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Exploring Financial Market Interconnectedness Through CDS Spreads: A Network Estimation Approach

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In an increasingly complex global financial system, this paper investigates the interconnectedness among financial institutions by exploiting the informational content of Credit Default Swap (CDS) spreads and their role in transmitting risk across the network of global finance. Using a network-based framework, we model the dynamic interdependencies among CDS spreads through the NETS (Network Estimation for Time Series) algorithm combined with Granger causality analysis. This methodology enables the construction of financial networks, through which we identify the principal actors driving contagion within the financial system. The results reveal a surprisingly central role of non-bank financial institutions in the contagion network—particularly insurance companies—partially challenging traditional assumptions that place banks at the core of systemic risk transmission. Moreover, risk transmission appears distributed rather than geographically concentrated, suggesting the importance of cross-border connections. The study also stimulates debate at the regulatory level, highlighting the need to strengthen regulation across different types of financial institutions, rather than focusing exclusively on banking sector supervision and monitoring.

Keywords: Credit Default Swap (CDS), interconnectedness, financial institutions, systemically important banks (SIBs), financial contagion, insurance companies

Introduction

Global financial integration and the increased complexity of financial products have promoted efficiency while simultaneously exposing the financial system to a higher degree of vulnerability to various types of risk. Over the past three decades, financial innovation and deregulation have progressively blurred the traditional distinctions between hedge funds, mutual funds, insurance companies, banks, and broker/dealers. While these transformations are a natural reflection of economic growth, they have also led to an increase in systemic risk within the financial system. Recent financial crises have demonstrated that the complex web of interconnections

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among economic agents can effectively transmit and amplify shocks throughout the system.

Given the increased complexity of financial systems, regulators, supervisors, policymakers, and scholars are constantly committed to preventing the failure or operational distress of certain institutions from transmitting shocks widely, revealing the complex nature of systemic risk. This latter manifests along three key dimensions: the size of an institution, which affects its potential market impact; the degree of interconnection with other institutions, which amplifies contagion; and the propensity of institutions to engage in collective risk-taking, potentially increasing the likelihood of coordinated distress or bailouts. These factors together shape the vulnerability of the financial system and determine how crises propagate, forming the conceptual basis of the "Too-Systemic-to-Fail" framework (Thomson, 2009).

In recent years, scholars have gradually recognized that the propagation of financial shocks cannot be fully understood by analysing individual institutions in isolation, but must be studied by considering the complex web of relationships between financial intermediaries (De Bandt & Hartmann, 2000; Upper, 2011). Our analysis concentrates on the interconnectedness dimension of the systemic risk, exploiting information embedded in institutions' Credit Default Swap (CDS) spreads, a market-based indicator of perceived default risk. In this context, CDSs have proved to be particularly informative instruments, providing timely measures of perceived credit risk and enabling empirical analysis of contagion dynamics (Peltonen, Scheicher, & Vuillemey, 2014; Elliott, Golub, & Jackson, 2014).

As is well known, CDSs are derivative contracts in which the protection seller agrees to compensate the counterparty if a third-party entity (the "reference entity") is unable to meet its financial obligations, in particular in the event of a default. In exchange for assuming this credit risk, the protection seller is remunerated through a payout, either at the time the contract is stipulated or through periodic payments over the life of the contract. The "CDS spread" represents a measure of the perceived credit risk of the referenced entity, as assessed by the market, and is expressed as the ratio between the annual payments made by the protection buyer and the notional value of the contract. This spread reflects the likelihood of a credit event, and the potential risk associated with the reference entity's ability to meet its financial commitments. Particularly in light of the global financial crisis, CDSs have gained increasing significance, as CDS spreads are often interpreted as long-term indicators of the probability of default and the overall health of the economic system. Trends in CDS spreads over time provide investors with a risk-neutral estimate of the probability of adverse credit events. Therefore, CDS spreads constitute a privileged observatory on the market's perception of the risk and creditworthiness of financial institutions. The structure of these instruments—which trigger payments only in the event of default—makes them particularly effective in providing a timely and direct measure of credit risk, less subject to the distortions of other traditional indicators. Furthermore, unlike other derivative instruments, CDS contracts are generally designed in a relatively simple way, without complex clauses or embedded options. This feature has fostered a rapid expansion of the CDS market over the last two decades, transforming it from a niche market into a highly active and liquid sector. Investors use CDS to trade, hedge, and speculate on the credit risks of reference entities, contributing to create a dynamic market that reflects the real-time perceptions of financial risk.

Our work builds on the growing literature that analyses systemic risk and financial contagion through network-based approaches. In particular, following the strand of research initiated by Billio, Getmansky, Lo, and Pelizzon (2012), who map the principal actors of financial contagion across banks, hedge funds, broker/dealers, and insurance companies, we focus on identifying the main systemic actors and understanding how inter-sectoral linkages can amplify risk. To this end, we draw on network theory, which offers a powerful framework for examining the structure of complex financial linkages and the transmission of systemic risk. Several studies have sought to represent the financial system as a network in which financial institutions are modeled as nodes and their mutual relationships as links. However, existing methodologies frequently rely on highly-parameterized large-scale models and typically depend on aggregate connectivity metrics or extensive datasets. These methodological constraints hinder their performance in empirical settings characterized by incomplete or high-dimensional financial information. Furthermore, by concentrating mainly on the banking sector, much of the literature underrepresents the systemic relevance of non-bank intermediaries. To overcome these limitations, we employ the Network Estimation for Time Series (NETS) framework proposed by Barigozzi and Brownlees (2019), which models financial time series as a Vector Autoregressive (VAR) process augmented with LASSO (Least Absolute Shrinkage and Selection Operator) regularization. This combination is specifically designed to mitigate the curse of dimensionality, allowing for the extraction of statistically robust and directional dependencies among institutions even in settings with limited or noisy data. Building on this methodological structure, we estimate Granger-causality relationships, which enables us not only to detect whether institutions are connected, but also to identify the direction in which shocks propagate throughout the system.

Our analysis, corroborated by a growing body of empirical evidence, Berdin and Sottocornola (2015), Darpeix (2015), Kanno (2016), reveals that institutions not traditionally regarded as systemically important, such as insurance companies, play a significant role in amplifying and transmitting financial shocks, thereby challenging the prevailing focus on banks that dominated the discourse during the 2007-2009 financial crisis and the 2010-2012 European sovereign debt crisis. Our results show that, over the period considered, non-bank institutions, particularly insurers, consistently occupy central positions in the contagion network, suggesting that stricter regulation and stronger capital buffers in the banking sector may have shifted the balance of systemic vulnerability. Moreover, risk transmission among banks appears relatively diffuse rather than concentrated in a few dominant entities. The balance sheet composition and investment strategies of insurance companies emerge as potential channels for amplifying and transmitting shocks, an aspect that is often overlooked in systemic risk monitoring. Finally, the scarcity of geographical clustering underlines the structural importance of cross-border interconnectedness, indicating that systemic vulnerabilities are deeply embedded in a global financial web rather than confined within national borders.

