia, ECS-STF), Ginette Eramo (Banca d'Italia, VIG-RAM), Francesco Ficarola (Ivass-NPV), Irene Mavilia (Banca d'Italia, ECS-STF), Claudia Miani (Banca d'Italia, VIG-RAM), Ivan Quaglia (Banca d'Italia, ECS-STF), Giuseppe Reale (Banca d'Italia, ECS-ARET TO), Francesco Sciarretta (Ivass-NPV), Riccardo Scimone (Banca d'Italia, VIG-SIF), Laura Sigalotti (Banca d'Italia, ARET AN).

1. Introduction[1]

Financial stability increasingly depends on the structure of interconnections among financial institutions. Connections between banks, insurance companies and investment funds—through credit exposures, securities holdings, and common portfolios—enable shocks to propagate beyond sectoral boundaries, amplifying systemic risk. Mapping and understanding these cross-sector linkages is therefore essential for assessing the resilience of the financial system.

Network analysis plays a pivotal role in characterizing, understanding, and modelling these complex systems of interconnections within the financial sector. The strength of network analysis lies in its flexibility and its ability to uncover hidden patterns of dependence, identify systemically important actors, evaluate structural vulnerabilities, and provide insights into collective dynamics—particularly in settings where the distress of one institution can trigger far-reaching consequences for the entire system. Many existing studies have however focused on the interbank market (e.g., (Boss, et al., 2004); (Soramäki, et al., 2007); (Iori, et al., 2008); (Mistrulli, 2011); (Bargigli, et al., 2015)), typically focusing on a single network layer—often the unsecured overnight market. While this approach has yielded important insights into contagion dynamics and systemic importance, it provides only a partial representation of the financial system. Such simplification has largely been driven by the limited availability of granular data on cross-sector exposures. Only a limited number of studies have attempted to move beyond this framework, either by considering multiple asset classes within the interbank market (Bargigli, et al., 2015) (Sam, et al., 2014), or by extending the analysis to different types of financial intermediaries while focusing on a single asset category (Billio, et al., 2012). However, as non-bank financial intermediaries (NBFIs), notably insurance companies and investment funds, have gained prominence, their role in the transmission of market shocks has become increasingly evident.

In such a context, the financial network cannot be accurately represented considering only one type of institution (i.e., banks). A comprehensive understanding of systemic risk requires accounting jointly for multiple categories of financial institutions and multiple types of financial relationships. For the Italian financial system, in particular, this calls for a framework that integrates banks, insurance companies and investment funds, as well as their diverse credit and asset-holding exposures: available data allow for a detailed and informative reconstruction of domestic interconnections and of the main channels which may propagate financial distress.

We make a novel contribution to the financial network literature by being the first to analyse the asset side of Italian financial institutions through a multilayer network framework, thereby uncovering previously unexplored interconnections and addressing three key research questions: (i) What are the most relevant features of the Italian financial network? (ii) How has the network evolved over time? and (iii) Which events have driven significant—albeit sometimes temporary—changes in the network's structure? This paper provides the first analysis on this type of network, since there are few direct precedents or benchmarks in the existing literature, which limits the scope for close comparisons but also highlights the novelty and exploratory nature of our contribution.

[1] We thank Alessio Anzuini, Giuseppa Bentivegna, Martina Bignami, Paolo Bisio, Marcello Bofondi, Emilia Bonaccorsi Di Patti, Francesco Cannata, Alessio de Vincenzo, Stefano Pasqualini, Anna Maria Rinaldi, Valerio Paolo Vacca for their useful comments.

We construct a new dataset that provides a comprehensive view of financial interconnections through both lending and securities holdings among financial institutions. The analysis draws on multiple supervisory and statistical data sources. Information on bank loans comes from AnaCredit, while data on securities holdings by banks and insurance companies are taken from supervisory reporting frameworks; for insurance companies, we exploit the detailed disclosures available under Solvency II. These sources allow us to map institution-level linkages, by matching issuers and holders of financial instruments.

We model the financial system as a multilayer network, composed of several interconnected layers, each capturing a distinct type of financial linkage. A first dimension captures the type of financial institution—banks, insurance companies, and investment funds—while a second dimension distinguishes among financial instruments, namely loans, equities, bonds, and fund shares. Combining these two dimensions yields twelve distinct layers, each corresponding to a specific institution–instrument pairing and thus representing a unique type of financial relationship. This representation allows us to analyse how risks propagate both within and across layers, providing a rich and realistic depiction of financial interdependence.

When aggregating all layers, the resulting multilayer network displays a highly interwoven structure. A bank-centred core emerges, surrounded by a more diffuse constellation of investment funds and an intermediate layer of insurance companies. Banks clearly dominate the overall network architecture, being larger hubs across layers. This reflects their central role in loan, bond, and equity markets and highlights their importance as potential vectors for shock propagation. Insurance companies, while less central in terms of connectivity, may nonetheless act as bridging institutions along specific transmission channels. Investment funds are instead widely connected but individually less influential, forming a broad periphery rather than a tightly knit core.

Turning to the evolution of network size, the total number of nodes, defined as the union of all institutions across sectors, remains broadly stable between 2019 and 2024. This apparent stability masks diverging sectoral dynamics, as the contraction in the number of banks and insurers (largely driven by consolidation activities) is offset by the expansion of the investment fund sector. While consolidation may reduce the number of potential contagion channels, it also increases the systemic importance of the remaining institutions, which become more central and more interconnected.

Connectivity patterns further highlight the importance of cross-sector linkages: the number of connections in the aggregated network is substantially larger than the sum of within-sector connections, indicating that the majority of links occur across sectors. By the end of the sample, approximately 70% of all interconnections are cross-sectoral, up from 58% in 2019, pointing to an increasing role of inter-sectoral channels in the propagation of financial shocks.

Standard network statistics, such as diameter, density and average path length describe a "small-world" financial network (Watts & Strogatz, 1998) (Newman, 2003), with the following characteristics: sparse (low density, around 0.2%)[2], segmented and selective (heterogeneous diameters across layers), overall, relatively compact (short average path lengths when the full system

---

[2] Density can range from 0% (no connections at all) to 100% (each node is connected to any other node); a low density indicates that most institutions lack direct connections to all other nodes.

is considered, around 2.8)[3]. The stability of these metrics across periods suggests that the topological structure of the financial system is persistent, with only incremental changes despite evolving exposures. Even though the network is sparse and scattered, institutions are not far apart in terms of network distance. This "small-world" property is particularly relevant for systemic risk, as it implies that distress can spread rapidly across the financial system, allowing even relatively small shocks to reach a large number of institutions within a short sequence of interactions.

Measures of node importance highlight a classic hub-and-spoke structure: most institutions exhibit low influence, but a small number of highly connected nodes exert disproportionate impact. The network is negatively assortative, meaning high-degree institutions tend to connect with low-degree ones—another characteristic feature of systems with central hubs.

Despite this overall stability, merger and acquisition (M&A) activity, particularly in early 2020, generated notable structural shifts. Consolidation episodes significantly altered the number of nodes, the distribution of edges and weighted exposures, and the concentration of connectivity. The share of edges that change between periods shows occasional spikes, revealing episodic portfolio reallocations or network restructuring. Weighted-network correlations remain high throughout the sample, consistent with strong persistence in the system's architecture, except for a pronounced temporary drop in 2020Q2 associated with M&A-driven reconfiguration.

Taken together, the multilayer analysis reveals complex interlinkages and vulnerabilities that are not visible from single-entity or single-sector perspectives. The growing web of connections between banks and non-bank financial intermediaries increases the scope for system-wide liquidity rebalancing and amplifies contagion risks. The high level of domestic exposures implies that shocks arising in one part of the financial system can propagate rapidly through mark-to-market losses, funding pressures, or counterparty failures. Mapping and monitoring these internal linkages are therefore prerequisites for assessing the resilience of the Italian financial system and for identifying the amplification channels that may become active under stress.

This paper is organized as follows. Section 2 reviews the related literature. Section 3 outlines the main episodes of consolidation among financial institutions. Section 4 describes the data. Section 5 introduces the network analysis framework and key metrics. Section 6 presents the Italian financial system as a multilayer network. Section 7 examines the evolution of the Italian financial network over time. Section 8 concludes.

2. Literature review

A financial system can be represented as a network in which financial institutions, including banks, insurance companies, investment funds, and other non-bank intermediaries, are represented as nodes, while their financial exposures to one another, such as lending relationships, derivative positions, securities holdings, or funding flows, form the connecting edges. Directionality and weights enrich

[3] (Milgram, 1967) was the first to popularize the idea that social networks are tightly interconnected, demonstrating how any two individuals can be linked through surprisingly short acquaintance chains. This led to the famous "six degrees of separation" concept, which is equivalent to the metric of shortest path length. Subsequently, (Watts & Strogatz, 1998) and (Newman, 2003) expanded on this research, showing that many real-world networks—such as neural networks, power grids, social networks and technological systems—exhibit these same small-world properties. The resulting average shortest path length of 2.8 is significantly lower than the social benchmark of 6, placing the Italian financial system among the aforementioned small-world networks.

this representation: a directed link may denote the flow of credit from one institution to another, whereas a weighted link reflects the magnitude or riskiness of the exposure. This framework allows systemic risk to be examined through the architecture of interlinkages. One common depiction is the core–periphery structure, where a small set of highly connected core institutions interact densely with one another, while peripheral institutions connect mainly to the core but not to each other. Another characterization relies on a bipartite configuration, in which nodes are partitioned into two distinct groups and links occur only across groups—never within them (see (Caccioli, et al., 2018) for a survey).

The structure of the network has important implications for how financial distress spreads. (Allen & Gale, 2000) highlights two central features, market completeness and connectivity, which shape the severity of contagion. In their framework, a fully connected system, where exposures are broadly shared, can absorb shocks more effectively, thereby limiting contagion. By contrast, when markets are only partially connected and exposures are unevenly distributed, localized weaknesses can cause shocks to propagate more intensely. This implies that the relationship between connectivity and stability is non-linear and context-dependent. (Elliott, et al., 2014) further refine this view by distinguishing integration from diversification. Diversification, which is the number of counterparties an institution interacts with, may either mitigate idiosyncratic risk or exacerbate systemic risk: while having more counterparties opens additional channels for shock transmission, it also reduces reliance on any single entity. Integration, that is the size and concentration of exposures, can lower the likelihood of a default in normal conditions by spreading risk, yet greater diversification can enhance stability in normal times by distributing risk more broadly, thereby lowering the probability of an initial failure.

An institution's specific location within the network is equally critical in shaping system fragility. Studies by (Mistrulli, 2011) and (Trapp & Wewel, 2013) demonstrate that the same shock can generate markedly different contagion patterns depending on which node is initially hit, underscoring that systemic risk depends not only on network density but also on the vulnerabilities of central actors. (Covi, et al., 2021) provide additional evidence that both the network structure and institution-specific characteristics jointly determine systemic fragility, with abrupt transitions occurring once certain thresholds are breached. These insights suggest that policy interventions should target both the robustness of vulnerable institutions and the broader configuration of the network to curtail potential losses.

Crucially, financial networks evolve over time, and contagion outcomes depend on the state of the system when a shock materializes. (Paltalidis, et al., 2015) shows that identical shocks can have very different effects depending on the prevailing network structure and macro-financial conditions. For instance, post-crisis increases in bank capitalization and stricter regulation have reduced the susceptibility of the banking sector to certain types of contagion.

When institutions are linked across multiple markets or exposure types, multiplex structures[4] can amplify contagion. In multilayer settings—spanning, for example, funding relations, derivatives

[4] A multiplex network is a type of complex network in which the same set of nodes is connected by multiple types of relationships or interactions, each represented as a separate layer or "dimension" of the network.

exposures, and securities positions—distress can propagate simultaneously through different channels, creating nonlinear reinforcement effects. Multiplex network models capture this multidimensional interdependence, revealing how risks can aggregate across overlapping layers. (Poledna, et al., 2015) (Bargigli, et al., 2015) show that these layers interact in ways that intensify systemic stress beyond what any single layer would imply.

We contribute to this literature by offering the first comprehensive characterization of the Italian financial network encompassing banks, insurance companies, and investment funds. Building granular bilateral exposures, we map the structure and evolution of the system over the period 2019–2025, documenting how patterns of interconnectedness, sectoral roles, and cross-market linkages have changed through time. To capture the distinct but overlapping channels through which contagion may propagate, we represent the system as a multiplex network, where each layer corresponds to a different combination of institution type and financial instrument. This multilayer perspective allows us to assess the relative importance of different sectors, identify systemically influential institutions, and analyse how interactions across layers shape the resilience or fragility of the financial system as a whole.

3. Consolidation dynamics in the Italian banking and insurance sectors

This section outlines the major consolidation events that have taken place in the Italian banking and insurance sectors from 2019 to 2025. We do not consider investment funds since these dynamics are not significant for funds.

Over the period 2019-25, the Italian banking system has undergone a substantial consolidation process, led by both large-scale mergers involving major banking groups and a series of medium-scale acquisitions. The following overview summarises the most significant transactions.

- *Intesa Sanpaolo: the integration of Banca IMI (2019–2020).* In December 2019, Intesa Sanpaolo (ISP) announced its plan to streamline its organisational and operational structure by fully integrating Banca IMI, the group's investment banking subsidiary. The merger by incorporation became effective on 26 February 2020, bringing all Banca IMI operations directly within ISP's Corporate & Investment Banking Division. In July 2020 Intesa Sanpaolo announced that the merger by incorporation of Banca IMI S.p.A. into the parent company Intesa Sanpaolo S.p.A. had been completed.
- *Intesa Sanpaolo: UBI Banca acquisition & incorporation (2020–2021).* On 17 February 2020, ISP launched a public exchange offer (OPS) for UBI Banca, aiming to consolidate a stronger national banking group. The offer successfully closed on 30 July 2020. UBI entered the Intesa Sanpaolo banking group on 5 August 2020, the settlement date of the OPS, with ISP acquiring more than 90% of UBI's share capital. To comply with antitrust requirements, ISP subsequently divested 587 branches to BPER Banca. The subsequent merger by incorporation was completed on 12 April 2021.
- *Crédit Agricole Italia — Credito Valtellinese (Creval) (2020–2021).* On 23 November 2020, Crédit Agricole Italia launched a tender offer for Credito Valtellinese (Creval), a bank with a strong franchise in Lombardy. The offer was successfully concluded in April 2021, allowing Crédit Agricole to exceed 90% ownership and bring Creval officially into its banking group the same month. The merger by incorporation was completed on 24 November 2021, resulting in the full absorption of Creval's approximately 350 branches.

- *BPER Banca — Banca Carige (2022–2023).* After years of supervisory intervention and restructuring, Banca Carige entered a decisive consolidation phase in 2022. On 3 June 2022, BPER Banca acquired 79.4% of Carige's share capital from the Interbank Deposit Protection Fund (FITD), bringing the bank into the BPER group immediately. The merger by incorporation, finalised on 27 November 2023, completed the operational and legal integration of Carige into BPER.

