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From Regulation to Interconnection: Mapping the Evolution of the U.S. Interbank Market

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Abstract

The U.S. interbank market, a critical component of financial stability, has undergone significant transformations over the past four decades, driven by regulatory reforms, technological advancements, and economic shocks. This paper investigates the evolution of the interbank network structure among mid-size and large U.S. banks from 1984 to 2024. We construct quarterly interbank networks based on the cosine similarity of interbank exposure profiles derived from Call Reports and analyze their topological properties, including density, centrality, community structure, and modularity. A key focus is mapping major legislative and regulatory changes (e.g., the Riegle-Neal Act, GLBA, and Dodd-Frank Act) to observed shifts in network topology and interconnectedness. Furthermore, we employ temporal graph neural networks (TGNNs), such as EvolveGCN or TGN, to model the dynamic network and detect anomalies that may signal heightened systemic risk or financial stress. Our findings reveal a trend towards increased modularity and community size in the post-GFC period and demonstrate a discernible impact of regulatory interventions on network architecture. The TGNN-based anomaly scores correlate with historical periods of financial stress and bank failures, highlighting their potential as an early warning tool. This research provides novel insights into the long-term dynamics of interbank networks, the influence of regulation, and the application of advanced machine learning for financial surveillance.

Keywords: Interbank network; systemic risk; financial regulation; temporal graph neural networks; anomaly detection; US banking system; network analysis; financial stability

1. Introduction

Mid-size and large banks significantly impact the U.S. economy. We aim to highlight their role in financial stability by examining historical trends, regulatory impacts, and employing advanced machine learning models to analyze their interactions. To clarify, mid-size and large banks are

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defined as financial institutions (banks) with an asset composition of between \$10 and \$100 billion.²

Firstly, the extant literature is limited on how the structure of the U.S. mid-size and large interbank network has evolved from 1984 to 2024, a period spanning over 40 years. In addition, key regulatory changes, such as the Dodd-Frank Wall Street Reform and Consumer Protection Act, the Riegle-Neal Interstate Banking and Branching Efficiency Act, the Financial Institutions Reform, Recovery, and Enforcement Act (FIRREA), the Federal Deposit Insurance Corporation Improvement Act (FDICIA), and the Gramm-Leach-Bliley Act (GLBA), that have influenced this evolution are also underexplored. Lastly, to our knowledge, there is a paucity of knowledge for the use of advanced temporal graph machine learning methods to detect anomalies in response to banking regulations, which may potentially indicate systemic stress (Acharya et al. 2017).

In this study, we tackle the aforementioned limitations in the theoretical and empirical literature and investigate the following research questions: First, what are the long-term trends in the number of active mid-size and large banks and their physical presence (branches)? Second, how have the interbank market's key network topological properties (density, centrality, community structure, and modularity) evolved over this period? Third, is there a discernible correlation between major U.S. banking legislation/regulation and shifts in these network properties? Fourth, can temporal graph neural networks (TGNNs) effectively model the temporal dynamics of the interbank network and identify anomalous periods or bank behaviors? Lastly, do detected anomalies correlate with known periods of financial stress or bank failures?

We make four contributions to the extant literature. First, we offer a comprehensive analysis of the U.S. interbank network spanning approximately four decades. Second, our study systematically maps regulatory changes to the structural evolution of the network. Third, we leverage the application and evaluation of TGNNs, such as evolving graph convolutional networks (EvolveGCN) or temporal graph networks (TGN), for anomaly detection in dynamic financial networks. Fourth, this study offers insights for policymakers and regulators on the structural evolution of mid-size to large banks spanning 40 years, mapping various regulations to their network activities, using a machine learning approach to detect anomalies in their network, and facilitating systemic risk monitoring.

The remainder of the paper is structured as follows: Section 2 provides a comprehensive literature review. Section 3 outlines the data and methodology, and Section 4 reports the results. Section 5 presents the discussion. Finally, Section 6 concludes.

2. Literature review

2.1 Interbank networks and systemic risk

Interbank networks serve as the backbone of financial systems by linking banks through credit exposures and liquidity interdependencies. The structure and dynamics of these networks critically influence systemic risk, contagion, and financial stability. Acemoglu et al. (2015) demonstrate that a dense financial network can enhance systemic stability when shocks are small, but the potential for contagion grows as interconnectedness increases. Freixas et al. (2000) and Allen and Gale

² <https://www.fdic.gov/system/files/2024-06/2023-guidelines-establishing-standards-for-corporate-governance-3064-af94-c-021.pdf>. Accessed June 6, 2025.

(2000) highlight that financial contagion can propagate through direct insolvency or liquidity shocks, with regional liquidity preferences influencing cross-regional exposures.

Diamond and Dybvig (1983) emphasize how deposit withdrawals can catalyze bank runs through network channels, while Shin (2009) reveals that securitization creates indirect contagion paths by linking banks' loan exposures. Acemoglu et al. (2015) further explain contagion amplification through heterogeneity in network structures, with financial institutions varying in connectivity and systemic importance.

Alvarez and Barlevy (2015) analyze the welfare implications of mandatory loss disclosures, linking transparency to contagion dynamics. Gai et al. (2011) argue that the concentration of unsecured claims raises contagion risk, which can be mitigated by macroprudential policies.

At the individual bank level, Hu et al. (2012) use network-based systemic risk measures to link asset correlations and interbank payments with systemic vulnerability during large shocks. Eisenberg and Noe (2001) provide a theoretical foundation for clearing payments in interbank systems, ensuring obligations are met uniquely under unsupervised conditions.