The rest of the paper is organized as follows. Section 2 provides a critical and comprehensive review of the literature on systemic risk and financial interconnectedness, tracing the evolution from bank-centric analyses toward broader frameworks that incorporate multiple types of financial intermediaries. Section 3 describes the methodology used to construct the financial network, namely the NETS (Network Estimation for Time Series). Section 4 provides an overview of the dataset, including the sample of financial institutions and the characteristics of the CDS spread data. Section 5 presents empirical findings, while Section 6 concludes by discussing the implications of the results for financial stability and regulatory oversight.

Inspiring Literature

In recent years, the increasing complexity of the financial system has prompted numerous scholars to investigate the dynamics of interconnection between banking institutions, using network estimation techniques based on market data (Billio et al., 2012; Acemoglu, Ozdaglar, & Tahbaz-Salehi, 2015; Huang, Zhuang, & Yao, 2009). This body of research reflects the growing recognition that risk cannot be fully understood by analysing individual institutions, rather it must be examined through the intricate network of relationships that connect them.

Systemic risk arises when financial difficulties in certain institutions can spread rapidly throughout the entire system, particularly when these institutions are very large or closely linked to other entities (Benoit, Colliard, Hurlin, & Perignon, 2017). These difficulties are generally triggered by an exogenous event that significantly affects a large number of financial institutions or markets, substantially compromising the proper functioning of the entire financial system (De Bandt & Hartmann, 2000). At the heart of this phenomenon is contagion, i.e., the intensive transmission of failures from one institution, market, or system to another. In this direction, The Basel Committee on Banking Supervision (2011) introduced macroprudential measures and stricter capital requirements, highlighting the crucial role of interconnections through derivatives. In particular, Credit Default Swaps (CDSs) play an ambivalent role: risk management tools on the one hand, potential amplifiers of instability on the other, especially in Over the Counter (OTC) markets.

The academic literature has devoted substantial attention to measuring systemic risk within financial networks, emphasizing how interconnections among institutions can amplify contagion. Our paper adds to this research by examining the structure of the CDS market, an instrument widely regarded by scholars and policymakers as central for monitoring financial stability and identifying systemic vulnerabilities.

Early contributions, for instance, Upper (2011), employed simulation methods to conduct empirical network analyses and assess contagion risk in interbank markets. While insightful, such simulation-based approaches often fail to capture the actual characteristics of financial institutions, potentially introducing discrepancies when measuring systemic risk from interpolated data. Building on this, a growing body of research analyzes the structure of the CDS network by applying network theory to finance, specifically in relation to systemic risk (Elliott et al., 2014; Peltonen et al., 2014; Acemoglu et al., 2015). In this field, the study most closely related to ours is Getmansky, Girardi, and Lewis (2016), which employs Granger causality to quantify connectivity within the financial system. Their findings show that highly concentrated interconnections heighten the system’s vulnerability to contagion, particularly in scenarios where one or more central counterparties default. This perspective is complemented by the work of Abbassi, Brownlees, Hans, and Podlich (2017), who broaden the scope of interconnectedness beyond direct exposures, such as those in the wholesale funding market, to include indirect channels related to securities management and credit supply, highlighting the pivotal role of liquidity management in amplifying systemic risk through both the asset and liability sides of banks’ balance sheets. Together, these studies emphasize that the network structure of the financial system—driven by CDS trading and internal balance sheet dynamics—constitutes a fundamental dimension for understanding financial fragility and shaping macroprudential regulation.

Furthermore, complex network theory has found extensive application in the analysis of financial markets. For instance, Huang et al. (2009) leverage stock market data in combination with threshold techniques to build unweighted, undirected networks of securities markets, while also examining their underlying topological properties. D’errico, Battiston, Peltonen, and Scheicher (2018) analyze risk transfers between market participants (i.e. how credit and counterparty risks are transferred) and the structure of the CDS market using network analysis tools. The authors introduce the notion of risk flow in a financial network and propose a graph-theoretical methodology to identify where the risk flow originates. Recent studies, such as Gong, Liu, Xiong, and Zhang

(2019), show that during periods of market stress, financial institutions become increasingly interconnected, and systemic risk measures like Systemic Risk (SRISK), Marginal Expected Shortfall (MES), and Conditional Value at Risk (CoVaR) can identify those institutions that play a central role in amplifying contagion. Armanious (2024) expands on this line of thinking by quantifying, in the context of the Eurozone, the dimensions of Too-Big-, Too-Interconnected- and Too-Many-To-Fail through an integrated set of systemic risk measures. The literature also highlights the role of market fundamentals: Market value-based levers and stock return volatility are significant determinants of bank credit risk (Hasan, Liu, & Zhang, 2016), with amplified effects in times of crisis. Within this strand of research, a substantial body of work concentrates on the banking sector and particularly on interbank networks. The study by Giacometti, Torri, Farina, and De Giuli (2020) makes a significant contribution by analysing credit risk from a systemic perspective. The authors analyse the network structure of the non-systemic risk component to assess how interbank linkages drive risk transmission. They uncover strong North-South differences: In Southern Europe, systemic risk is heavily influenced by idiosyncratic and national-financial factors, particularly during the sovereign debt crisis, while in Northern Europe financial and idiosyncratic shocks dominate with little national impact. Despite this heterogeneity, the network remains highly interconnected, with Spanish, German, and UK banks persistently emerging as central nodes that shape contagion dynamics and amplify systemic risk. Mikropoulou and Vouldis (2023; 2025) extend the simulation framework of Gai, Haldane, and Kapadia (2011) to model financial contagion within the euro area interbank network, incorporating both direct and indirect transmission channels. Using supervisory data on bilateral exposures among systemically important banks, the study shows that indirect contagion—driven by time-varying risk aversion and procyclical haircuts—can generate nonlinear amplification effects, often exceeding the impact of direct contagion and turning localized shocks into systemic events. In a different context, Mananga, Lin, and Zhang (2025) investigate contagion within the South African interbank market using an agent-based model combined with the DebtRank algorithm, focusing on how interbank exposures and capital structures shape systemic vulnerability. They find that banks with higher interbank-lending-to-equity ratios are significantly more fragile, and that network-based measures outperform market-based ones in capturing systemic risk.

To further investigate the dynamics of systemic contagion, Caiazzo and Zazzaro (2023) analyse systemic risk in the euro area banking sector using a multilevel network approach, which integrates interbank exposures, market linkages, and holdings of common assets. Their results highlight how interactions between different layers can amplify the spread of contagion, with liquidity and market channels often reinforcing balance sheet effects. The study demonstrates that multilevel networks provide a more realistic assessment of systemic vulnerability than single-layer models, especially in stress scenarios, confirming the importance of considering the complexity of interconnections between financial institutions.