In the analysed period, the Italian insurance market also experienced a pronounced phase of structural consolidation driven by four interacting forces: (i) domestic horizontal integration among leading entities, (ii) targeted acquisitions of Italian portfolios and insurers by large foreign groups, (iii) a strategic re-configuration of bancassurance relationships (including internalisations), and (iv) active supervisory gatekeeping by IVASS to preserve policyholder protection and market stability. The following overview summarises the most significant events.

- *Progressive integration of Cattolica into Assicurazioni Generali (2020–2022)*. This operation strengthened Generali's retail footprint and distribution control and was completed through a staged acquisition process culminating in Cattolica's delisting in 2022.
- *Foreign entities reallocated capacity into Italy through bolt-on acquisitions of P&C targets.* Notably, Allianz acquired Aviva Italia (2021) and TUA Assicurazioni (2024), which re-shaped the competitive structure of the non-life market and transferred agency networks across groups.
- *Banco BPM Vita completed a strategic internalisation of its life bancassurance business by acquiring Vera Vita and Vera Financial from Generali in December 2023*, while concurrently entering a long-term non-life/protection partnership with Crédit Agricole Assurances, which acquired a 65% stake in Banco BPM Assicurazioni, Vera Assicurazioni and Vera Protezione — reorganising the bank's insurance footprint across life and non-life segments and affecting the distribution and ownership structure of bancassurance in Italy.
- *Internal consolidation within the Unipol Group (2024–2025).* The merger of UnipolSai into Unipol Group, completed between late 2024 and early 2025, resulted in the unified entity "Unipol Assicurazioni". This reorganisation — essentially a corporate simplification aimed at streamlining governance, distribution and capital management — reinforced Unipol's position among the principal domestic players and contributed to the broader reduction in the number of standalone corporate entities operating in the Italian market.
- *Creation of a dedicated vehicle (Cronos Vita) to receive Eurovita's life portfolio (2023-2025).* This arrangement reflects both private restructuring choices and supervisory oversight to secure continuity of coverage for policyholders and financial stability. The resolution process ultimately resulted in the allocation of Eurovita's former life insurance portfolio among the five largest life insurers operating in Italy, leading to an increase in market concentration in the life segment.
- *Shift in bancassurance governance models — UniCredit (2025).* UniCredit's internalisation of its life bancassurance activities in mid-2025 marks a paradigmatic shift from parity joint ventures toward direct ownership and vertical integration of distribution and product governance.

Collectively, these transactions compressed the number of standalone Italian banks and insurers, concentrated distributional control among fewer economic groups, and altered the transmission channels through which shocks to banks, insurers and distribution networks may propagate —

implications that are material for applied econometric analyses of concentration, market power, and systemic risk across 2019–2025.

4. Data description

Our dataset covers three main categories of financial institutions: banks, insurance companies and investment funds. Our analysis focuses on the asset side of balance sheets —specifically banks' financial loans and financial securities towards domestic banks, insurers and investment funds— and relies on individual data. Exposures from derivatives and structured notes are excluded by our analysis.

4.1. Banking sector

We construct bilateral links between individual domestic banks and their domestic financial counterparties, such as other banks, insurance companies and investment funds. For each bank, we identify its exposures through loans and security holdings, mapping the corresponding borrowers or issuing institutions. The dataset thus provides counterparty-level information on financial loans, financial securities, and shareholdings (e.g., from investment funds), as well as other financial equity[5] positions held by banks.

More specifically, we used AnaCredit[6] to construct banks' loan exposures to the aforementioned individual financial institutions. Credit exposures include term loans, revolving credit, drawn credit lines, reverse repo, and other short-term deposits.

Individual supervisory data were employed to map securities issued by domestic financial institutions and held in banks' portfolios. These data include ISIN codes, allowing us to identify the main characteristics of the issuers; accounting portfolios—namely *Hold to Collect*, *Hold to Collect and Sell*, and *Held for Trading*— are mapped as well, which is crucial for quantifying potential losses under market shocks. We identified three main categories, characterized by different levels of risk: equities, bonds, and fund shares.

Several identifiers—such as fiscal codes, LEIs, and RIAD codes—enable us to merge information from additional sources, including supervisory registers, thereby offering a more accurate picture of the underlying risks faced by each bank.[7]

The dataset focuses on the asset side of banks' balance sheets and does not include bank liabilities.

4.2. Insurance sector

We exploit highly granular supervisory data collected under the Solvency II framework to analyse the network of domestic financial exposures among Italian insurance entities. The use of harmonized Solvency II reporting templates ensures consistency and comparability across insurers, facilitating the integration of insurance data into the broader system-wide framework. The dataset consists of a

---

[5] "Other equity" refers to ownership claims not represented by listed shares or investment fund shares, such as unlisted shares or participating interests.

[6] https://www.ecb.europa.eu/stats/ecb_statistics/anacredit/html/index.en.html. Bank borrowers with a total loan amount below 25,000 euros are not included in AnaCredit. Banks granting loans, for a total amount below 2% of the Italian system, are excluded (bancaditalia.it/statistiche/raccolta-dati/segnalazioni/rilevazione-dati-granulari/disposizioni-normative-nazionali/Circolare-297-Rilevazione-dati-granulari-sul-credito-3-aggiornamento.pdf). Among the loans available in AnaCredit, only those recognized on the balance sheet are currently considered.

[7] For instance, to identify intragroup transactions.

panel of individually supervised insurance companies and captures links between insurers and their domestic financial counterparties exclusively through security holdings. These exposures are drawn from market-value information reported in the Solvency II asset-by-asset template, where each instrument is observed at the security level, mapped via ISIN codes, and classified into three main asset classes: bonds, equities, and fund shares. This granular structure allows us to reconstruct insurer-level portfolios on a security-by-security basis and to trace their market-value exposures to governments, other insurers, banks, investment funds, and non-financial corporations, enabling a high-resolution reconstruction of the insurance network and the analysis of contagion and market shocks transmission across the financial system.

Importantly, the analysis captures interconnectedness only through the asset side of insurers' balance sheets. The liability side—dominated by insurance policies, which may themselves create additional channels of interdependence (e.g., credit, cyber, or catastrophe coverages transfer the risk to insurers from banks, other financial and non-financial entities)—cannot be reconstructed at a comparable level of granularity and is therefore excluded.

4.3. Investment fund sector

We map the financial securities of open-ended investment funds towards domestic banks, insurers and other funds.

Individual supervisory reports provide highly granular data on funds' assets, comparable with the quality of banks securities holdings. We consider holdings, on an ISIN-by-ISIN basis, in the portfolio of all Italian UCITS and non-UCITS open-ended investment funds. Funds are mapped relying on their national identifier and the ISIN(s) code(s) of their shares, which are used jointly to map interconnections while minimizing errors; funds' LEI codes, which are not legally required for every Italian investment fund, are tracked but not actually used in the present analysis.

The choice of reducing the scope of open-ended funds to Italian entities, while providing maximum homogeneity and quality of data, limits the coverage of our analysis excluding, for example, non-Italian EU funds which are distributed in Italy. As regards Italian closed-ended funds, we do not map their assets in our analysis, which focuses on those connections that might be contagion channels to the end of financial stability; they are however included in the network as "passive nodes", when their shares are held by banks, insurers or open-ended funds.

5. Key metrics of network analysis

In this section we present the main network metrics that are used to analyse the network (or graph) of the interconnections among domestic banks, insurance companies and investment funds. Indeed, these metrics can provide the foundation for interpreting the system's resilience, simulating stress scenarios, and guiding macroprudential policy. In other words, quantifying the network means moving from a qualitative map to a set of indicators that explain how vulnerable the system is and through which channels shocks can propagate.

Definition. A graph is defined as an object $G = (V, E)$, where $V = \{1, \dots, n\}$ is the finite set of nodes, while $E \subseteq V \times V$ is the finite set of edges linking nodes. The canonical form of a network is the *undirected graph*, in which two nodes are either connected or they are not. However, a directed version of the graph also exists, usually called *digraph* (i.e., directed graph). A digraph differs from an undirected graph for the presence of the *directionality* of its edges. In other terms, there are networks, including our Italian financial network, in which one node may be connected to a second without the second being connected to the first.

In our network nodes represent financial institutions, while edges (or links) are the connections among them. Specifically, nodes are categorised into banks, insurers and funds, while edges include loans, equities, bonds and fund shares.

Basic concepts of networks. Networks are usually evaluated and categorized on the basis of some properties. The topological and metric properties of our Italian financial system are evaluated for the period 2019–2025 by comparing the properties of the individual layers in isolation with those of the total network. Indeed, since each layer forms its own sub-network, the related metrics for a given layer are computed using that layer as the reference network. Here we introduce some preliminary concepts and properties of networks.

Size of the network and cardinality of the edge set. The cardinality of the node set, namely $|V|$, denotes the size of the network, while the cardinality of the edge set, i.e. $|E|$, strictly depends on the number of nodes and the density of the network. The maximum number of edges in a digraph is $|E| = n(n-1)$, where $n = |V|$ is the total number of nodes.

Weight. The weight of an edge $w(e)$ denotes the intensity (or, in our case, the exposure of the investment) of the relationship between the two nodes i and j in the edge e. A graph is a *weighted graph* if a weight is assigned to each of its edges (Joshi, 1989).

Neighbourhood. Another fundamental concept of networks is the neighbourhood. The neighbourhood of a node i is the set of vertices that i is linked to. In the case of digraph, we must separate the concept of neighborhood in two sub-sets: *successors* as $S(i) = \{j: e_{i,j} = 1\}$ and *predecessors* as $P(i) = \{j: e_{j,i} = 1\}$.

Degree. The degree of a node i is the number of its incident edges. In the case of a digraph, the degree of a node i is the sum of *in-degree*, defined as $d^{-}(i) = |P(i)|$, and *out-degree*, namely $d^{+}(i) = |S(i)|$.

Weighted degree. The weighted degree is defined similarly to the degree, with the only difference that the weighted version also considers the weight of incident edges. More formally, let W is the $n \times n$ weighted adjacency matrix[8] of digraph G having a weight $w_{i,j}$ on each edge (i,j). Thus, the weighted degree of a node i is defined as the sum of the *weighted in-degree* and the *weighted out-degree*:

$$wd(i) = \sum_{j \in S(i)} w_{i,j} + \sum_{j \in P(i)} w_{j,i}$$

Topological network metrics. In mathematics and computer science, graph theory is a research area studying properties of graphs. We have seen that networks can be visualised and analysed using some basic concepts and measures. In addition, we introduce some topological metrics, describing the main

[8] A weighted adjacency matrix for a weighted graph $G = (V, E)$ is a square matrix $A \in \mathbb{R}^{|V| \times |V|}$ defined as: $A_{ij} = \begin{cases} w(i,j), & if\ (i,j) \in E \\ 0, & otherwise \end{cases}$, where $w(i,j)$ is the weight of the edge between nodes i and j.

structural properties of the graph (Diestel, 2000) (Jackson, 2010), which will be investigated on our network.

Average (weighted) degree. In addition to analyse the single node degrees, it is also useful to examine the average degree of the graph to better understand what kind of structure shapes the network. Thus, the number:

$$d(G) = \frac{1}{|V|}\sum_{i \in V} d(i)$$

denotes the average degree of G. Similarly, its weighted version:

$$wd(G) = \frac{1}{|V|}\sum_{i \in V} wd(i)$$

denotes the average weighted degree of G.

Walks, paths and diameter. A walk in a graph between two nodes i and j is a finite sequence of edges $(i_1, i_2), (i_2, i_3), \dots, (i_{K-1}, i_K)$ such that $(i_k, i_{k+1}) \in E$ for each $k \in \{1, \dots, K-1\}$, with $i_1 = i$ and $i_K = j$. Similarly, the path is defined as the walk, but with the additional constraint that each node in the sequence $i_1, \dots i_K$ must be distinct. The shortest path between nodes i and j is called geodesic, while the longest one is called *diameter*. In other terms, the diameter is the longest shortest path between any two nodes in the network and it measures the maximum number of steps required for information, shocks, or exposures to travel across the network's most distant connected nodes. Then, the *average shortest path* length of a graph is computed as the average of all geodesics. It measures how many steps, on average, it takes to move from one institution to another in the network.

Density. Another key metric giving an idea on the structure of the graph is density, which is the ratio of actual connections to all possible links in a network. It measures how densely connected the network is. More formally, it is defined as

$$\lambda(G) = \frac{|E|}{n(n-1)}$$

Modularity and communities' detection. The main difference between a completely random network and a real-world network is that the latter often exhibits interesting properties regarding its corresponding structure. One of these features is the community structure, namely the division of nodes into groups within which the network connections are dense, but between which they are sparser. This property is better known as modularity (Newman, 2006) since its name derives from the measurement of the division of the network into "modules" (or communities). Among the most widely used algorithms is the Louvain method (Blondel, et al., 2008) (Dugué & Perez, 2015), which optimizes the modularity function in a hierarchical, greedy manner. The algorithm proceeds iteratively in two phases: (i) local optimization, where each node is initially assigned to its own community. Nodes are then moved to neighbouring communities if such a move increases modularity; (ii) aggregation, where communities identified in the first phase are collapsed into super-nodes, and the process is repeated until no further modularity gain is possible. The modularity function Q to be maximized is defined as:

$$Q = \frac{1}{2w}\sum_{i,j}\left[w_{ij} - \frac{wd(i)wd(j)}{2w}\right]\delta(c_i, c_j)$$

where:

- $w = \frac{1}{2}\sum_{i,j} w_{ij}$ is the total weight of all edges in the network,
- w_{ij} is the weight of edge between nodes i and j,
- $wd(i)$ is the weighted degree of node i
- c_i is the community assignment of node i,
- $\delta(c_i, c_j)$ is 1 if nodes i and j belong to the same community, and 0 otherwise.

Centrality. One of the most important indicators in graph theory is centrality, which is a measure able to identify the most influent nodes within a network. The *degree centrality* is the historically first and conceptually simplest index belonging to the centrality class. It indicates how well a node i is connected and it is defined as:

$$C_d(i) = \frac{d(i)}{n-1}$$

Of course, the degree centrality misses a lot of other aspects of a network. For instance, it does not measure how well-located a node is in a network. In other words, a node with a high degree centrality could be located at the border of a graph and linked to a certain number of nodes already well-linked to other nodes, and thus having low relevance in terms of structure and impact, while another node with low degree centrality could be located in the middle of the network linking two subgraphs (bridge), and so being more important for the connectivity of the whole graph.