In more recent developments, the literature has also highlighted the growing importance of advanced tools for analysing interconnections and risk propagation. In particular, the use of machine learning techniques makes it possible to process large amounts of market data and identify non-linear configurations that traditional models struggle to capture (Kou et al., 2019). These approaches complement network analysis methods, providing dynamic estimates of the relationships between financial institutions and improving the ability to monitor contagion mechanisms in CDS markets. This is the context for NETS (Network Estimation for Time Series), a tool particularly suited to study the temporal evolution of connections between intermediaries, as it allows networks to be constructed based on financial variables and analyses to be carried out on how shocks are transmitted through the system over time.

Also based on network-oriented approaches, Billio et al. (2012) propose a set of econometric tools to quantify intersectoral connectivity, applying principal component analysis and Granger causality tests to the monthly returns of banks, hedge funds, broker/dealers, and insurance companies. Their results show a marked increase in financial interdependence over the past decade, with banks playing a central role in the propagation of shocks. This asymmetry is particularly evident during times of crisis—such as the 2007-2009 period—where banks and insurers exerted a stronger influence on other financial entities than vice versa. Furthermore, Kanno (2016) applies network methods to analyze systemic risk in the non-life insurance market, highlighting how the structure of interconnections can amplify vulnerabilities. Similarly, Berdin and Sottocornola (2015) investigate the contribution of insurance companies to systemic risk relative to banks and non-financial firms, using CoVaR, Dynamic Marginal Expected Shortfall (DMES), and Granger causality tests. Their results show that, although insurers generally contribute less to systemic risk than banks, certain institutions within the sector can play a significant role during periods of market stress, underscoring the heterogeneous nature of systemic exposure in insurance activities.

While earlier evidence, such as Nyholm (2012), points to a symmetric interdependence between banks and insurers, subsequent studies reveal a more complex dynamic. Chen, Cummins, Viswanathan, and Weiss (2014) show that shocks transmitted from banks tend to have stronger and more persistent effects on insurers, indicating that the banking sector remains the main driver of systemic contagion. However, more recent analyses suggest that the insurance sector itself has become increasingly systemically relevant. In particular, Darpeix (2015) argues that, although traditional insurance activities were long viewed as stabilizing forces within the financial system, structural and technological developments, such as reinsurance concentration, closer ties with banks through bancassurance groups, and the use of securitization and derivatives, have amplified insurers' potential to propagate systemic risk.

These findings confirm the need to monitor and understand the dynamics of interconnectedness among banks, as their position in the financial network is crucial for predicting and mitigating contagion risks in future crises. The literature on CDS and systemic risk has three main limitations: (i) high-dimensional models that do not allow for the identification of robust directional connections; (ii) an excessive focus on the banking sector, with the role of insurance companies and non-bank intermediaries still largely unexplored; (iii) predominantly regional studies that do not allow for comparisons between different geographical networks. Our work contributes by overcoming these limitations through the use of the NETS framework Barigozzi and Brownlees (2019) applied to CDS, allowing us to estimate globally sparse Granger-causal networks. We show that, contrary to the dominant bank-centric approach, the insurance sector emerges as the main driver of risk transmission, with clear differences between Europe and the United States.

Data

We download data from the Refinitiv Database, obtaining weekly frequency data for financial institutions worldwide from January 1, 2015, to December 1, 2022. Specifically, we collect CDS spreads for senior unsecured instruments, in line with the selection criteria of Jorion and Zhang (2007), as these are the most liquid and represent the largest segment of the overall CDS market. CDSs are particularly suitable for our analysis because they are unique financial instruments that replicate the payment structure of an insurance contract. In a CDS contract, certain debt securities of a reference entity serve as the underlying asset, and the CDS seller provides protection to the buyer against default on these securities. The buyer does not need to hold an insurable interest in the reference entity to purchase protection and pays a periodic spread to the seller. If the reference entity defaults, the seller compensates the buyer for the notional amount of the contract, depending on the nature of the default. Consequently, CDSs allow both buyers and sellers to diversify their portfolios, while the reference entity can observe how the market perceives its default risk. To ensure data quality, we exclude series with low variability, specifically those with a coefficient of variation (the ratio of the standard deviation to the absolute value of the mean) below 0.1, which may indicate poor liquidity in the traded CDS. As a result, the initial sample of 234 financial institutions is reduced to 88, which are categorized into five types of financial intermediaries: banks, insurance companies, leasing companies, real estate intermediaries, and other financial intermediaries. Moreover, the data are first-differenced to ensure the stationarity of the time series. The Appendix provides detailed information on the financial intermediaries included in the analysis. To complement this data, the following table illustrates the geographical and sectoral representativeness of the banks in the sample.

Table 1

Geographical and Sectoral Composition

	Sectoral composition						
Country	Other financial intermediaries	Banks	Insurance	Leasing	Real estate intermediaries	Numerosity	Tot
USA	13	8	12	1	4	38	43.18%
UK	8	3	1		1	13	14.77%
ITA		4	1			5	5.68%
FRA	2	3	1		3	9	10.23%
SPA		1				1	1.14%
LUX	2					2	2.27%
SWE		2				2	2.27%
SWI	1	1				2	2.27%
DEU	1	2	2			5	5.68%
NLD	1	2	1			4	4.55%
DEN		1				1	1.14%
POR		1				1	1.14%
NOR		1				1	1.14%
IRL	1					1	1.14%
IRE	1					1	1.14%
BERMUDA		1				1	1.14%
JPY				1		1	1.14%
Tot	30 (34.09%)	30 (34.09%)	18 (20.45%)	2 (2.27%)	8 (9.09%)	88	100%

Source: Authors own work.

Methodology Description

To address the proposed aim, we employ a network-based estimation approach for time series data, utilizing the NETS (Network Estimation for Time Series) framework proposed by Barigozzi and Brownlees (2019) to analyse default contagion and interconnectedness in the financial sector. The methodology begins with data collection and preprocessing, where weekly financial time series data are first differenced to ensure comparability and satisfy the assumptions underlying the proposed model. To capture the interconnectedness of financial institutions, we construct a Granger-causal network, where nodes represent financial institutions and directed edges indicate significant predictive relationships. The underlying dependencies are modelled using a sparse

Vector Autoregression (VAR) model of order, given by:

$$X_t = A_1 X_{t-1} + A_2 X_{t-2} + \cdots + A_p X_{t-p} + \epsilon_t$$

where $\{X_i\}_{i=t,t-1,t-2\ldots t-p}$ repesents the matrix (txn) of financial data and its lag versions, A_p are coefficient matrices, and $\epsilon_t \sim \mathcal{N}(0,\Sigma)$ is the error term. Since our data have been first-differenced, and after verifying stationarity, we propose estimation with only one lag ($p = 1$). Moreover, we use Granger causality as a measure of dynamic interdependence in this context, that formally could be expressed with the following inequality:

$$\mathrm{E}\left[\left(x_{i,t+k} - \mathrm{E}\left(x_{i,t+k} \mid \{x_{1,t} \cdots x_{n,t}\}\right)\right)^2\right] \neq \mathrm{E}\left[\left(x_{i,t+k} - \mathrm{E}\left(x_{i,t+k} \mid \{x_{1,t} \cdots x_{n,t}\} \setminus x_{jt}\right)\right)^2\right]$$
$$\forall k > 1$$

Formally there is a Granger causality of x_{jt} on $x_{i,t}$ if the prediction of the future value of $x_{i,t}$ is improved (in terms of Mean squared error) when the series of x_{jt} is included in the model.

To reduce estimation complexity, ensure sparsity, and improve interpretability, we incorporate a LASSO regularization into the model. First of all, the equation of VAR is rewritten in equation-by-equation format:

$$x_{it} = \sum_{k=1}^{p} \sum_{j=1}^{n} \alpha_{ijk} x_{j,t-k} + \epsilon_{it}$$

where α_{ijk} represents the $i - j$ component of the A_k coefficient matrix where k = 1…p.

This could be rewritten as in Barigozzi and Brownless (2019) as:

$$x_{i,t} = \sum_{k=1}^{p} \sum_{j=1}^{n} \left(\alpha_{ij,k} - \sum_{\substack{l=1 \\ l \neq i}}^{n} \rho^{il} \sqrt{\frac{c_{ll}}{c_{ii}}} \alpha_{lj,k} \right) x_{j,t-k} + \sum_{\substack{h=1 \\ h \neq i}}^{n} \rho^{ih} \sqrt{\frac{c_{hh}}{c_{ii}}} x_{\mathrm{h},t} + u_{i,t}$$

where $\rho^{ij} = corr(\epsilon_{i,t}, \epsilon_{j,t} | \{\epsilon_{k,t} : k \neq i,j\}$ is the partial correlation of VAR innovations and c_{ii} which is the (i,i) element of the long-run concentration matrix[1]. The authors finally proposed the LASSO estimation in the following way:

$$\min_{a,\rho,c} \left[\frac{1}{T} \sum_{t=1}^{T} \sum_{i=1}^{n} \left(x_{it} - \sum_{k=1}^{p} \sum_{j=1}^{n} \left(\alpha_{ijk} - \sum_{\substack{l=1 \\ l \neq i}}^{n} \rho^{il} \sqrt{\frac{c_{ll}}{c_{ii}}} \alpha_{ljk} \right) x_{jt-k} - \sum_{\substack{h=1 \\ h \neq i}}^{n} \rho^{ih} \sqrt{\frac{c_{hh}}{c_{ii}}} x_{ht} \right)^2 \right.$$
$$\left. + \lambda_T^{\mathrm{G}} \textstyle\sum_{k=1}^{p} \sum_{i,j=1}^{n} \dfrac{|\alpha_{ijk}|}{|\tilde{\alpha}_{Tijk}|} + \lambda_T^{\mathrm{C}} \sum_{\substack{l,h=1 \\ l>h}}^{n} \dfrac{|\rho^{lh}|}{|\tilde{\rho}_T^{lh}|} \right]$$

where the term in blue represents the penalizing factor that affects Granger causality (and thus also the long-run relationship), while the term in red influences the contemporaneous correlation. λ_T^{G} and λ_T^{C} represent the tuning parameter that controls the number of nonzero entries. The authors demonstrated mathematically that the regularization augmentation has the oracle property and so is efficient in discarding ineffective links among the financial players. We focus on long-run influences by employing Granger causality networks, as the primary objective of this paper is to uncover structural and persistent interdependencies, rather than short-term dynamics that may be driven by transitory or momentary shocks.

[1] This matrix is obtained from the moving average representation of the process and encapsules information on how shocks accumulate over time and influence the system's long-run variability.

Empirical Findings

In this section the results of the analysis described above are shown. Figure 1 presents the estimated financial network obtained using the NETS (Network Estimation for Time Series) algorithm, developed by Barigozzi and Brownlees (2019), applied to changes in CDS spreads for a sample of 88 financial institutions. This methodology captures Granger-causal relationships among CDS movements, thereby uncovering the interdependence structure underlying systemic risk transmission. In the graph, a directed arrow from Node A to Node B indicates that past values of A help predict future values of B, i.e., A Granger-causes B. Network visualization reflects both the presence of Granger-causal links and the out-degree centrality of each node, which measures the number of institutions influenced by a given financial entity.

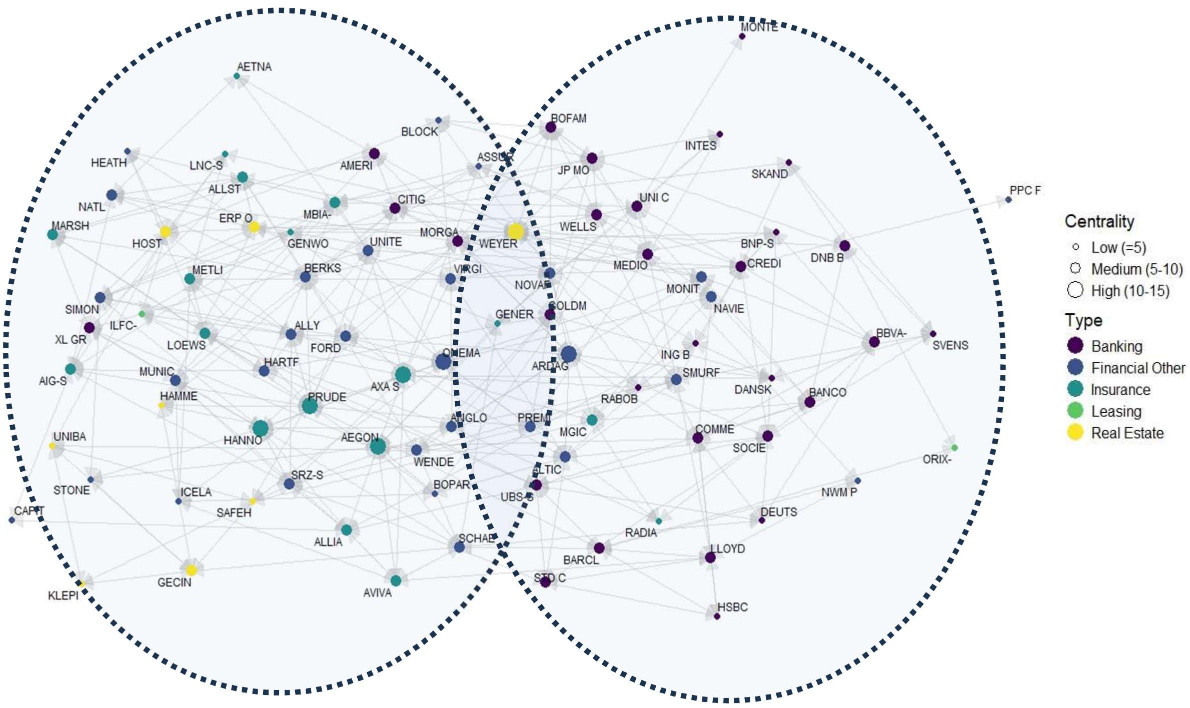

Figure 1. Granger causation in the entire set differentiated by sector type.
Source: Authors own work.