PageRank. A more effective measure of centrality[9] is PageRank (Page, et al., 1999). The basic metaphor behind PageRank considers a random surfer that starts from a randomly chosen node. At every node it visits, the random surfer either gets bored and quits navigation with a fixed probability, or it selects one of its outgoing neighbours uniformly at random. If the node has no outgoing links (i.e., a *sink*), the surfer jumps to a node selected uniformly at random in the network. So, the rank of a node, according to the PageRank algorithm, is the probability that a random surfer stops at that node. In other terms, PageRank quantifies how "influential" a financial institution is, based on its connections to other institutions. A higher PageRank indicates that an institution is not only highly connected but also connected to other influential entities, which can reflect its systemic importance or potential impact on network stability. While average PageRank captures the "typical" influence in

[9] Among all the most refined centrality measures, we selected the PageRank, because: *(i)* Betweenness centrality basically captures the role of nodes as bridges by measuring how often they lie on shortest paths between other nodes, so making it particularly suitable for identifying intermediary nodes in undirected networks. *(ii)* Closeness centrality is also based on shortest paths and reflects how close a node is to all others, but it is highly sensitive to network disconnections, directionality and the interpretation of edge weights. *(iii)* Eigenvector centrality assigns importance recursively based on the importance of neighbours, but it performs poorly in directed and sparse networks, especially in the presence of dangling nodes. Therefore, PageRank ex-tends this idea by modelling authority through random walks, providing a more robust and well-defined measure for directed networks and capturing systemic influence in a dynamic and recursive manner.

the layer, maximum PageRank identifies the most central nodes, highlighting potential hubs or systemically important institutions.

Assortativity. It is a measure of the tendency of nodes in a network to connect to other nodes that are similar with respect to some attributes (e.g., node degree). So, if nodes tend to connect to others that resemble them (e.g., similar degree), the network is assortative (e.g., collaboration networks). Vice versa, if nodes systematically connect to others that are different, the network is disassortative (e.g., financial networks). Specifically, a positive assortativity value indicates that nodes with many connections tend to link with other highly connected nodes, or nodes with few connections tend to link with other low-degree nodes, so producing a more clustered or peer-to-peer structure. A negative value indicates that highly connected nodes tend to connect with sparsely connected nodes, generating a hub-and-spoke or hierarchical structure, which is typical in financial networks.[10] A value close to zero suggests the absence of any systematic tendency, with connections formed independently of node degree.

Fraction of changing edges. This metrics (Ficarola, 2015) helps to better understand what kind of dynamic a network has over time since it gives quick insights on connections change. It is defined as:

$$\psi\big(E(t+1), E(t)\big) = \frac{|E(t+1) - E(t)| + |E(t) - E(t+1)|}{|E(t+1) \cup E(t)|}$$

where $E(t)$ is the edge set at time *t*. A value close to 1 suggests a fast-evolving network, in which topology exhibits little short-term correlation, while a value close to 0 indicates a high structure stability over time.

Pearson and Spearman correlations. The Pearson's correlation coefficient is defined as the covariance of the two variables X and Y divided by the product of their standard deviations:

$$\rho_P(\mathrm{X}, \mathrm{Y}) = \frac{cov(X, Y)}{\sigma(X)\, \sigma(Y)}$$

This ratio can range between -1 and $+1$. Values near to such borders indicate that the two variables are strongly correlated, negatively or positively. On the contrary, values near to 0 suggest that X and Y are not correlated. Therefore, the Pearson correlation measures how well two variables move together along a straight line: *(i)* if one increases and the other tends to increase proportionally, Pearson is high and positive; *(ii)* if one increases while the other decreases proportionally, Pearson is high and negative. It thus captures linear relationships being sensitive to outliers.

The Spearman's rank correlation is a nonparametric measure of the monotonicity of the relationship between two variables. Unlike the Pearson's correlation, the Spearman's rank correlation does not assume that both variables are normally distributed. Thus, the raw variables X and Y, containing n

[10] A hub-and-spoke structure describes a network in which a small number of highly connected nodes—the hubs—serve as central intermediaries linking to many other nodes, the spokes, which have few connections among themselves. In this configuration, most interactions flow through the hubs rather than occurring directly between peripheral nodes. As a result, the network becomes strongly hierarchical: hubs occupy a central, system-critical position, while the spokes depend on them for access to the rest of the network. This structure is common in financial systems, where large banks often act as hubs that provide services or funding to many smaller institutions.

values, are first converted to rank variables x and y (Jerome L Myers, Arnold Well, and Robert Frederick, 2010).

$$\rho_S(x,y) = 1 - \frac{6\sum_{i=1}^{n}(x_i - y_i)^2}{n(n^2-1)}$$

Similarly to Pearson, the Spearman's rank correlation coefficient varies between -1 and $+1$ with 0 implying no correlation. Therefore, the Spearman correlation measures how well the relationship between two variables can be described by a consistent ordering, not by a straight line. If higher values of one variable always correspond to higher values of the other (even in a curved pattern), Spearman will be high.

Recurrence Plot. The Recurrence Plot (RP) is an advanced technique of nonlinear data analysis able to visualize a corresponding square matrix in which each element coincides with the time at which a state of a dynamical system recurs. In other words, a RP shows all the times T at which a phase space trajectory visits roughly the same area in the phase space up to a threshold ε.

Thus, a recurrence $r_{i,j}$ can be defined by the following binary function:

$$r_{i,j} = \begin{cases} 1, if\ \|x(i) - x(j)\| \le \varepsilon \\ 0, otherwise \end{cases}$$

where $r_{i,j}$ is the element of the full matrix $\boldsymbol{R}$ comparing the two states at time i and j.

We apply the RP on rank vectors x and y relating only to the nodes set $V_{xy} = V_x \cap V_y$ which is the result of the *intersection* of the two nodes sets V_x and V_y. However, since rank vectors are n-dimensional trajectories, then a simple subtraction between them is not feasible. Using the Spearman's rank correlation coefficient, a more suitable measure of distance is proposed by (Van Dongen & Enright, 2012):

$$d(x,y) = \sqrt{\left(1 - \rho_S^2(x,y)\right)}$$

Then, after empirical measures and tests, we set ε as the 30° percentile of the upper triangle of the distance matrix. To visually analyse $\boldsymbol{R}$, a RP is built by putting a black square at all those coordinates (i,j) for which $r_{i,j} = 1$.

6. The Italian financial system as a multilayer structure

We analyse the architecture of the Italian financial network by decomposing it into several layers, so that we obtain a so-called *multilayer network*. A multilayer network can incorporate different "aspects" that help distinguish among types of exposures (Aldasoro & Alves, 2018). In our setting, one aspect reflects the type of financial institution (banks, insurers and funds), while another reflects the type of financial instrument (loans, equities, bonds and fund shares). By taking the intersection of these two aspects, we obtain twelve peculiar layers, each representing a distinct type of financial relationship. The twelve layers are reported below:

1) *Bloans*: only loans held by banks,
2) *Bequities*: only equities held by banks,
3) *Bbonds*: only bonds held by banks,
4) *Bfund_shares*: only share of funds held by banks,

5) *Iloans*: only loans held by insurers,
6) *Iequities*: only equities held by insurers,
7) *Ibonds*: only bonds held by insurers,
8) *Ifund_shares*: only share of funds held by insurers,
9) *Floans*: only loans held by funds,
10) *Fequities*: only equities held by funds,
11) *Fbonds*: only bonds held by funds,
12) *Ffund_shares*: only share of funds held by investment funds.

As a further clarification, within each layer we include institutions that hold a given financial instrument[11], even if the issuer belongs to a different sector. For example, the *Bfund_shares* layer includes banks that invest in fund shares, although these instruments are typically issued by investment funds rather than by banks. Similarly, the *Iloans* layer includes insurers that hold loans, even though loans are usually originated by banks, not insurers.

In addition to these individual layers, we build, for each investment instrument type and for each financial institution type, the total networks, which are given by the union of all the corresponding layers.

Table 1 reports the total exposures by layer. Panel (a) shows the size, in terms of exposures, of each layer in the Italian financial network; Panel (b) restricts exposures to within-sector links, removing all cross-sector connections.

Panel (a) shows that the financial network is a small but structured subset of the broader Italian economy and it highlights several clear patterns. Within it, the main exposures are bank loans and bank bonds, alongside insurers' growing holdings of fund shares. Outstanding amounts evolve heterogeneously across layers. Bank loans are still the largest asset class but have declined steadily since 2022, likely due to mergers or incorporations, deleveraging, weaker credit demand and portfolio shifts toward securities amid changing monetary and financial conditions. For insurers, equity holdings have risen gradually, while bond positions remain fairly stable. Their fund shares holdings, however, have surged since 2023–2024, signalling continued diversification toward fund-based products. For investment funds, equity, bond, and fund share positions are broadly stable, indicating limited shifts in intra-financial exposures.

Comparing Panels (a) and (b) clarifies the role of within- versus cross-sector interactions. Positive exposures in Panel (a) that drop to zero in Panel (b) reflect purely cross-sector links, while Panel (b) shows within-sector exposures. Banks exhibit extensive interbank lending and maintain substantial bond and equity positions in other banks, reflecting a high degree of interconnectedness within the banking sector. By contrast, insurers and investment funds display much smaller within-sector exposures overall. Exceptions include insurers' holdings of equities issued by other insurers and investment funds' holdings of shares issued by other funds, both of which remain sizeable and indicate meaningful intra-sector linkages.

[11] We consider only direct exposures in the analysis, no look-through has been applied due to the lack of data.

Table 1. Exposures in the Italian financial network (billions of euros)[12]

Layers	2019	2020	2021	2022	2023	2024	2025*
	a) Domestic financial network						
Banks - Loans	325	245	259	265	229	207	210
Banks - Equities	32	33	33	31	31	37	43
Banks - Bonds	58	45	46	41	44	44	46
Banks - Fund shares	6	8	9	9	12	14	14
Insurers - Equities	28	28	33	32	32	37	35
Insurers - Bonds	14	14	12	9	9	11	12
Insurers - Fund shares	27	31	36	38	40	68	63
Funds - Equities	3	2	3	2	2	3	4
Funds - Bonds	9	9	9	8	10	12	13
Funds - Fund shares	10	10	11	9	9	8	9
Coverage (% of total assets of the system)	12.4%	9.8%	9.9%	10.5%	9.9%	10.3%	10.3%
	b) Within sector						
Banks - Loans	312	230	241	238	212	188	190
Banks - Equities	18	21	18	16	15	18	19
Banks - Bonds	58	44	45	41	44	43	45
Banks - Fund shares	0	0	0	0	0	0	0
Insurers - Equities	25	26	29	29	28	30	26
Insurers - Bonds	2	2	2	2	1	1	2
Insurers - Fund shares	0	0	0	0	0	0	0
Funds - Equities	0	0	0	0	0	0	0
Funds - Bonds	0	0	0	0	0	0	0
Funds - Fund shares	10	10	11	9	9	8	9
Coverage (% of total assets of the system)	10.3%	7.7%	7.6%	7.9%	7.3%	6.7%	6.7%

(*) For the year 2025 we consider Q2, which is the last quarter available.

Figure 1 illustrates the structure of our multilayer Italian financial network in 2025, decomposed by both instrument type (rows) and institutional sector (columns). Each panel represents a distinct sub-network revealing how different sectors and financial instruments contribute to the overall topology of the financial system. The *size of a node* represents its related degree, while the *thickness of an edge* indicates its corresponding weight.

For each layer, nodes can be connected or isolated. This means that if a panel shows only nodes with no linking edges, there are financial institutions holding that specific instrument, but their counterparties belong to a different sector. This occurs, for example, in the *Floans* and *Iloans* layers, where nodes appear without any connections. In these cases, funds and insurers are the loan holders, whereas the lender does not belong to either sector; rather, it is a bank.

Across all instrument-type layers, except fund shares, banks (in green colour) are pretty interconnected, with several large nodes acting as hubs (Figure 1, Column *Banks*). In the *Bfund_shares* layer, banks do not exhibit any within-sector links (only isolated nodes). However, they

[12] Total assets of the system are computed as the sum of the assets of banks, insurance companies and investment funds.

are connected to other financial institutions, as shown by the links between banks and investment funds in the *Fund shares–Total* layer.

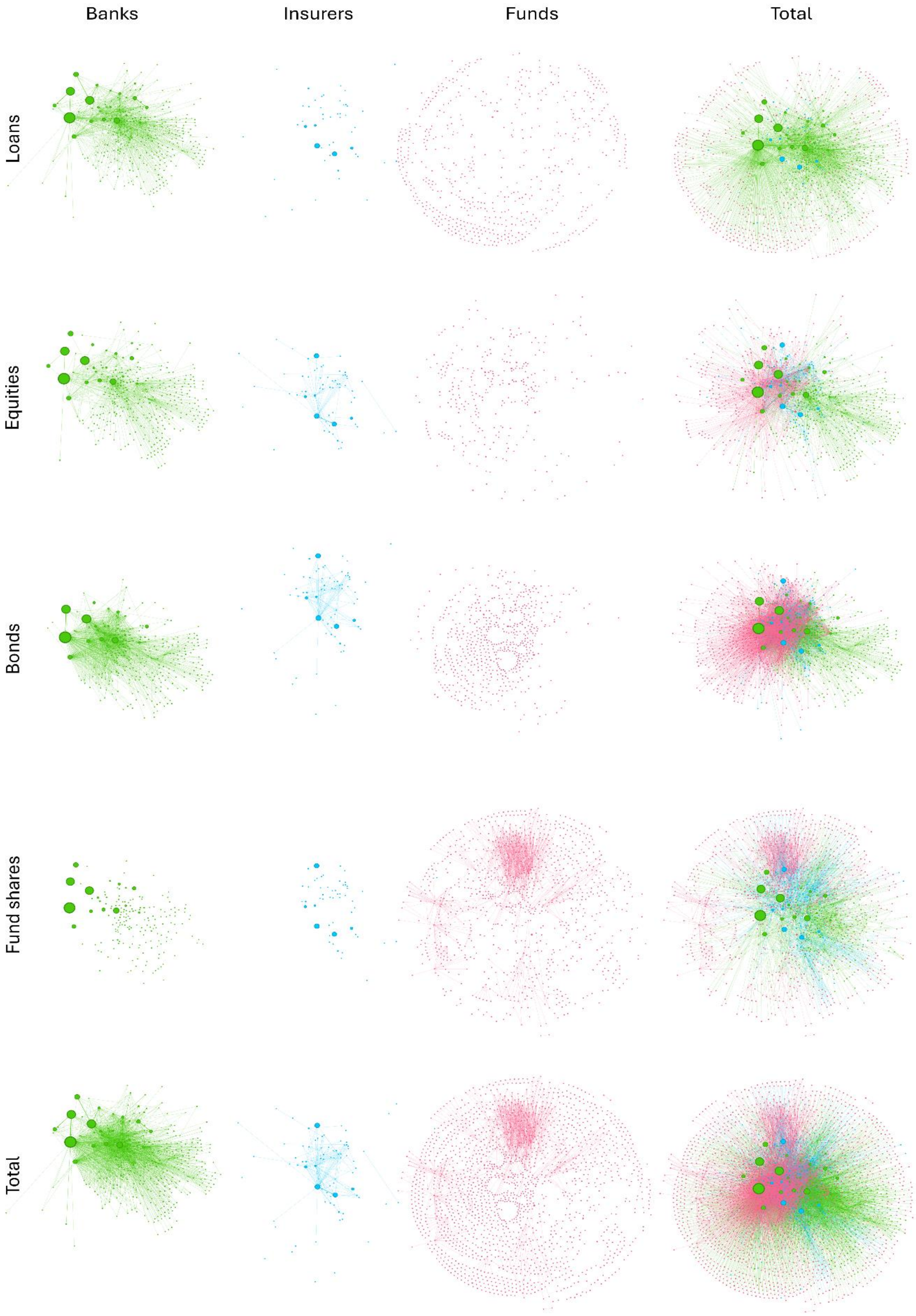
Insurers (in blue colour) form much sparser, moderately interconnected sub-networks (Figure 1, Column *Insurers*). The interconnections with other insurers appear substantial in the *Iequities* and *Ibonds* layers, while they are basically absent in the *Iloans* and *Ifund_shares* layers. As for the banks, we can identify a few nodes acting as hubs.