Tables 2 and 3 summarise the main empirical results concerning the centrality of financial intermediaries within the contagion network constructed through Granger causality relationships between weekly variations in CDS spreads.

Table 2 reports descriptive statistics of centrality by institution type (mean, maximum and median). The results indicate that insurance companies have the highest mean centrality value (7.44), followed by real estate companies (6.88) and other financial intermediaries (6.80). Banks, traditionally considered central nodes in systemic risk transmission mechanisms, show a slightly lower average centrality (6.60), while leasing companies are marginal (3.50). This evidence suggests a possible reconfiguration of contagion channels, in which non-bank actors assume a more marked systemic role.

Table 2

Centrality by Institution Type

Type	Avg centrality	Max centrality	Median centrality
Insurance	7.44	13	7.00
Real estate	6.88	15	5.50
Financial other	6.80	11	7.00
Banking	6.60	10	7.00
Leasing	3.50	5	3.50

Source: Authors own work.

Table 3 reinforces this observation by listing the 10 institutions with the highest values of network centrality. It can be observed that nine out of 10 belong to sectors other than banking (real estate, insurance and other financial intermediaries). In particular, WEYER (real estate), PRUDE, and AEGON (insurance) occupy the top positions with centrality values between 12 and 15. The only bank in the Top 10 is CITIG, with a centrality value of 10. These empirical results highlight how, in the period and in the sample analyzed, systemic centrality is not exclusive to the banking sector but is shared—and in some cases dominated—by non-banking financial intermediaries. These entities, often characterized by less regulation than traditional banking institutions, may be more exposed to market fluctuations and, therefore, play a crucial role in systemic risk propagation processes.

Table 3

Centrality Bins by Institution

Name	Type	Centrality	Centrality_bin
WEYER	Real estate	15	High (10-15)
PRUDE	Insurance	13	High (10-15)
AEGON	Insurance	12	High (10-15)
ARDAG	Financial other	11	High (10-15)
AXA S	Insurance	11	High (10-15)
HANNO	Insurance	11	High (10-15)
ONEMA	Financial other	11	High (10-15)
ALLY	Financial other	10	Medium (5-10)
BERKS	Financial other	10	Medium (5-10)
CITIG	Banking	10	Medium (5-10)

Source: Authors own work.

The network represented in Figure 1 shows the interconnectedness structure across institutions, highlighting who is influencing whom. A notable observation is that banks, traditionally considered central in financial contagion, appear more dispersed toward the periphery even though they Granger-cause other institutions in the sample. In contrast, insurance companies and other non-bank financial institutions exhibit higher centrality, suggesting a more prominent role in risk propagation. This result indicates that, within this particular dataset and time period, non-bank financial institutions may have played a more significant role in driving CDS fluctuations. This reversal of expected roles implies potentially different perspectives on the determinants of systemic vulnerability in the observed period. Potential explanations of this phenomenon include differences in market exposure, regulatory constraints, or liquidity dynamics. Specifically, banks may have exhibited greater stability, likely due to stronger regulatory oversight, higher capital buffers, stricter post-crisis regulatory frameworks, such as Basel III, and may have reduced banks' exposure to financial contagion by improving their resilience to market shocks, reducing their susceptibility to acting as channels of systemic risk propagation. Moreover, access to Central Bank liquidity facilities during periods of market stress may have further cushioned banks from destabilizing shocks. In contrast, non-bank financial institutions, operating under different regulatory constraints, may have been more vulnerable to market fluctuations, leading to greater volatility in their CDS spreads and a more central position in the network. In addition to these findings, Figure 1 reveals the presence of sectoral clustering, where financial institutions belonging to the same sector—particularly insurance companies and other non-bank intermediaries—tend to be more interconnected among themselves. This pattern suggests that risk transmission mechanisms are often stronger within sectors before spreading across the broader financial system. This sectoral segmentation of risk transmission mechanisms has important implications for macroprudential policy, as it highlights the importance of monitoring systemic risk at the aggregate level, but also in terms of the specific vulnerabilities of certain sectors. Furthermore, the network structure exhibits a core-periphery configuration: A small group of highly interconnected institutions acts as central hubs, while the majority of entities remain relatively peripheral. This topology implies that only a few institutions exhibit centrality in both transmitting and receiving shocks, while the majority, typically the largest and most solid institutions, appear to be less affected by outward-pushing forces. Finally, the absence of pronounced geographical clustering suggests that systemic interdependencies transcend national boundaries, highlighting the importance of cross-border linkages in the global transmission of financial contagion. To further refine these insights, we differentiate institutions by geographical origin in Figure 2.

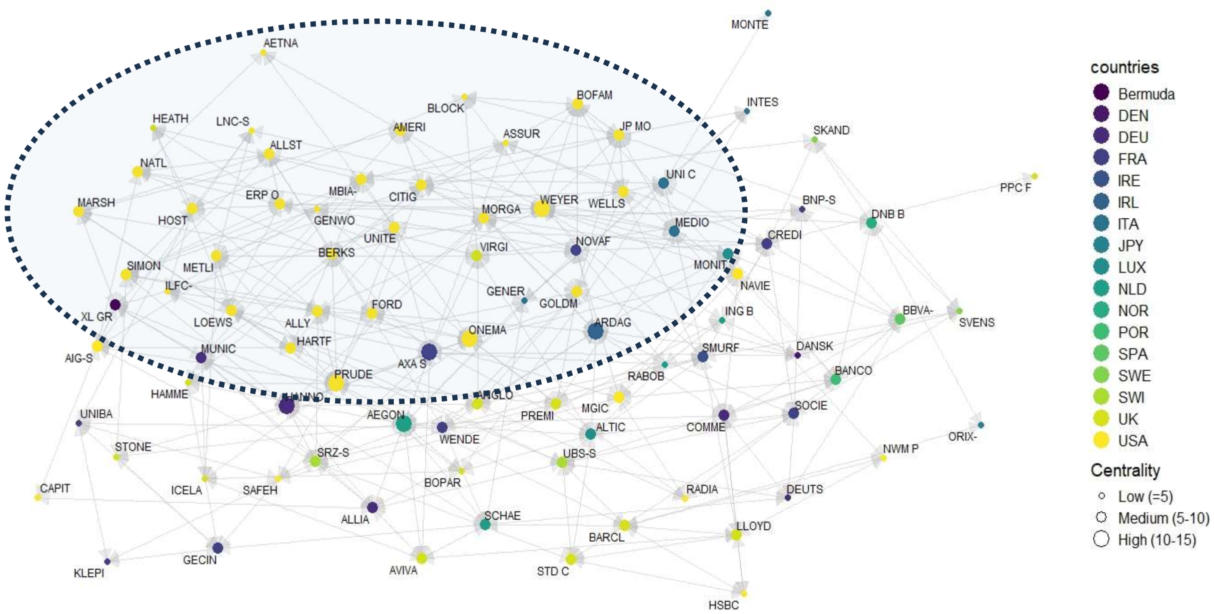

Figure 2. Granger causation in the entire set differentiated by geographical origin.

Source: Authors own work.

Figure 2 displays the financial network differentiated by geographical origin. A noticeable pattern of country-level polarization emerges, with financial institutions from the same region or country tending to cluster together, displaying denser interconnections among themselves, particularly within the US market. This suggests a stronger flow of predictive influence within national or regional boundaries, highlighting the role of geographic proximity or shared market conditions in shaping systemic linkages. In addition to the geographical clustering,

Figure 2 visually highlights the strong concentration of U.S. financial institutions, represented by a dense aggregation of yellow nodes. This visual pattern underscores not only the numerical predominance of U.S. institutions in the sample, but also their significant degree of interconnection, suggesting that systemic risk transmission within the U.S. market may be particularly intense. In contrast, institutions from other countries appear more scattered and less densely interconnected, reflecting varying levels of internal systemic vulnerability. In addition, the network suggests the presence of key cross-border connectors, where a few institutions link different regional clusters, acting as potential channels for international contagion. These observations emphasize the dual importance of both domestic systemic dynamics and transnational linkages in understanding the propagation of financial shocks. In summary, the results shown in Figures 1 and 2 highlight a complex and evolving pattern of systemic risk transmission, in which non-bank financial institutions and cross-sector and cross-border linkages play a key role. This has potential implications in terms of systemic risk monitoring policies and prudential supervision of the financial system as a whole. To gain deeper insights, we narrow our analysis to the banking sector and present the resulting network obtained through the proposed methodology in the following graph.

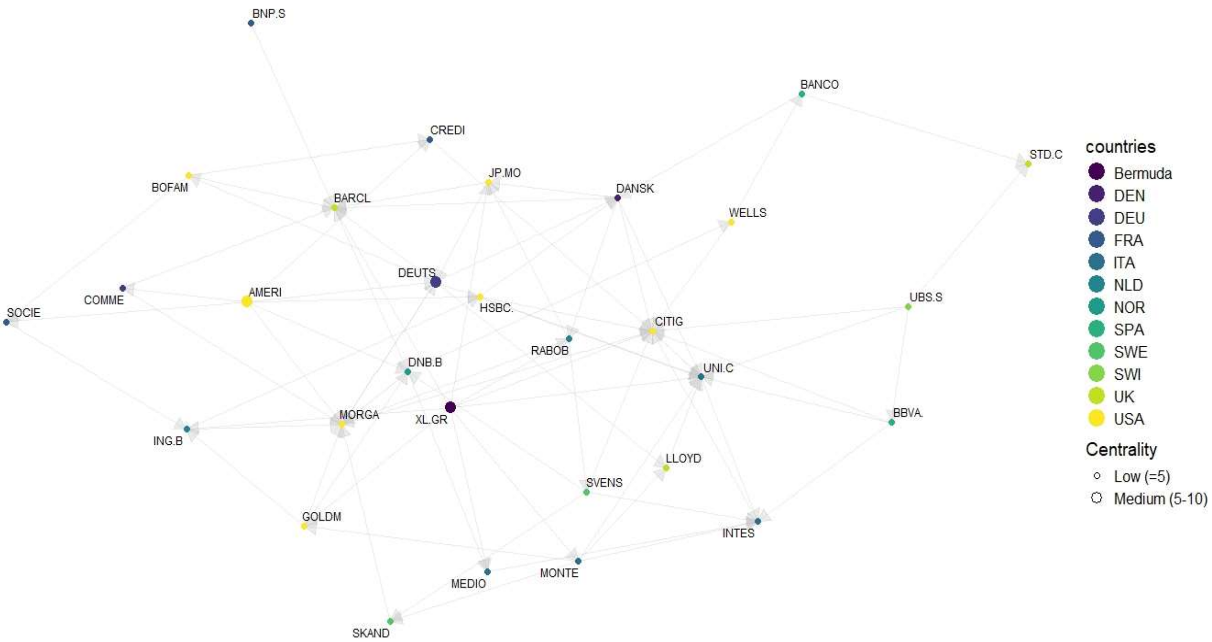

Figure 3. Granger causation in the banks set.
Source: Authors own work.

Banks appear relatively dispersed, with no clear single dominant institution. This suggests that systemic risk transmission in the banking sector is relatively distributed rather than being concentrated in a few key players. Some banks, such as XL.GR, DNB.B, and HSBC, exhibit higher centrality, implying they play a larger role in transmitting financial shocks. These institutions could be more interconnected and potentially more vulnerable to systemic events. Peripheral banks, such as BNP.S and BANCO, have low centrality, indicating they do not significantly influence or transmit risk to the broader system. This might suggest either a more stable financial position or reduced exposure to interbank contagion channels. Geographic clustering is limited, meaning systemic risk transmission does not seem to be strongly country-dependent. This suggests that international banking linkages play an important role in financial contagion.

Figure 4 depicts the network of causal relationships between the insurance companies included in the sample, constructed by applying the NETS algorithm to weekly changes in CDS spreads. The nodes indicate individual insurance companies, while the directional links represent Granger causal relationships, i.e. situations in which changes in the CDS of one entity help predict those of another. The node size reflects the degree of centrality (measured as out-degree), while the colour identifies the country of origin. Several significant findings emerge from the representation. First, a high density of connections is observed, indicating a strong interdependence between insurance companies. The average centrality in the insurance sector (as already indicated in Table 2) is the highest among all categories of intermediaries, and the figure offers a visual confirmation of this: Many companies show a medium degree of centrality (circles with contours), and some are highly connected, such as LOEWS, METLI, GENWO and PRUDE, which act as true hubs in the system. Moreover, another relevant element is the strong concentration of US entities (yellow nodes), consistent with the composition of the sample, but also indicative of a structural dominance of the US insurance market in the propagation of systemic risk. These institutions seem to constitute a particularly integrated subsystem, characterised by numerous internal connections, but also by cross-border links with European companies (e.g. AXA S, AEGON, GENER). This reinforces the idea, already emerging from the previous figures, that sectoral interconnections are not limited to national borders, but rather reflect global market dynamics. Finally, the network shows a core-periphery pattern: Some companies hold central positions in the transmission of shocks, while others, although connected, remain in peripheral positions (e.g. MBIA, QBE.I). This pattern is particularly relevant from a regulatory perspective, as it highlights the existence of a systemically relevant core of insurers that, in the event of exogenous shocks, could rapidly amplify or transmit risk to the rest of the financial system.