Investment funds (in pink colour) display a radically different topology (Figure 1, Column *Funds*). Their networks are extremely large but peripheral, characterised by numerous small nodes and minimal clustering. This indicates a highly fragmented structure. Interconnections among funds are substantial within the *Ffund_shares* layer, whereas they are largely absent in the *Floans*, *Fequities*, and *Fbonds* layers. The nodes in these latter three layers indicate that some funds maintain links with other financial institutions through specific instruments. Among them, the *Fbonds* layer is the most populated, suggesting that interactions involving this instrument are more prevalent than those related to loans or equities.

Figure 1, Column *Total* combines all layers, producing rich, interwoven networks where the bank-centric core is surrounded by the diffuse constellation of funds and the intermediate layer of insurers. Across all layers, banks clearly dominate the network architecture, as shown by the larger hubs. This reflects banks' central role, in particular in the loan market, and highlights their importance as potential vectors for shock propagation. With respect to insurers, while they are not major generators of systemic connectivity, they may still act as important bridge institutions for specific channels. Funds are widely exposed but individually less influential, forming a broad periphery rather than a core.

Overall, the figure highlights how different financial instruments contribute to the shape of the system. Equity and bond networks show more pronounced hub structures, while fund shares exposures are dominated by funds' wide but shallow connections. The multilayer perspective is crucial: no single layer captures the full complexity of exposures but taken together they reveal a tightly interconnected system in which banks form the backbone, insurers connect selective clusters, and funds contribute to the breadth and dispersion.

Figure 1: The 2025 Italian financial system depicted as a multilayer network



Note: the illustrated layers are the following: 1° column: *Bloans, Bequities, Bbonds, Bfund_shares*, Ball; 2° column: *Iloans, Iequities, Ibonds, Ifund_shares, Iall*; 3° column: *Floans, Fequities, Fbonds, Ffund_shares, Fall*; the complete system is reported in the corner on the bottom-right, that is the union of the three networks in the same row, or the union of the four networks in the same column.

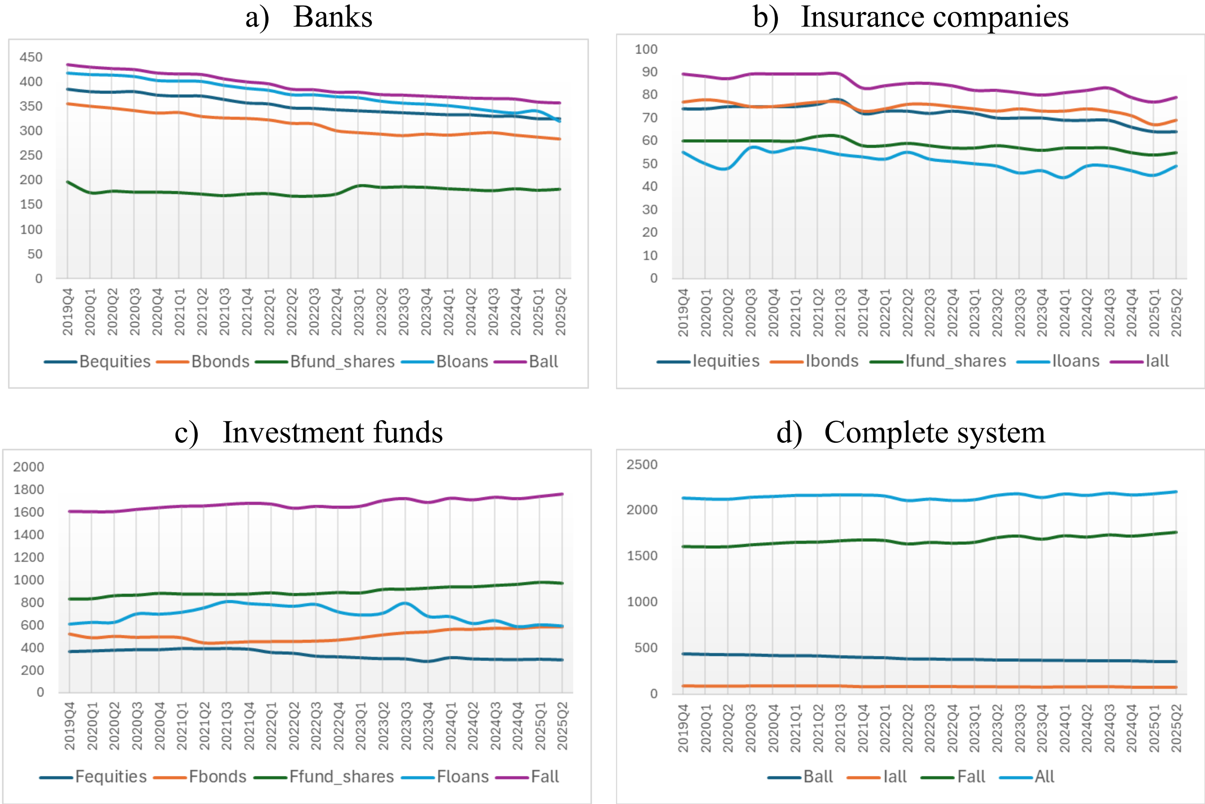
7. The evolution of the Italian financial network over time

This section describes the fundamental architecture of the network of the Italian financial system over time: how many elements it contains, how they are connected, and how easily information or influence can flow through the system. The basic network measures provide a global understanding of the network's size, cohesion, and internal distances across nodes and how they change over time.

7.1. Nodes evolution

Figure 2 displays the evolution of the number of nodes for banks, insurance companies, investment funds and for the overall financial system, across the four asset classes: loans, equities, bonds, and fund shares. Since a single node can participate in multiple financial instruments, the total number of nodes in each sector is not equal to the sum of the nodes across individual instruments, but it is simply the union.

Figure 2. Number of nodes by sector layers



For banks, the number of nodes shows a gradual decline over time across all bank layers. Between 2019 and 2025, the total number of banks (*Ball*) falls by about 18%, with the sharpest decreases observed among banks active in the bond market (from 355 in 2019 to 283 in 2025) and those engaged in lending (from 418 to 320). Banks involved on fund shares investments are the smallest in number and the most stable, fluctuating within a narrow range (170–190), suggesting that banks' exposure to fund shares is relatively limited and stable over time. This evidence points to a banking network that is becoming smaller. The trend may reflect a growing concentration of exposures among fewer institutions, likely driven by mergers, acquisitions, and subsequent integrations. Notable reductions in the number of bank nodes occurred in 2020Q4, 2021Q3, and 2022Q2, possibly following major corporate events: Intesa Sanpaolo's integration of Banca IMI (February 2020), its acquisition and incorporation of UBI Banca (August 2020), the divestment of branches to BPER Banca (April 2021), and the integration of BPER Banca and Banca Carige (June–November 2022). The contraction in the number of nodes may reduce potential contagion channels, but it also increases the systemic importance of the remaining, more interconnected nodes.

For insurance companies, the network appears smaller and displays moderate fluctuations. The total number of nodes (*Iall*) declines slightly, from 89 in 2019 to 79 in 2025, corresponding to a 11% reduction over more than five years. The largest declines occurred in 2021Q4 and in 2024Q4–2025Q1, coinciding with periods of consolidation. These included the progressive integration of Cattolica into Assicurazioni Generali, Allianz's acquisitions, and the developments related to the Eurovita case. The drop in the number of nodes in the individual securities and loans layers was similar in size. Moreover, as insurers are not granting loans, the nodes in the loan layers capture those institutions that borrows from other sectors.

In the case of investment funds, the number of nodes is considerably higher than in other sectors and follows an upward trend (from 1610 in 2019 to 1763 in 2025; +10%). Nodes in the fund share layer dominate the network, growing from 831 to 974 (+17%). This sustained expansion reflects the increasing interlinkages among funds themselves, likely due to expanded growing fund-of-funds structures. Nodes with bond exposures also expand significantly—from 522 to 584 (+12%)—indicating broader diversification and greater integration into fixed-income markets. Funds taking on loans from banks, the smallest category, do not show a clear trend, pointing to limited and stable engagement in credit instruments.

Finally, regarding the complete system, the overall number of nodes (*All)*, which is given by the union of the total nodes of each type of financial institutions, remains relatively stable, with only a slight upward drift (from 2,134 in 2019 to 2,199 in 2024; +3%) that masks diverging sectoral trends, where the declining number of nodes of banks and insurers is offset by the increasing one of funds.

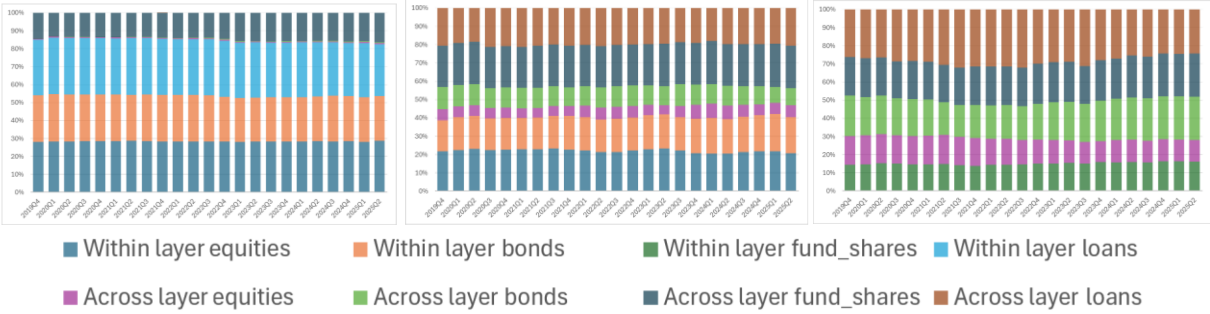
We also distinguish how many nodes exhibit connections exclusively within a sector and how many span across sectors. As shown in Figure 3, the vast majority of bank nodes reflect only within-sector edges. By contrast, most fund nodes are connected across sectors. For insurers, we observe a more balanced pattern, with nodes distributed across both within-sector and cross-sector connections.

7.2. Connections over time

The total number of connections in a network reflects the potential for interaction, influence, and contagion among its participants. It thus matters because it determines how shocks, information, or liquidity flow through the system.

Figure 3. Number of nodes (within and across sectors)

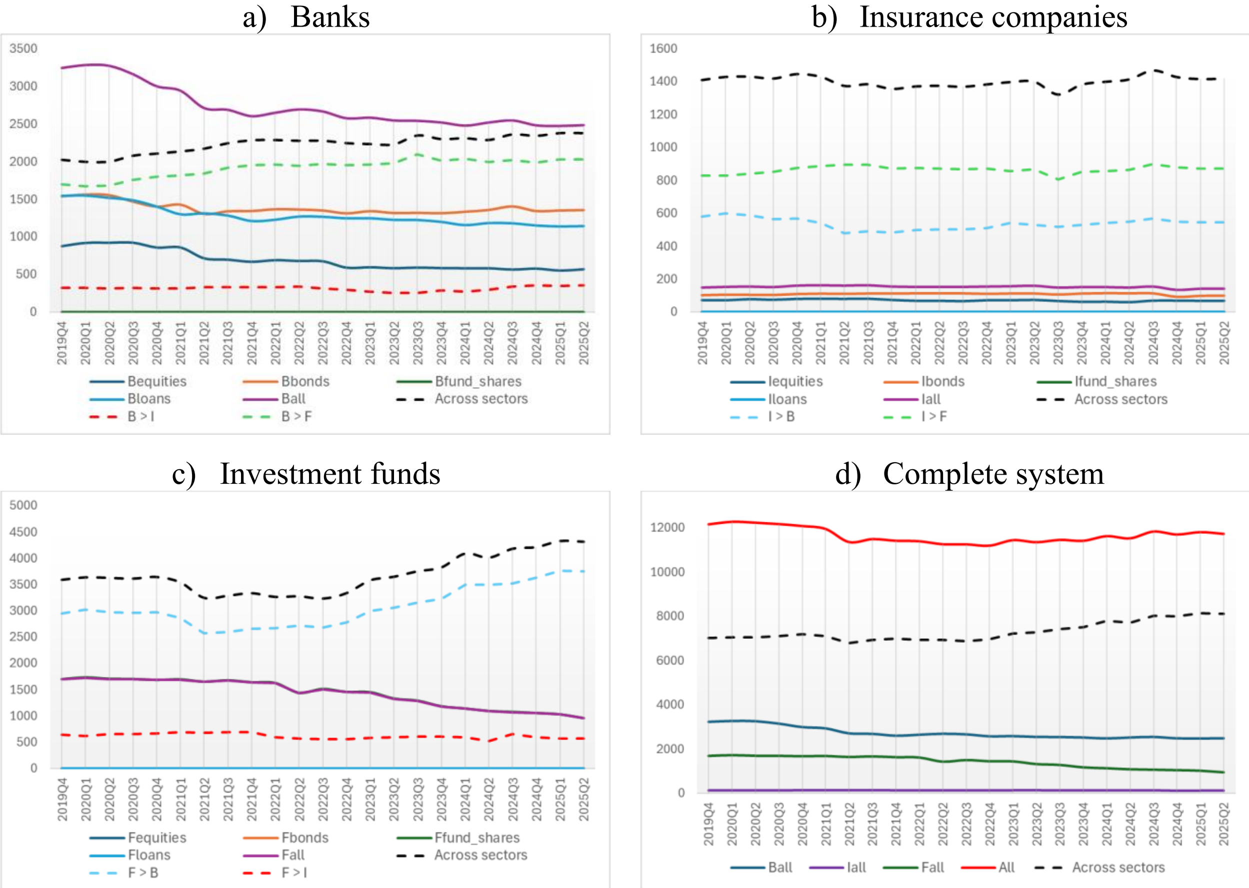
a) Banks b) Insurance companies c) Investment funds



When analysing the connections within each layer, it is important to remind that, for any layer, we consider links between two institutions of the same type that hold or issue a particular financial instrument. Within the banking network (i.e. considering links between banks alone), connections contract markedly across all asset classes (Figure 4, Panel (a)). Between 2019 and 2025, equity links fall by 35%, loan-based links by 26%, and bond links by 12%, reducing total connections from 3,250 to 2,487 (–23.5%); fund shares links remain zero. The sharpest drop occurs between 2020Q3 and 2021Q1, when about 10 banks exit, consistent with merger activity (e.g., Intesa Sanpaolo – IMI) that significantly reshapes linkages. Insurance companies show low and relatively stable connectivity with their peers (Figure 4, Panel (b)): total links fluctuate around 150–160 before declining slightly to 142 by 2025, concentrated in bonds and equities, with no loan links as insurers are not granting loans to other insurers. Investment funds display a high connectivity but experience the largest within-sector contraction (Figure 4, Panel (c)). Their fund shares-based links fall from 1,697 to 955 (-43.7%) over the period, with the steepest declines in 2022–2023.