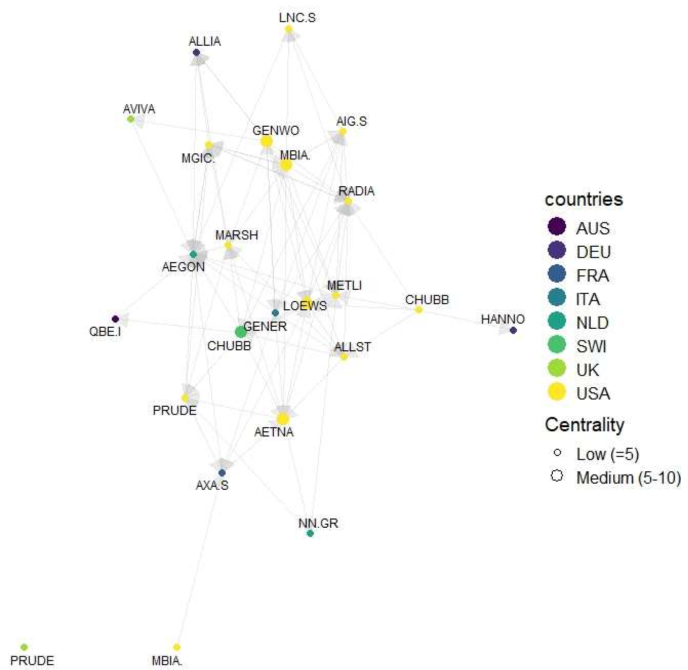

Figure 4. Granger causation in the insurance set.
Source: Authors own work.

Overall, Figure 4 underlines the importance of reconsidering the role of insurers in assessing and managing systemic risk, moving beyond the traditionally bank-centric approach. Their network positioning and degree of interconnectedness make them crucial players in the contagion network, with direct implications for supervisory policies and the construction of more inclusive macroprudential tools. To further explore the geographical dimension of systemic risk transmission, we replicate the network analysis separately for European and U.S. financial institutions.

Figure 5 illustrates the contagion network among European intermediaries. The structure appears relatively heterogeneous, with centrality dispersed across both banks and insurers, and a strong incidence of cross-border connections. Institutions from Germany and France emerge as relatively more central, yet the overall configuration does not reveal the dominance of a few actors, but rather a distributed system of interconnectedness.

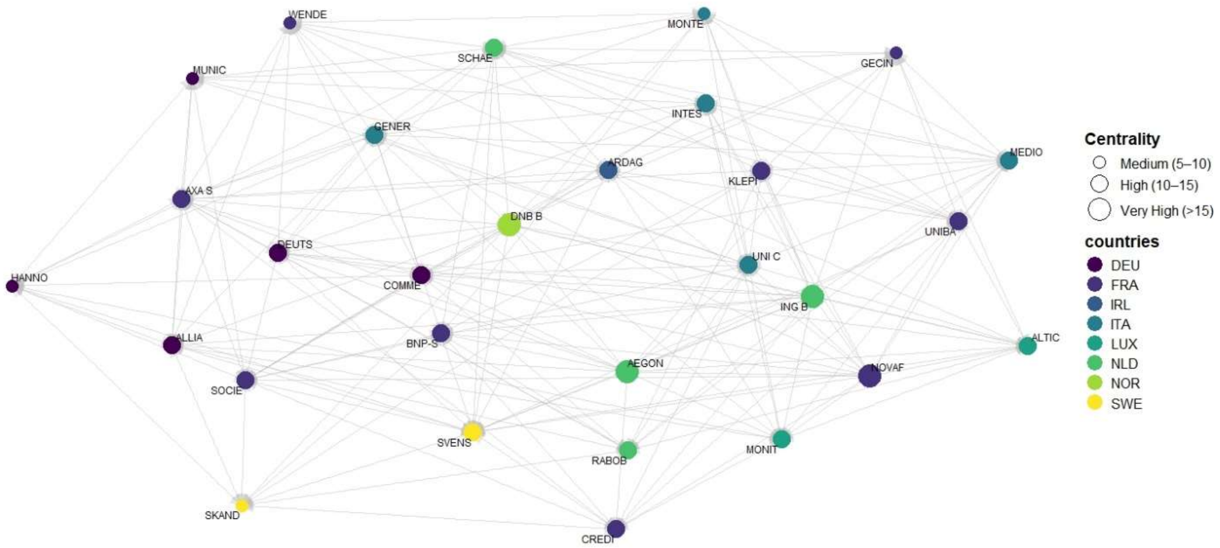

Figure 5. Granger causation in the European set of financial institutions.
Source: Authors own work.

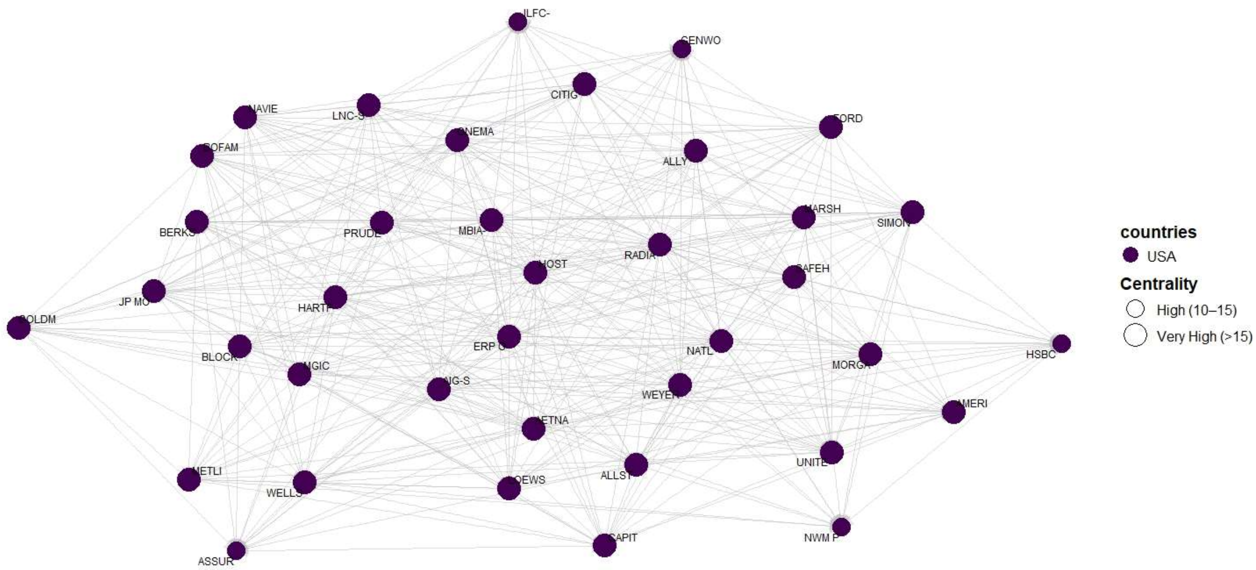

Figure 6. Granger causation in the U.S.A. set of financial institutions.
Source: Authors own work.