At the aggregate level, the number of system-wide connections (*All*) is much higher than the sum of the single sectors (Figure 4, Panel (d)), indicating the majority of links occur across sectors. In particular, in 2025Q2 the total number of connections are 11,743 and the sum of those within the banking, investment fund and insurance sectors are equal to only about 3584. This indicates that 69% of all interconnections occur across sectors (it was 58% in 2019). Over time the number of total interconnections has slightly declined (-3.5%), reflecting two counteracting effects. On the one hand, within each single sector the number of interconnections declined, on the other hand the interconnections across sectors increased (by about 15.5%, from around 7,032 in 2019 to 8,124 in 2025). Interconnections across institutions decreased slightly in 2021Q2 (-4.4%), driven by some central nodes in the banking system incorporated and disappeared due to the aforementioned merger activity. Starting from 2023, interconnections across sectors have begun to grow. In a context of tighter monetary conditions, which started in 2022, higher bond yields attracted flows into fixed-income instruments held by banks, funds, and insurers alike. Finally, we find that funds shifted heavily towards instruments issued by banks, insurers maintained an overall stable number of connections with investment funds, while banks diversified beyond traditional lending into fund participations.

Figure 4. Number of edges



7.3. Intensity of the connections

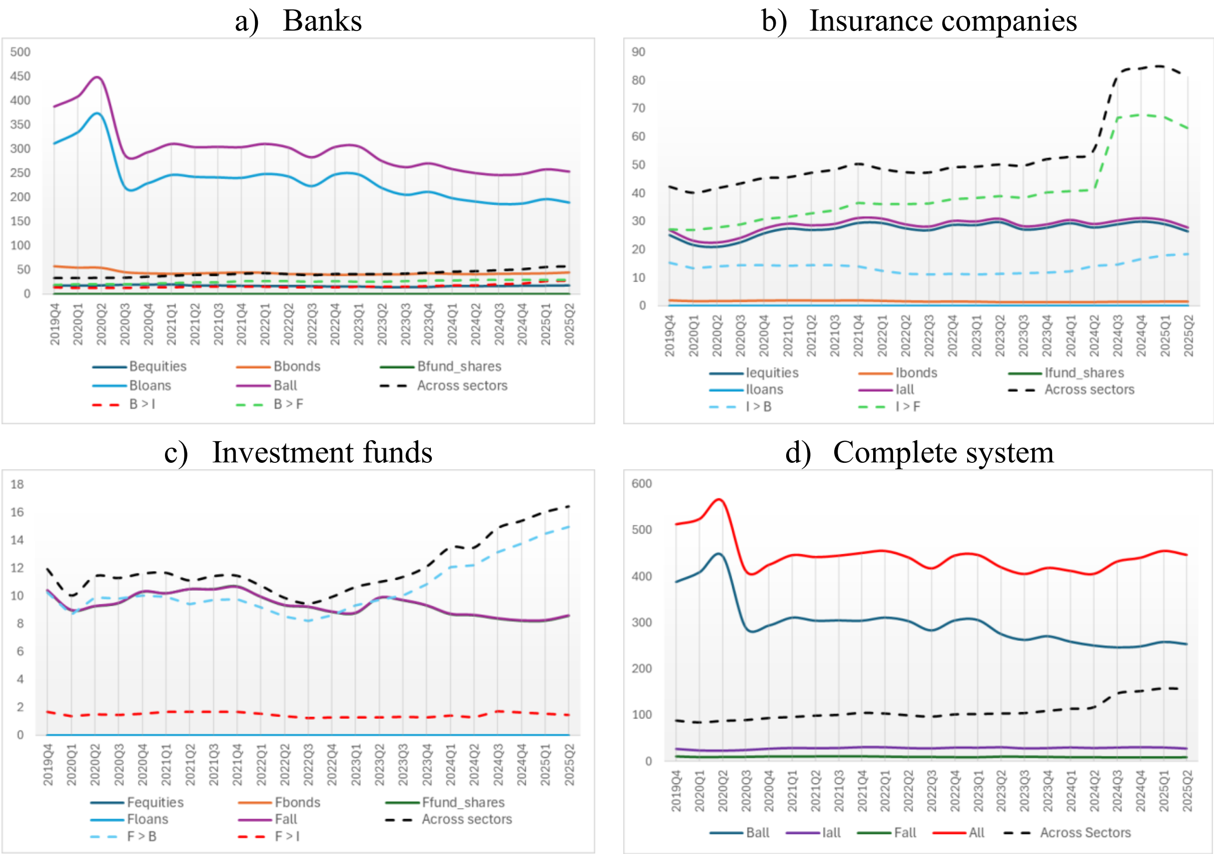
Figure 5 shows the weighted connections which measure the intensity of financial exposures between institutions, not just the existence of a link. While an unweighted network tells us who is connected to whom, a weighted network shows how much is at stake in each connection. The weights represent the value of financial instruments (loans, equities, bonds, fund shares) held by one institution and issued by another. Because weights reflect the size of exposures, large weighted links are potential channels through which losses can propagate and sectors with consistently high weights (e.g., banks) are more likely to amplify systemic shocks. Weighted networks thus could reveal where losses would matter the most.

The weighted exposures of banks (Figure 5, Panel (a)) show a pronounced peak at the end of 2019 and early 2020, followed by a sharp contraction in 2020Q2, likely following integration activities. This drop concerns all bank-related instruments, but it is particularly strong for bank loans (*Bloans*), which dominate the overall magnitude of connections. After mid-2020, the network stabilizes at a lower level, with only mild fluctuations over time.

For insurance companies (Figure 5, Panel (b)), weighted exposures decrease in 2020Q2, then begin to rise again and eventually stabilize around the levels observed in 2021. Investment funds (Figure 5, Panel (c)) show a similar pattern: exposures dip slightly in early 2020 and then increase, with some modest fluctuations throughout the sample period.

At the system level, the early-period dynamics largely mirror those within the banking sector; however, in the latter part of the sample, we observe a noticeable increase in weighted cross-sector links, which reflects dynamics observed particularly for the insurance sector. A marked increase in across sectors weighted links occurred in 2024, when approximately 25 billion euros of insurance investments in multi-asset funds entered the network (Figure 5, Panel (b)). These exposures, concentrated in Poste Vita, were linked to the repatriation to Italy of Banco Posta's funds originally managed by a Luxembourg SICAF.

Figure 5. Weighted edges (in billions of Euros)



7.4. Measuring financial connectivity: the role of node degree

In a financial network context, the degree is a critical measure for analysing systemic risk and financial contagion. Nodes with a high degree (so-called hubs) have numerous connections, making them highly central and potentially the most influential players. Should a hub fail, its extensive connectivity dramatically increases the likelihood that the shock will propagate throughout the entire system. Conversely, nodes with a low degree are less connected, and their failure has a lower potential for widespread contagion. Therefore, the degree provides a powerful and immediate indicator of a financial actor's relevance and its potential for risk transmission within the network structure.

Table 2, Panel (a) reports the average number of incoming connections for each node at the end of each year, shown separately for each layer (columns 1–12), for each aggregate sector (columns 13–15) and for the complete financial system (column 16).

Banks receive far more incoming links than insurers or investment funds (over 7, compared with 2 and 1, respectively), largely reflecting exposures arising from bank bond holdings and bank lending.

The most notable declines in incoming connections occur in the bank-equities and bank-loans layers in 2021—mainly due to consolidation activities—and remained at a lower level thereafter. By contrast, the bank-bonds layer shows an increase in average incoming connections (up by 0.45, from 4.3 in 2019 to 4.8 in 2025). As these opposite movements partially offset each other, the overall reduction in average connections per bank between 2019 and 2025 is relatively small, at about 0.50 (from 7.5 to 7).

For insurers, the average degree in the equities and bonds within-layers remains broadly stable at low levels: on average, each insurer has only one or two other insurance companies investing in its equity or bonds. This indicates that the investor base for insurers changed very little over the period.

For investment funds, the incoming degree associated with fund shares investments declines gradually over time, suggesting that funds may have shifted toward alternative investment strategies.

For the layers *Iloans, Floans, Fequities, Fbonds, Bfund_shares, Ifund_shares* (columns 2, 3, 6, 9, 10, 11) the average degree is zero, indicating that no institution in these categories is connected to another institution of the same type through these specific financial instruments.

At the system level, the reduction in the average number of incoming links is smaller compared with the declines observed for banks or funds individually; indeed, the average number of connections per financial institution remains between 5 and 6 (column 16). This pattern suggests a rise in cross-sector investment activity: institutions appear to receive a more diversified set of connections from different sectors, even as within-sector linkages weaken.

Panel (b) reports the average out-degree, which mirrors the in-degree distribution, as expected in a closed directed system, so the same temporal dynamics apply. The decline in out-degree for banks and funds implies that these institutions increasingly spread their exposures across fewer counterparties.

Panel (c) presents the average total degree, which declines over time. The total average degree exhibits the same directional patterns but with clearer magnitude. The complete network continues to exhibit relatively high levels of total connectivity (on average each institution is connected with 11 other institutions), indicating that, despite some contraction within sectors, the financial system remains enough interconnected overall.

In the bottom three panels of Table 2, we report the maximum in-degree, out-degree and degree, across the individual layers and for the complete financial network. Three patterns emerge.

First, the bank equities and bank bonds layers consistently exhibit the highest maximum in-degrees across the sample. This indicates that, within these layers, a small number of banks receive a disproportionately large number of incoming links, suggesting a high concentration of exposures directed toward the most prominent institutions. The substantial decline in the maximum in-degree for the bank equities layer in 2022 points to a gradual reduction in concentration, whereas the maximum degree in the bank bonds layer declines much less, implying more persistent concentration of debt exposures. Moreover, we observe a significant decrease in the maximum average in the fund shares layer for funds, indicating a gradual reduction in concentration also for this sector. Instead, for insurance companies we observe minimal fluctuations.

Second, on the out-degree side, the bank loans layer exhibits the highest maximum values throughout the entire sample. This reflects the presence of highly connected institutions that act as major lenders to many counterparties. The gradual decline in the maximum out-degree of bank loans suggests some de-concentration in loan-supply relationships, although this layer remains the most dominant channel for outgoing connections. Symmetrically, we observe a marked increase in the out-degree for bank bonds, indicating that a small number of banks have been augmented their counterparties within the sector in the issuance of bank bonds.

Table 2. Average and maximum degree

	Bloans (1)	Iloans (2)	Floans (3)	Bequities (4)	Iequities (5)	Fequities (6)	Bbonds (7)	Ibonds (8)	Fbonds (9)	Bfund_shares (10)	Ifund_shares (11)	Ffund_shares (12)	Ball (13)	Iall (14)	Fall (15)	All (16)
Average degree																
a) IN																
2019	3.70	0.00	0.00	2.27	0.99	0.00	4.34	1.34	0.00	0.00	0.00	2.04	7.47	1.67	1.05	5.71
2020	3.48	0.00	0.00	2.30	1.07	0.00	4.18	1.47	0.00	0.00	0.00	1.91	7.19	1.81	1.02	5.63
2021	3.12	0.00	0.00	1.87	1.03	0.00	4.14	1.55	0.00	0.00	0.00	1.87	6.52	1.87	0.97	5.28
2022	3.36	0.00	0.00	1.73	0.99	0.00	4.38	1.48	0.00	0.00	0.00	1.63	6.80	1.85	0.88	5.31
2023	3.37	0.00	0.00	1.75	0.90	0.00	4.49	1.55	0.00	0.00	0.00	1.27	6.80	1.90	0.70	5.34
2024	3.41	0.00	0.00	1.75	1.06	0.00	4.62	1.31	0.00	0.00	0.00	1.09	6.81	1.71	0.61	5.41
2025	3.57	0.00	0.00	1.76	1.08	0.00	4.80	1.45	0.00	0.00	0.00	0.98	6.97	1.80	0.54	5.34
b) OUT																
2019	3.70	0.00	0.00	2.27	0.99	0.00	4.34	1.34	0.00	0.00	0.00	2.04	7.47	1.67	1.05	5.71
2020	3.48	0.00	0.00	2.30	1.07	0.00	4.18	1.47	0.00	0.00	0.00	1.91	7.19	1.81	1.02	5.63
2021	3.12	0.00	0.00	1.87	1.03	0.00	4.14	1.55	0.00	0.00	0.00	1.87	6.52	1.87	0.97	5.28
2022	3.36	0.00	0.00	1.73	0.99	0.00	4.38	1.48	0.00	0.00	0.00	1.63	6.80	1.85	0.88	5.31
2023	3.37	0.00	0.00	1.75	0.90	0.00	4.49	1.55	0.00	0.00	0.00	1.27	6.80	1.90	0.70	5.34
2024	3.41	0.00	0.00	1.75	1.06	0.00	4.62	1.31	0.00	0.00	0.00	1.09	6.81	1.71	0.61	5.41
2025	3.57	0.00	0.00	1.76	1.08	0.00	4.80	1.45	0.00	0.00	0.00	0.98	6.97	1.80	0.54	5.34
c) IN+OUT																
2019	7.41	0.00	0.00	4.55	1.97	0.00	8.69	2.68	0.00	0.00	0.00	4.08	14.94	3.35	2.11	11.41
2020	6.97	0.00	0.00	4.60	2.13	0.00	8.36	2.93	0.00	0.00	0.00	3.81	14.38	3.62	2.05	11.25
2021	6.25	0.00	0.00	3.75	2.06	0.00	8.28	3.10	0.00	0.00	0.00	3.74	13.04	3.73	1.95	10.56
2022	6.73	0.00	0.00	3.45	1.97	0.00	8.77	2.96	0.00	0.00	0.00	3.27	13.61	3.69	1.77	10.63
2023	6.74	0.00	0.00	3.50	1.80	0.00	8.98	3.10	0.00	0.00	0.00	2.54	13.60	3.80	1.40	10.68
2024	6.82	0.00	0.00	3.51	2.12	0.00	9.24	2.62	0.00	0.00	0.00	2.18	13.62	3.42	1.22	10.82
2025	7.13	0.00	0.00	3.51	2.16	0.00	9.60	2.90	0.00	0.00	0.00	1.96	13.93	3.59	1.08	10.68
Maximum degree																
d) IN																
2019	110	0	0	221	24	0	181	39	0	0	0	77	269	44	77	781
2020	107	0	0	187	26	0	157	40	0	0	0	73	251	46	73	771
2021	101	0	0	180	28	0	126	41	0	0	0	77	244	46	77	758
2022	100	0	0	121	26	0	130	38	0	0	0	64	211	44	64	706
2023	100	0	0	119	21	0	132	40	0	0	0	46	211	43	46	770
2024	94	0	0	117	25	0	129	39	0	0	0	37	203	44	37	776
2025	92	0	0	114	23	0	133	38	0	0	0	27	206	42	27	777
e) OUT																
2019	214	0	0	26	9	0	29	5	0	0	0	31	222	11	31	342
2020	203	0	0	22	9	0	48	6	0	0	0	28	210	11	28	569
2021	181	0	0	24	6	0	88	8	0	0	0	27	192	9	27	692
2022	156	0	0	24	6	0	87	8	0	0	0	27	166	9	27	635
2023	143	0	0	24	5	0	94	7	0	0	0	28	155	9	28	577
2024	132	0	0	20	5	0	94	6	0	0	0	33	148	8	33	469
2025	111	0	0	19	5	0	94	6	0	0	0	34	131	8	34	464
f) IN+OUT																
2019	324	0	0	229	26	0	210	39	0	0	0	77	491	46	77	973
2020	314	0	0	192	29	0	205	40	0	0	0	73	483	49	77	978
2021	318	0	0	188	31	0	204	41	0	0	0	77	485	49	78	978
2022	313	0	0	129	30	0	148	38	0	0	0	64	480	48	77	1367
2023	310	0	0	129	25	0	156	40	0	0	0	47	461	49	73	1340
2024	296	0	0	124	27	0	153	39	0	0	0	38	448	50	75	1354
2025	294	0	0	126	25	0	159	39	0	0	0	34	442	51	74	1437

Third, when considering out-degree across all institutions and all instruments (column 16), the average out-degree has increased relative to 2019. This rise is more pronounced than the changes observed for individual sectors, suggesting that an increasing number of institutions are forming cross-sector linkages.

Finally, when aggregating all layers, the maximum total degree increases over time. This highlights the presence of a greater set of institutions that are systemically central across multiple layers simultaneously. Overall, the distribution of maximum degree across layers underscores the heterogeneity of systemic importance across markets. Despite some de-concentration within individual layers, the system is characterized by a limited set of highly interconnected institutions that could act as major conduits for the propagation of shocks.

Figure 6. Weighted and unweighted average degree (millions of euros and units)

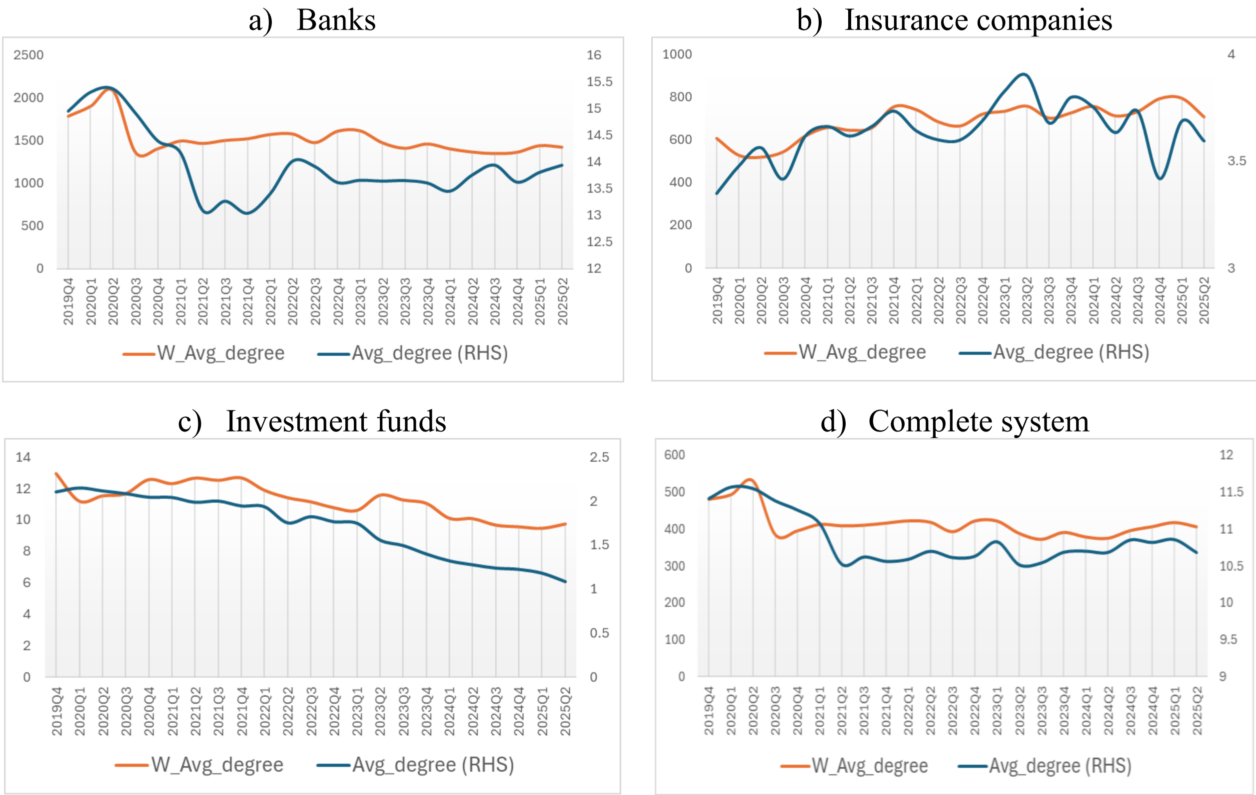


Figure 6 illustrates weighted and unweighted average degree for each entire sector, i.e. when aggregating over instruments. Within each sector, the dynamics are similar for unweighted and weighted degree. For the complete system, the main driver of dynamics is clearly the banking sector. However, in general, the average weighted degree of the complete system is lower than those of banks and insurers, mainly due to the high number of funds with low weighted degrees.

7.5. Density

Network density remains very low across all layers (Table 3, Panel (a)), indicating sparse graphs, which is an expected feature of financial networks that tend to have many fewer links than all possible ones (Torri, et al., 2018). Equity layers for banks and insurers (*Bequities* and *Iequities*) show average densities under 1% and 2% respectively, suggesting that investment relationships are highly selective. Bonds layers (*Bbonds* and *Ibonds*) present slightly higher densities, reflecting a broader investor base compared with equities, though still at modest levels. Fund shares layer for funds (*Ffund_shares*) is on very low levels, reflecting the limited role of within sector relationship.

Across periods, density remains remarkably stable, with only few minimal variations. The modest increase in the *Iequities, Ibonds* and *Bbonds* layers suggest a slight expansion of connectivity for insurance and bank-related links. Conversely, the system-wide density (*All*) remains extremely low throughout, indicating that when all institutions and instruments are combined, the financial network retains a stable, overall sparse, core–periphery structure.

Table 3. Network Topology Across Layers: Density, Diameter, and Path Length Over Time

	Bloans	Iloans	Floans	Bequities	Iequities	Fequities	Bbonds	Ibonds	Fbonds	Bfund_shares	Ifund_shares	Ffund_shares	Ball	Iall	Fall	All
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
a) Density																
2019	0.9%	0.0%	0.2%	0.6%	1.4%	0.0%	1.2%	1.8%	0.0%	0.0%	0.0%	0.2%	1.7%	1.9%	0.1%	0.3%
2020	0.9%	0.0%	0.2%	0.6%	1.4%	0.0%	1.2%	2.0%	0.0%	0.0%	0.0%	0.2%	1.7%	2.1%	0.1%	0.3%
2021	0.8%	0.0%	0.2%	0.5%	1.4%	0.0%	1.3%	2.1%	0.0%	0.0%	0.0%	0.2%	1.6%	2.3%	0.1%	0.2%
2022	0.9%	0.0%	0.2%	0.5%	1.4%	0.0%	1.5%	2.0%	0.0%	0.0%	0.0%	0.2%	1.8%	2.2%	0.1%	0.3%
2023	1.0%	0.0%	0.1%	0.5%	1.3%	0.0%	1.5%	2.1%	0.0%	0.0%	0.0%	0.1%	1.8%	2.4%	0.0%	0.2%
2024	1.0%	0.0%	0.1%	0.5%	1.6%	0.0%	1.6%	1.9%	0.0%	0.0%	0.0%	0.1%	1.9%	2.2%	0.0%	0.2%
2025	1.1%	0.0%	0.1%	0.5%	1.7%	0.0%	1.7%	2.1%	0.0%	0.0%	0.0%	0.1%	2.0%	2.3%	0.0%	0.2%
b) Diameter																
2019	6.0	0.0	0.0	8.0	5.0	0.0	6.0	1.0	0.0	0.0	0.0	3.0	7.0	5.0	3.0	7.0
2020	5.0	0.0	0.0	8.0	5.0	0.0	7.0	2.0	0.0	0.0	0.0	3.0	5.0	5.0	3.0	6.0
2021	6.0	0.0	0.0	8.0	4.0	0.0	5.0	3.0	0.0	0.0	0.0	3.0	6.0	7.0	3.0	7.0
2022	5.0	0.0	0.0	9.0	3.0	0.0	5.0	3.0	0.0	0.0	0.0	3.0	6.0	7.0	3.0	7.0
2023	5.0	0.0	0.0	9.0	2.0	0.0	5.0	2.0	0.0	0.0	0.0	3.0	6.0	7.0	3.0	7.0
2024	7.0	0.0	0.0	7.0	2.0	0.0	5.0	0.0	0.0	0.0	0.0	3.0	7.0	7.0	3.0	7.0
2025	6.0	0.0	0.0	9.0	3.0	0.0	5.0	3.0	0.0	0.0	0.0	2.0	7.0	7.0	2.0	7.0
c) Average shortest path length																
2019	2.73	0.00	1.40	3.74	2.91	0.00	2.70	1.38	0.00	0.00	0.00	1.40	2.55	2.84	1.40	2.99
2020	2.74	0.00	1.39	3.73	2.90	0.00	2.66	1.63	0.00	0.00	0.00	1.39	2.54	2.73	1.39	2.89
2021	2.74	0.00	1.39	3.52	2.89	0.00	2.62	1.64	0.00	0.00	0.00	1.39	2.54	3.01	1.39	2.83
2022	2.71	0.00	1.34	3.74	2.93	0.00	2.65	1.67	0.00	0.00	0.00	1.34	2.57	3.01	1.34	2.82
2023	2.73	0.00	1.29	3.58	2.63	0.00	2.75	1.50	0.00	0.00	0.00	1.29	2.58	2.93	1.29	2.78
2024	2.85	0.00	1.16	3.88	2.44	0.00	2.81	1.38	0.00	0.00	0.00	1.16	2.67	3.04	1.16	2.82
2025	2.83	0.00	1.15	3.48	2.62	0.00	2.75	1.94	0.00	0.00	0.00	1.15	2.67	2.95	1.15	2.82

7.6. Diameter

Diameter values vary substantially across layers, reflecting heterogeneous network structures (Table 3, Panel (b)). Bank-related layers (*Bequities, Bbonds, Ball*) consistently exhibit the largest diameters, indicating longer maximum distances and implying that shocks, from a peripheral node, would require more steps to propagate through these specific layers. Insurer and fund layers, by contrast, often show smaller diameters, which indicates that the observed networks in these layers are extremely small and, thus, shocks propagate quickly within interconnected institutions.

Over time, some layers show a modest increase in diameter (e.g., *Bequities* and *Ibonds)* suggesting that these networks have become slightly more stretched or fragmented. Instead, the system-wide diameter (*All*) maintains a stable value of 7, implying that the shock propagation speed remains stable over time: since any two nodes are maximum 7 links away, then information, shocks or contagion can propagate across the entire network in at most 7 steps.

7.7. Average shortest path length

The average shortest path length mirrors, in this case, the behaviour of the diameter but in smoother form (Table 3, Panel (c)). Bank equity and bond layers (*Bequities, Bbonds*) show the longest average shortest path lengths, consistent with their relatively higher diameters. Bank loan layer (*Bloans*) also maintains moderate path lengths, suggesting relatively dense connection structures among lenders and borrowers. Layers such as equity or bond securities for insurers show shorter paths, reflecting tighter components.

In the complete system (*All*), the average path length remains below 3 throughout, indicating that on average, one can go from any one institution in the largest connected part of the network to any other institution in fewer than three steps (i.e., through two intermediate institutions or fewer). This is noteworthy because the network is quite scattered. Indeed, despite this sparseness, institutions are still not far apart in terms of network distance, i.e. the structure of the network is such that shocks can travel quickly from one institution to others, because the paths connecting them are short. This is important for systemic risk, because it means that contagion can propagate through the network in only a few steps and even small shocks can reach many institutions relatively quickly.

The values of average path length across layers and for the entire system remain fairly stable over time, implying persistent structural properties.

7.8. Communities

This section documents the evolution of the number of communities and the size of the largest community in the multilayer network. The indicators capture the degree of fragmentation and cohesion within and across sectors over time.

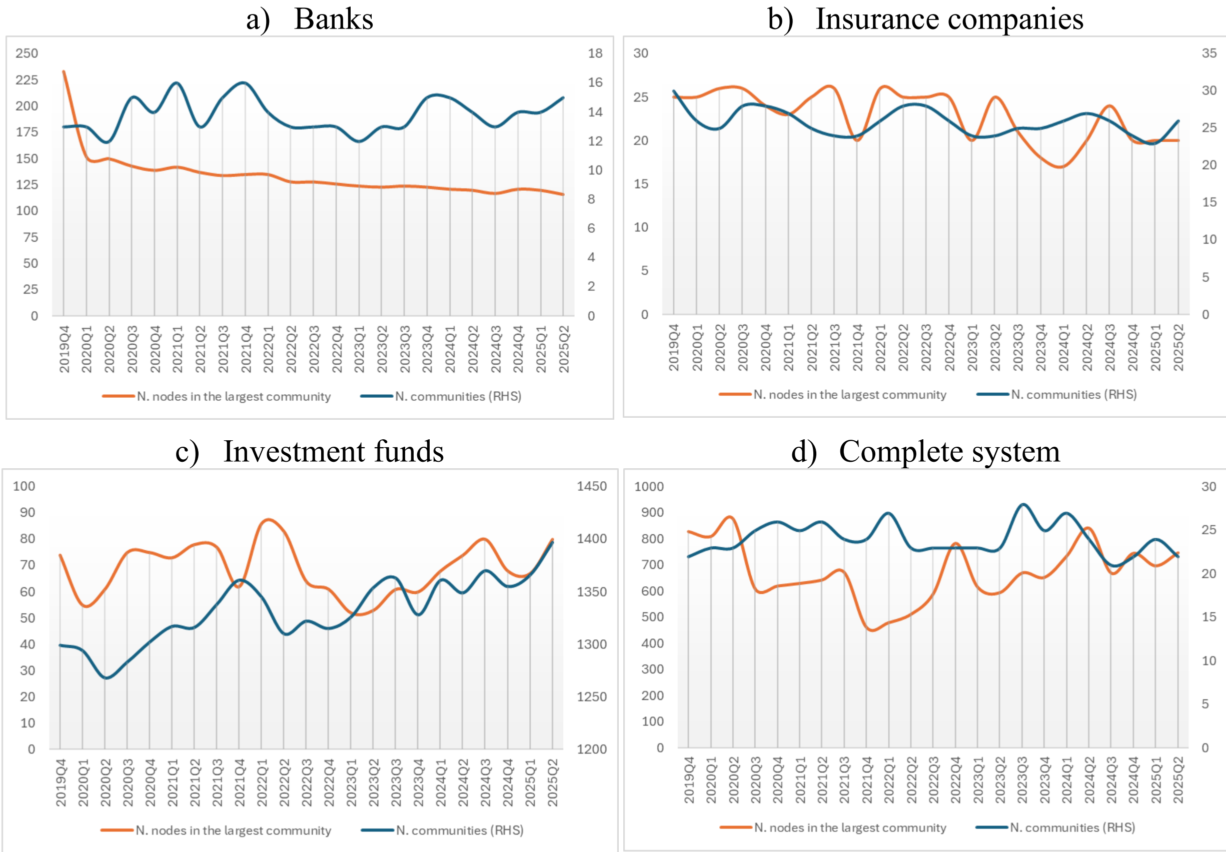
The banking network is characterized by a relatively stable number of communities, typically between 12 and 16, suggesting no major shifts in the modular structure of the sector. In contrast, the size of the largest community exhibits a clear downward trend over the entire period. From roughly 230 nodes in 2019Q4, the largest community contracts steadily to just above 115 nodes by 2025Q2; the largest drop is observed in 2020Q1. This persistent reduction in the number of nodes is not cyclical, but it appears structural.