Figure 6 presents the network of U.S.A. financial institutions, which exhibits a much denser topology and a higher concentration of central nodes. In this case, large banks and insurance companies play a dominant role, acting as hubs that connect multiple segments of the financial system and amplifying the potential for shock propagation. This comparison highlights a key structural difference: While the European network reflects a more fragmented and diversified pattern of systemic vulnerability, the U.S. network reveals a concentrated configuration, where systemic risk is more likely to be channeled through a limited number of highly interconnected institutions. These findings suggest that contagion mechanisms are shaped not only by sectoral specialization but also by regional market structures and regulatory environments.

Conclusion

This paper examines the interconnectedeness across financial institutions by analysing movements in Credit Default Swap (CDS) spreads within a network-theoretic framework. Employing the NETS algorithm to estimate sparse Granger-causal relationships, we construct a directed network that captures both the strength and direction of contagion channels. This approach enables the identification of institutions that occupy central positions in the transmission of shocks. Our results point to a notable departure from conventional expectations: Banks appear relatively peripheral within the CDS-based contagion network, while insurance companies and other non-bank financial intermediaries exhibit pronounced centrality. This asymmetry may reflect the regulatory environment of our sample, which includes numerous European banks operating under the Basel post-crisis framework. The strengthening of capital standards and macroprudential supervision likely enhanced their resilience, thereby limiting their role as systemic transmitters.

In contrast, non-bank financial intermediaries—often subject to looser prudential constraints—seem to play a more prominent role in propagating market shocks. Within the banking sector, systemic influence appears diffuse rather than concentrated. Although certain institutions exhibit higher centrality, the European network does not display clear country-level clustering. This contrasts with the U.S. financial system, which features a more hub-and-spoke structure where a small set of key institutions can serve as powerful amplifiers of shocks. The comparatively decentralized European architecture may thus confer greater robustness by preventing contagion from being channelled through a few dominant nodes.

The policy implications are substantial. Macroprudential frameworks remain predominantly bank-centric; yet, our evidence underscores the rising systemic relevance of non-bank financial institutions. Enhancing regulatory oversight of these entities—particularly insurance companies—appears critical. Although insurers have traditionally been viewed as less systemically sensitive due to their long-term liabilities, their increasing engagement in derivatives markets, securities lending, and other activities tightly linked to market conditions elevates their susceptibility to contagion. Combined with their comparatively limited inclusion in stress-testing and macroprudential assessments, this creates a material regulatory blind spot. Strengthening cross-sector monitoring tools, adapting solvency requirements to better reflect cross-institutional linkages, and more systematically integrating insurers into systemic risk frameworks would represent important regulatory advancements. These conclusions are consistent with warnings issued by the Financial Stability Board (2020) concerning the need to broaden the macroprudential perimeter, as well as recommendations by the Basel Committee on Banking Supervision (2010), which highlighted interconnectedness—particularly via derivatives exposures—as a critical channel of systemic amplification.

Methodologically, our results demonstrate the value of network-based and causality-driven approaches in studying systemic risk. Such techniques reveal complex, dynamic interdependencies that traditional entity-level analyses often overlook. Future research may benefit from expanding the temporal scope of the analysis, incorporating higher frequency or institution-level balance sheet data, evaluating the impact of major macroeconomic shocks on network structure, or comparing the performance of alternative network estimation methods.

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Appendix A

Table A

Samples

	Tag	Sector	Country		Tag	Sector	Country
1	AEGON	Insurance	NLD	46	INTES	Banking	ITA
2	AETNA	Insurance	USA	47	JP MO	Banking	USA
3	ALLIA	Insurance	DEU	48	KLEPI	Real estate	FRA
4	ALLST	Insurance	USA	49	LNC-S	Insurance	USA
5	ALLY	Financial other	USA	50	LLOYD	Banking	UK
6	ALTIC	Financial other	LUX	51	LOEWS	Insurance	USA
7	AMERI	Banking	USA	52	MARSH	Insurance	USA
8	AIG-S	Insurance	USA	53	MBIA-	Insurance	USA
9	ANGLO	Financial other	UK	54	MEDIO	Banking	ITA
10	ARDAG	Financial other	IRL	55	METLI	Insurance	USA
11	GENER	Insurance	ITA	56	MGIC	Insurance	USA
12	ASSUR	Financial other	USA	57	MONIT	Financial other	LUX
13	AVIVA	Insurance	UK	58	MORGA	Banking	USA
14	AXA S	Insurance	FRA	59	MUNIC	Financial other	DEU
15	MONTE	Banking	ITA	60	NATL	Financial other	USA
16	BBVA-	Banking	SPA	61	NWM P	Financial other	USA
17	BANCO	Banking	POR	62	NAVIE	Financial other	USA
18	BOFAM	Banking	USA	63	NOVAF	Financial other	FRA
19	BARCL	Banking	UK	64	ONEMA	Financial other	USA
20	BERKS	Financial other	USA	65	ORIX-	Leasing	JPY
21	BLOCK	Financial other	USA	66	PREMI	Financial other	UK
22	BNP-S	Banking	FRA	67	PRUDE	Insurance	USA
23	BOPAR	Financial other	UK	68	PPC F	Financial other	UK
24	CAPIT	Financial other	USA	69	RADIA	Insurance	USA
25	CITIG	Banking	USA	70	SAFEH	Real Estate	USA
26	COMME	Banking	DEU	71	SCHAE	Financial other	NLD
27	RABOB	Banking	NLD	72	SRZ-S	Financial other	SWI

28	CREDI	Banking	FRA	73	SIMON	Financial other	USA
29	DANSK	Banking	DEN	74	SKAND	Banking	SWE
30	DEUTS	Banking	DEU	75	SMURF	Financial other	IRE
31	DNB B	Banking	NOR	76	SOCIE	Banking	FRA
32	ERP O	Real estate	USA	77	STD C	Banking	UK
33	FORD	Financial other	USA	78	STONE	Financial other	UK
34	GECIN	Real estate	FRA	79	SVENS	Banking	SWE
35	GENWO	Insurance	USA	80	UBS-S	Banking	SWI
36	GOLDM	Banking	USA	81	UNIBA	Real estate	FRA
37	HAMME	Real estate	UK	82	UNI C	Banking	ITA
38	HANNO	Insurance	DEU	83	UNITE	Financial other	USA
39	HARTF	Financial other	USA	84	VIRGI	Financial other	UK
40	HEATH	Financial other	UK	85	WELLS	Banking	USA
41	HOST	Real estate	USA	86	WENDE	Financial other	FRA
42	HSBC	Banking	USA	87	WEYER	Real estate	USA
43	ICELA	Financial other	UK	88	XL GR	Banking	Bermuda
44	ING B	Banking	NLD				
45	ILFC-	Leasing	USA				