The insurance sector maintains a consistently fragmented structure, with 24 to 30 communities throughout the sample. The size of the largest community oscillates only mildly, remaining within a narrow band of 17–26 nodes. There is no discernible long-term trend in either the number of communities or the size of the largest community. This stability suggests that the insurance sector's network structure is relatively mature and exhibits limited sensitivity to short-term financial conditions or sector-specific shocks. Insurance remains the most structurally stable and uniformly fragmented of the sectors considered.

The investment fund layer is the most fragmented network in terms of communities, with approximately 1,300 to 1,400 communities at any point in time. The high number of communities indicates that investment funds do not form true communities among themselves; rather, they appear as small groups or even isolated nodes. This occurs because, in most cases, funds are primarily connected to different types of financial institutions, such as banks or insurance companies, rather than to other funds. The size of the largest community varies between 52 and 86 nodes, with no clear upward or downward trend.

The complete network exhibits a moderate degree of fragmentation, with the total number of communities fluctuating between 21 and 28 over the sample period. These movements do not indicate a clear long-term trend but reflect cyclical adjustments, particularly around periods of market stress or reorganizations of the system. The size of the largest community displays more pronounced variation. It declines substantially during 2020–2021, falling from approximately 830 nodes at the end of 2019 to a low of around 460 nodes by late 2021, suggesting a temporary fragmentation of the network that is consistent with M&A. After 2021, the largest community gradually expands again, reaching roughly 840 nodes in mid-2024, before stabilizing in the 700–750 range in 2024–2025. These dynamics indicate that the overall market's connectedness is not monotonic but responsive to sector-specific and macro-financial shocks.

Figure 7. Communities



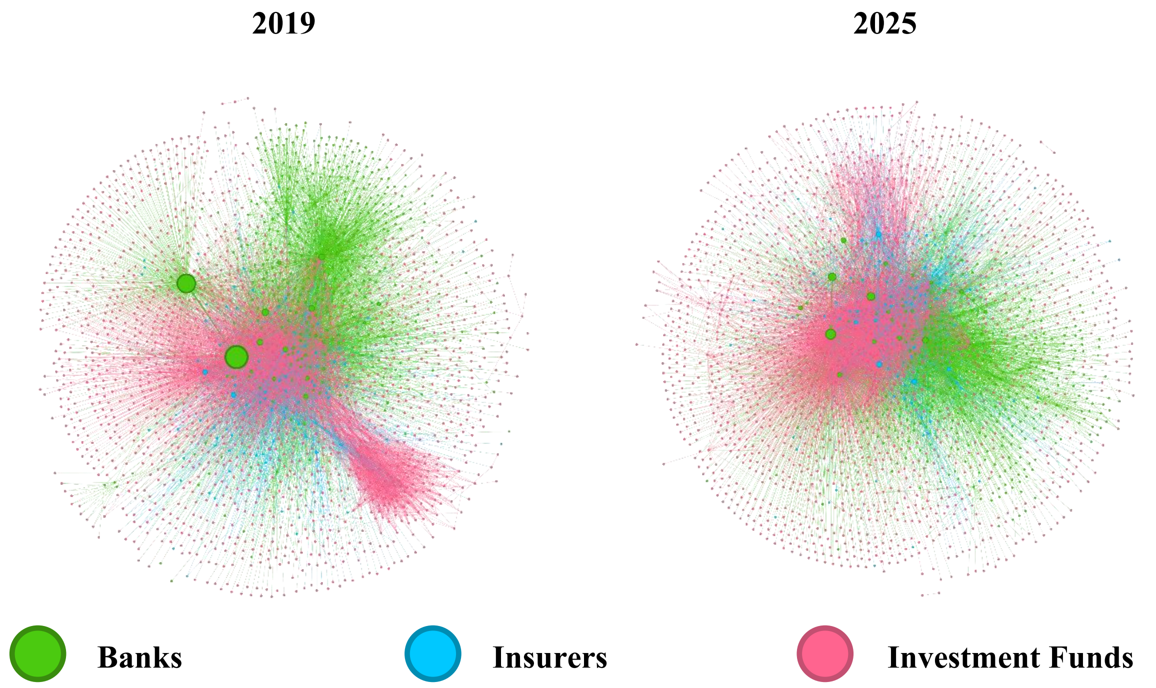
Taken together, the results highlight important differences in network evolution across sectors. Banks are the only sector exhibiting a sustained decline in the size of the largest community, pointing to a decreasing cohesiveness in the core of the banking network. Insurance shows no comparable structural drift, its structure remains fairly stable over time. Lastly, funds' network is highly fragmented since the substantial number of their single connections do not allow them to join communities. At the aggregate level, the network responds more strongly to macro-financial events/M&A, most noticeably during the pandemic period, but subsequently recovers much of its cohesion. These findings underscore the heterogeneity in how financial subsectors contribute to the overall structure of market interconnections and suggest that sector-specific dynamics, especially in banking, play a key role in shaping the evolution of systemic connectivity.

7.9. Influence, positioning and similarity of connections

This section focuses on metrics that capture the relative importance and structural roles of individual nodes within the network. These measures identify which nodes occupy central positions, exert influence, or serve as key intermediaries, and they help describe the network's hierarchical or directional properties. Indeed, similarity analysis is a relevant tool in assessing financial stability: diffusion properties —and therefore contagion— in a network depends on the similarity of connections (Gómez, et al., 2013).

From 2019 to 2025 the network has become more compact[13] (Figure 8). In 2019, the different groups appear more separate and distinct. By 2025, the visual impression shifts significantly: many of these clusters have merged into one large core. The whole structure appears more unified, with fewer isolated groups and more links pulling everything toward the centre.

Figure 8. Italian financial system network evolution over time



PageRank. For any layer and for the complete system, average PageRank values are generally very small, indicating that most nodes have low individual influence in the network (Table 4, Panel (a)). Conversely, maximum PageRank values are significantly higher than the averages (Table 4, Panel (b)), indicating that a small number of highly ranked nodes exert a disproportionate influence on the network, a classic feature of financial systems with hub-like institutions. Regarding the complete system, maximum PageRank drops sharply in 2020, in line with the network structure change previously observed, and continues to decline gradually thereafter, suggesting a weakening influence of these previously dominant nodes.

Assortativity. Layers for banks, insurance companies and the entire system consistently show negative assortativity throughout 2019–2025 (Table 4, Panel (c)). Negative assortativity means that high-degree financial institutions tend to connect with low-degree entities, a typical "hub-and-spoke" structure. We also observe that the value of assortativity in equity layers is increasingly negative over time (around –0.39 to –0.52), suggesting growing disassortativity, i.e. the largest institutions increasingly interact with smaller ones. Bond layers are slightly less negative, but still in the –0.26 to –0.46 range, indicating similar hub-dominated structure in funding relations. Loans layers are stable at about –0.40 to –0.47, confirming that lending relationships remain heavily disassortative. The system-wide complete layer (*All*) measure remains negative across all years (in the range –0.26 to –

[13] This structural evolution is quantitatively corroborated by the **average clustering coefficient** (Watts & Strogatz, 1998), which increased by a significant shift in the order of magnitude (from 0.000044 in 2019 to 0.0002 in 2025), reflecting higher local densification and the formation of a more tightly interconnected systemic core.

0.32). This is indicative that the multilayer network behaves as a disassortative financial system. This is consistent with financial systems in which large banks and insurers act as intermediaries among many smaller institutions.

Only funds layers show positive assortativity but declining over time, indicating that connections occur more frequently among similarly connected nodes, i.e., clusters of similar-size or similar-activity fund shares exposures. However, the decline suggests that that interconnectedness becomes less clustered and more diffuse.

Table 4. PageRank and Assortativity

	Bloans	Iloans	Floans	Bequities	Iequities	Fequities	Bbonds	Ibonds	Fbonds	Bfund_shares	Ifund_shares	Ffund_shares	Ball	Iall	Fall	All
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
a) Average PageRank																
2019	0.0024	0.0182	0.0012	0.0026	0.0135	0.0027	0.0028	0.0130	0.0019	0.0051	0.0167	0.0012	0.0023	0.0112	0.0006	0.0005
2020	0.0025	0.0182	0.0011	0.0027	0.0133	0.0026	0.0030	0.0133	0.0020	0.0057	0.0167	0.0011	0.0024	0.0112	0.0006	0.0005
2021	0.0026	0.0189	0.0011	0.0028	0.0139	0.0026	0.0031	0.0137	0.0022	0.0058	0.0172	0.0011	0.0025	0.0120	0.0006	0.0005
2022	0.0027	0.0196	0.0011	0.0029	0.0137	0.0031	0.0033	0.0133	0.0021	0.0058	0.0175	0.0011	0.0026	0.0119	0.0006	0.0005
2023	0.0028	0.0213	0.0011	0.0030	0.0143	0.0036	0.0034	0.0137	0.0018	0.0054	0.0179	0.0011	0.0027	0.0125	0.0006	0.0005
2024	0.0030	0.0213	0.0010	0.0030	0.0152	0.0034	0.0034	0.0141	0.0018	0.0055	0.0182	0.0010	0.0027	0.0127	0.0006	0.0005
2025	0.0031	0.0204	0.0010	0.0031	0.0156	0.0034	0.0035	0.0145	0.0017	0.0055	0.0182	0.0010	0.0028	0.0127	0.0006	0.0005
b) Max PageRank																
2019	0.091	0.018	0.023	0.176	0.098	0.003	0.132	0.277	0.002	0.005	0.017	0.023	0.130	0.158	0.014	0.123
2020	0.105	0.018	0.025	0.162	0.098	0.003	0.115	0.282	0.002	0.006	0.017	0.025	0.135	0.152	0.015	0.074
2021	0.105	0.019	0.017	0.188	0.117	0.003	0.144	0.282	0.002	0.006	0.017	0.017	0.141	0.153	0.010	0.076
2022	0.105	0.020	0.014	0.127	0.106	0.003	0.159	0.262	0.002	0.006	0.018	0.014	0.129	0.131	0.008	0.066
2023	0.103	0.021	0.012	0.127	0.191	0.004	0.151	0.279	0.002	0.005	0.018	0.012	0.119	0.147	0.008	0.060
2024	0.098	0.021	0.013	0.119	0.163	0.003	0.133	0.298	0.002	0.005	0.018	0.013	0.121	0.238	0.008	0.058
2025	0.103	0.020	0.017	0.119	0.160	0.003	0.120	0.356	0.002	0.005	0.018	0.017	0.124	0.158	0.010	0.052
c) Assortativity																
2019	-0.400	NA	NA	-0.397	-0.392	NA	-0.256	-0.402	NA	NA	NA	0.229	-0.338	-0.428	0.229	-0.305
2020	-0.419	NA	NA	-0.432	-0.418	NA	-0.306	-0.412	NA	NA	NA	0.221	-0.365	-0.422	0.221	-0.268
2021	-0.399	NA	NA	-0.406	-0.449	NA	-0.400	-0.445	NA	NA	NA	0.273	-0.359	-0.426	0.273	-0.262
2022	-0.438	NA	NA	-0.458	-0.453	NA	-0.431	-0.401	NA	NA	NA	0.292	-0.392	-0.367	0.292	-0.267
2023	-0.452	NA	NA	-0.460	-0.481	NA	-0.452	-0.424	NA	NA	NA	0.199	-0.398	-0.357	0.199	-0.289
2024	-0.463	NA	NA	-0.500	-0.524	NA	-0.452	-0.456	NA	NA	NA	0.153	-0.404	-0.427	0.153	-0.317
2025	-0.473	NA	NA	-0.524	-0.415	NA	-0.451	-0.407	NA	NA	NA	0.063	-0.405	-0.376	0.063	-0.314

7.10. Temporal Stability

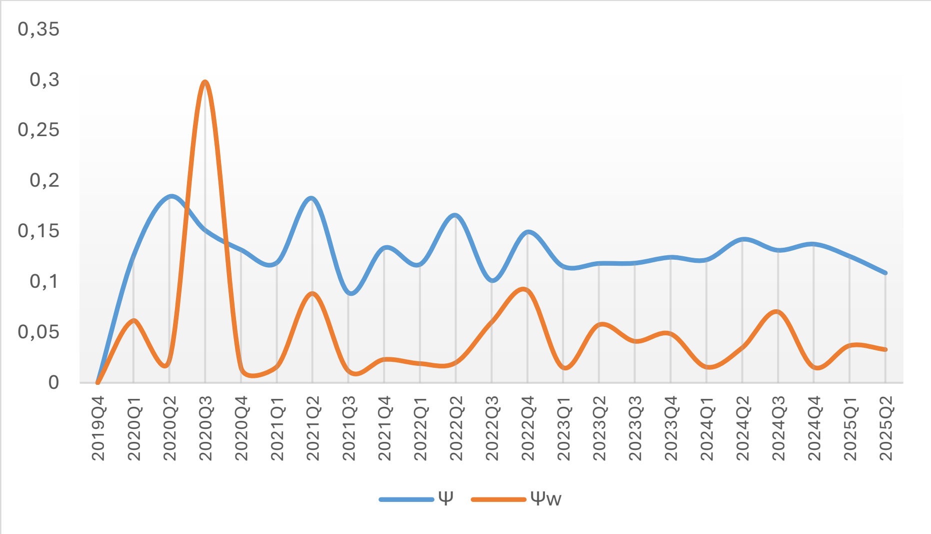
This section examines more in detail the network's dynamics over time, tracking how relationships change, how persistent the structure is, and how closely network configurations in different periods align with one another. These measures help characterize volatility, recurrence, and long-term structural patterns. We analyse the stability of the network by measuring its similarity structure over time. In general, a system can have very similar topological properties in two different instants of time, however the existence of a link between two nodes at time t may give no information on the probability that the same two nodes are linked at time $t+1$ as well. When two networks are the realizations of the same layer at two different instants of time, the similarity between the two is a measure of the stability over time of the network structure of the layer.

Share of edges that change from one period to the next. Figure 9 plots the fraction of changing edges for the complete system over *consecutive quarters* (e.g., 2019Q4 and 2020Q1, 2020Q1 and 2020Q2, and so on) for both the unweighted network (blue line, Ψ) and the weighted network (orange line, Ψw). Both measures spike in early 2020, with Ψw showing a very large peak in 2020Q3, which is compared to 2020Q2. This suggests substantial reshuffling of exposures after the M&A shock, particularly in terms of weights rather than simple link presence. Indeed, a high Ψ indicates a more dynamic layer, with relationships forming and dissolving frequently, while a low Ψ indicates stable exposures and persistent links.

After 2021, the fraction of changing edges gradually declines but remains well above zero through the entire sample. Ψ stabilizes around 10–15%, indicating that a meaningful fraction of links continues to appear/disappear each quarter. Ψw stabilizes at a lower level (typically below 5%), consistent with more stable position sizes relative to changes in link structure.

Moreover, both series exhibit intermittent peaks (e.g., in 2021Q4, 2022Q3, 2024Q1), suggesting episodic periods of portfolio reallocation or network restructuring. From 2023 onward, both measures trend slightly downward, implying a gradual consolidation of the network structure, with fewer major reallocations.

Figure 9. Fraction of changing edges over time



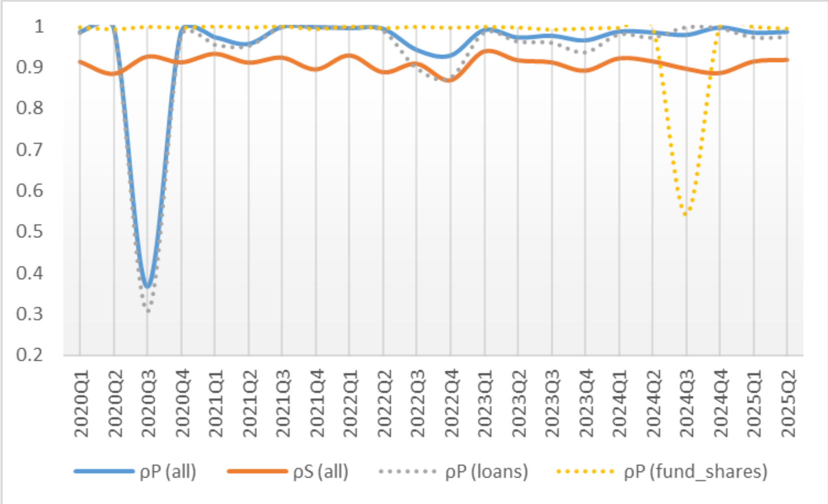
Pearson and Spearman correlations. Figure 10 shows a high degree of temporal stability in the network, with both Pearson and Spearman correlations between *consecutive quarters* remaining close to one for most of the sample. The Pearson correlation for the aggregate network (*ρP(all)*) remains above 0.9 throughout the period, indicating that the overall structure of weighted connections changes only marginally from one quarter to the next. The only notable deviation occurs in 2020Q3, when Pearson values drop sharply, reflecting a temporary reconfiguration of the network; as already observed on the fraction of changing edges, this is consistent with the M&A. After this disturbance, the network quickly returns to its highly persistent structure. This means that before 2020Q3 the network exhibited a type of structure, while, after that quarter, its structure underwent a change and then it remained fairly stable over time.

The Spearman correlation (*ρS(all)*), which captures rank stability rather than the exact magnitude of links, is slightly lower than the Pearson measure but still very high, mainly between 0.85 and 0.95. This suggests that, although the exact values of exposures occasionally adjust, the financial institutions rank order remains highly stable. Even during stress episodes, the hierarchy of relationships in the system is largely preserved.

The behaviour of the complete network tends to mirror individual layers. In particular, the loans layer (*ρP(loans)*) faces a significant dip in 2020Q3, confirming that the shock affected traditional credit exposures. Vice versa, the fund shares layer exhibits a drop in 2024Q3 due to the repatriation of Banco Posta's funds, but this had little influence on the overall correlation, since these were low-rank nodes.

Overall, the figure illustrates that the financial network is extremely persistent over time, with only a few episodes of disruption, and that structural stability is especially strong in the core balance-sheet layers.

Figure 10. Pearson and Spearman correlations between quarter t and quarter t-1



Recurrence plot. Figure 11 displays recurrence plots for the banking (top-left), insurance (top-right), investment fund (bottom-left) layers and for the complete system (bottom-right). By using the Spearman correlation measure, each plot shows how similar the rankings are over time. We mark a recurrence when the similarity is high enough, based on a cutoff chosen from the data (threshold ε corresponds to the lowest 30% of distances between all time points).

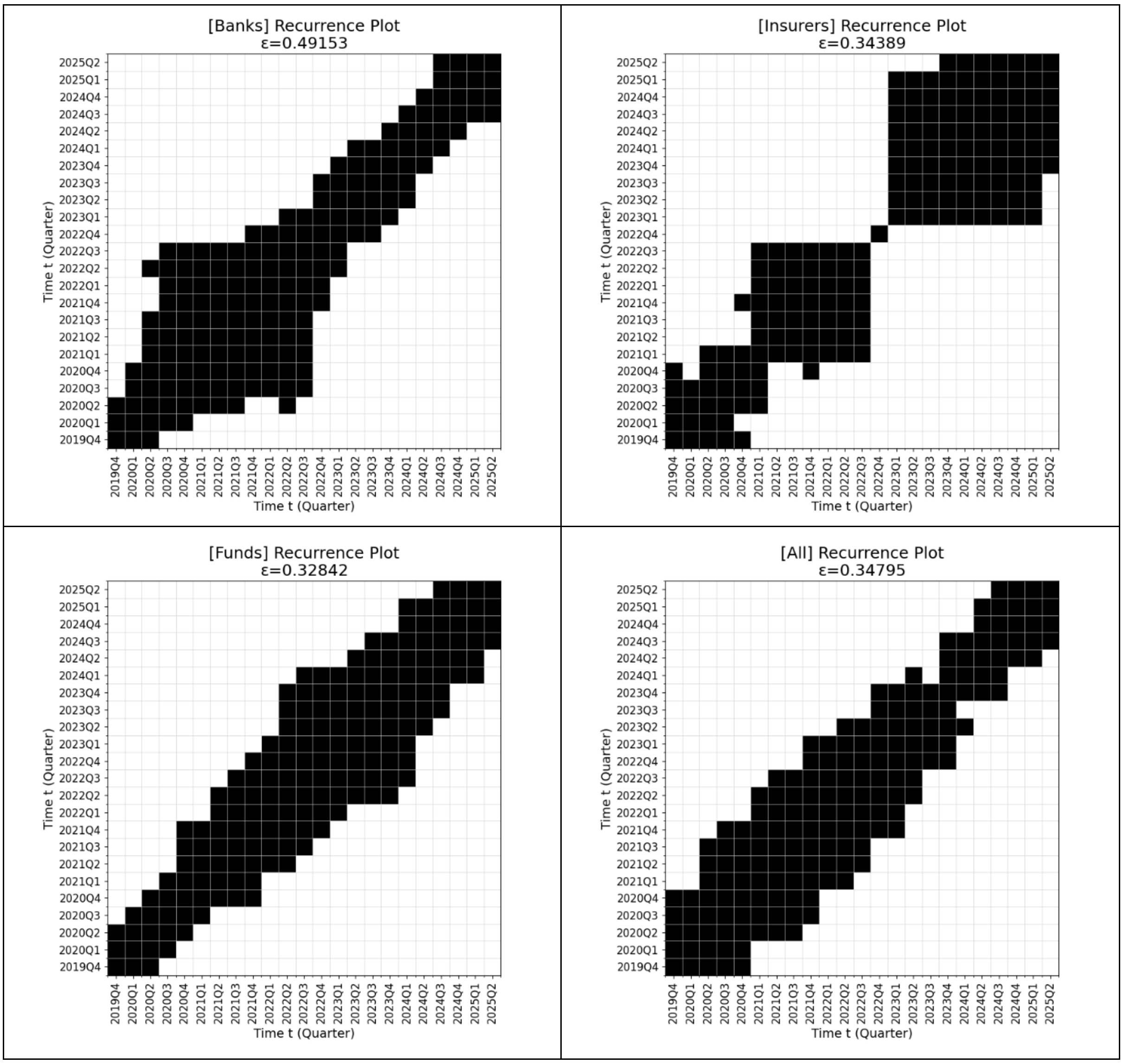
The banking network shows the greatest variation in rankings compared with the other sectors (as indicated by the highest threshold ε ≈0.49). Similarities are concentrated along the diagonal, i.e. nearby time periods, especially from late 2020 to late 2022. This suggests that the evolution of rankings in the banking sector tends to change slowly and the network remains stable for a while, rather than characterized by abrupt regime shifts.

The insurance network shows a clear change over time, with two main periods where rankings are similar: one from early 2021 to late 2022, and another from early 2023 to mid-2025. The break at the end of 2022 reflects a major reordering of rankings, after which the system settles into a new configuration. This behaviour points to a structural transition in insurers' relative positioning, likely driven by consolidation and portfolio reallocation (see Cattolica acquisition in Section 3).

Funds exhibit a pattern similar to banks, where rankings are mainly similar between nearby time periods. Given the large number of fund nodes with generally low rank values, similarities stay limited to short time spans, reflecting ongoing small adjustments rather than major structural changes. This confirms the flexible and adaptive nature of the fund sector.

Finally, the *complete network* reflects the patterns of the individual sectors, but it is mainly shaped by banks and funds because they include many more entities. As a result, the overall pattern mostly shows the same gradual changes seen in these sectors, with only a small effect from the shift observed in insurance. This underscores the importance of analysing sector-specific layers alongside the full system: aggregate measures can mask heterogeneity in structural dynamics.

***Figure 11. The recurrence plots on the complete network and single-layer graphs*[14]**



8. Conclusions and next steps

In this paper, we provide a comprehensive analysis of the Italian financial system through a multilayer network framework that captures interconnections across institutions and financial instruments. Our findings highlight a bank-centred core, significant cross-sector linkages, and the persistence of a sparse yet "small-world" network structure, which together shape the potential propagation of financial shocks. Sectoral consolidation and expansion, particularly in the investment fund sector, generate episodic structural shifts, but the overall architecture remains stable over time.

This analysis opens several avenues for further research. The availability of granular data would allow an investigation of how consolidation events, regulatory interventions, and market disruptions affect the evolution of network topology. Moreover, analysing the evolution of the network metrics without

[14] A plot shows the recurrence, at each coordinate (i, j), computed on the set of nodes resulting from the intersection between G_i nodes and G_j nodes.

intragroup exposure could provide additional insights on the Italian financial network. The metrics introduced here could serve as practical tools for supervisory authorities to closely monitor changes in the structure of the financial system. More broadly, the proposed multilayer perspective offers a flexible and powerful framework for tracking and assessing systemic risk, providing both researchers and policymakers with a deeper understanding of the interdependencies that underpin financial stability.

In addition, an important extension would be to examine how losses during crises depend on the topological characteristics of both the overall network and individual nodes. This analysis would further enhance the policy relevance of this approach.

Finally, extending the analysis to non-financial corporations would allow for a more complete assessment of potential propagation channels in the event of credit or default shocks to the system.

References

Aldasoro, I. & Alves, I., 2018. Multiplex interbank networks and systemic importance: An application to European data. *Journal of Financial Stability,* Volume 35, pp. 17-37.

Allen, F. & Gale, D., 2000. Financial Contagion. *Journal of Political Economy,* 108(1), pp. 1-33.

Bargigli, L. et al., 2015. The multiplex structure of interbank networks, Quantitative Finance. *Quantitative Finance,* 15(4), pp. 673-691.

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

Blondel, V. D., Guillaume, J.-L., Lambiotte, R. & Lefebvre, E., 2008. Fast unfolding of communities in large networks. *Journal of Statistical Mechanics: Theory and Experiment,* p. P10008.

Boss, M., Elsinger, H., Summer, M. & Stefan, T. 4., 2004. Network topology of the interbank market. *Quantitative Finance,* 4(6), pp. 677-684.

Caccioli, F., Barucca, P. & Kobayashi, T., 2018. Network models of financial systemic risk: a review. *Journal of Computational Social Science,* Volume 1, pp. 81-114.

Covi, G., Gorpe, M. Z. & Kok, C., 2021. CoMap: Mapping Contagion in the Euro Area Banking Sector. *Journal of Financial Stability,* Volume 53.

Diestel, R., 2000. *Graph Theory.* s.l.:Springer-Verlag Berlin and Heidelberg GmbH & Company KG.

Dugué, N. & Perez, A., 2015. *Directed Louvain : maximizing modularity in directed networks,* s.l.: Université d'Orléans.

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

Ficarola, F., 2015. Computing on evolving social networks. *Doctoral Dissertation.*

Gómez, S., Fernández, A., Granell, C. & Arenas, A., 2013. Structural patterns in complex systems using multidendrograms. *Entropy,* pp. 5464-5474.

Iori, G. et al., 2008. A network analysis of the Italian overnight money market. *Journal of Economic Dynamics and Control,* 32(1), pp. 259-278.

Jackson, M. O., 2010. *Social and economic networks.* s.l.:Princeton University.

Jerome L Myers, Arnold Well, and Robert Frederick, 2010. *Research design and statistical analysis..* s.l.:s.n.

Joshi, K., 1989. *Foundations of Discrete Mathematics.* s.l.:Wiley.

Milgram, S., 1967. The Small World Problem. *Psychology Today,* Volume 2, pp. 60-67.

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

Newman, M. E. J., 2003. The Structure and Function of Complex Networks. *SIAM Review,* 45(2), pp. 167-256.

Newman, M. E. J., 2006. *Modularity and community structure in networks.* s.l., s.n., pp. 8577–8582,.

Page, L., Brin, S., Motwani, R. & Winograd, T., 1999. *The pagerank citation ranking: Bringing order to the web.* s.l.:s.n.

Paltalidis, N., Gounopoulos, D., Kizys, R. & Koutelidakis, Y., 2015. Transmission channels of systemic risk and contagion in the European financial network. *Journal of Banking & Finance,* Volume 61, pp. S36-S52.

Poledna, S. et al., 2015. The multi-layer network nature of systemic risk and its implications for the costs of financial crises. *Journal of Financial Stability,* Volume 20, pp. 70-81.

Sam, L., Liu, Z. & Ota, T., 2014. Mapping the UK interbank system. *Journal of Banking & Finance,* Volume 45, pp. 288-303.

Soramäki, K. et al., 2007. The topology of interbank payment flows. *Physica A: Statistical Mechanics and its Applications,* 379(1), pp. 317-333.

Torri, G., Giacometti, R. & Paterlini, S., 2018. Robust and sparse banking network estimation. *European Journal of Operational Research,* 270(1), pp. 51-65.

Trapp, M. & Wewel, C., 2013. Transatlantic systemic risk. *Journal of Banking & Finance,* 37(11), pp. 4241-4255.

Van Dongen, S. & Enright, A. J., 2012. *Metric distances derived from cosine similarity and pearson and spearman correlations,* s.l.: arXiv.

Watts, D. J. & Strogatz, S. H., 1998. Collective dynamics of 'small-world' networks. *Nature,* Volume 393, pp. 440-442.