Recent empirical studies employ topological and causality analyses to identify systemic risk precursors. Gong et al. (2019) utilize network connectedness to detect financial crises, while Wang et al. (2024) apply Granger-causality tests to reveal risk spillovers primarily originating from the real estate and banking sectors toward insurance and diversified finance firms.

A complex network of interbank credit poses two problems: 1) disruption and 2) influence (Wang 2024). We follow his example that a disruption of the interbank credit network may occur as a result of the failure of a bigger or more powerful bank, which will have a ripple effect on the rest of the network in terms of liquidity flow, leading to systemic risk propagation and amplification (Acemoglu et al. 2015). Regarding the influence problem, if the rationale is to forestall systemic liquidity shortages, then the financially prudent approach is to lower the interest rate, thereby facilitating the flow of liquidity from surplus banks, which are usually big banks. To this end, it is reasonable for small regional or community banks to maintain low liquidity risk through the interbank market. However, these two problems that plague interbank credit networks often interact and co-exist in several situations.

As the lender of last resort, governments have provided bailouts to big banks to prevent bankruptcy propagation, which is challenging in the current global financial network. For instance, during the Global Financial Crisis (GFC) of 2008-2009, the federal government bailed out the big banks, which prevented the government from raising interest rates and diminished the chances of bankruptcy propagation in the short term (Miron 2009), but failed to eliminate systemic risk. In sum, it is important to improve the structures of resilience to disruption in interbank credit networks, where small banks have more resources for liquidity (Georg 2013).

Pu and Cui (2015) extensively studied the degree of vulnerabilities in social networks. The growing body of knowledge from research on social and economic networks has laid the foundation for understanding the nature and behavior of interbank credit networks (Munshi 2011). As such, interbank activities, including but not limited to liquidity interdependence, financial exposures, and payment systems, provide us with an avenue to model and simulate the behavior of these types of complex networks in mid-size and large banks, mapping them to major U.S. regulations. At the heels of this, Krause and Giansante (2012) noted that “too big to fail” and “too interconnected to fail” banks in interbank credit networks can cause massive disruptions in cash flows, leading to the spread of bankruptcy.

Together, these studies underscore that the topology and dynamics of interbank credit networks are critical to understanding systemic risk and inform regulatory interventions aimed at promoting resilience.

2.2 Financial regulation

Financial regulation has profoundly shaped banking structures, market dynamics, and interconnectedness. Anderson et al. (2019) trace how the National Banking Act of 1863-1864 concentrated deposits, creating systemically important banks. Later reforms, such as the Depository Institutions Deregulation and Monetary Control Act (DIDMCA) of 1980, deregulated interest rates and fostered competition, with Allen and Wilhelm (1988) documenting its impact on bank profitability and market risk.

Madura and Wiley (2000) examine the Financial Institutions Reform, Recovery, and Enforcement Act (FIRREA) of 1989, noting its mixed effects on the risk profiles of savings and loan institutions. Mansur and Elyasuani (1994) and Bryant and Martzoukos (1998) find that FIRREA influenced firm values and stock returns, particularly among smaller thrifts.

The Riegle-Neal Interstate Banking and Branching Efficiency Act (IBBEA) of 1994 removed geographic restrictions, promoting branching and competition. Carlson and Mitchener (2006) and Johnson and Rice (2008) suggest these changes reduced systemic risk through diversification, and Avery et al. (1999) and Rice and Davis (2007) note increases in branch offices per capita.

The Gramm-Leach-Bliley Act (GLBA) of 1999 repealed Glass-Steagall provisions, allowing consolidation across banking, securities, and insurance sectors. Zhao and He (2014) report post-GLBA expansion into market-sensitive businesses, weakening the value of accounting information. Chen et al. (2018) find governance improvements post-GLBA, while Ghosh (2020) links the act to shifts in bank risk and profitability.

The Dodd-Frank Act (DFA) of 2010, enacted after the Global Financial Crisis, introduced stricter capital and liquidity rules, the Consumer Financial Protection Bureau, and proprietary trading restrictions via the Volcker Rule. Acharya (2012) highlights the DFA's macroprudential regulation strengths but critiques Basel III's shortcomings. Studies by Cho et al. (2017) and Gangopadhyay and Yook (2022) explore the DFA's limitations and market impacts, while Gao et al. (2018) show that systemic institutions experienced more negative stock returns yet positive bond returns post-DFA.

Additional research emphasizes how regulations influence bank size, mergers, and market interconnectedness. Hassan and Giouvriss (2021) find that large acquirers reduce systemic risk in cross-border mergers, while Gao et al. (2018) note increased market reactions for more interconnected banks.

In sum, regulation shapes the evolving structure and risk profile of banking networks, balancing stability and competition.

2.3 Temporal networks and anomaly detection

Dynamic analysis of financial networks and anomaly detection are increasingly central to systemic risk monitoring. Paschalidis and Smaragdakis (2009) introduce spatio-temporal network anomaly detection, demonstrating the ability to detect short-lived anomalies, even within limited data windows, using both model-free and model-based approaches.

Cai et al. (2021) propose STrGNN, a structural temporal graph neural network designed to identify anomalies at graph edges in dynamic financial networks, showing promise in early threat detection and incident response optimization. Similarly, Shen et al. (2020) develop temporal hierarchical one-class (THOC) networks for capturing temporal dynamics in time series anomaly detection, while Zhao and He (2014) utilize temporal convolutional networks (TCNs) for similar purposes.

Ranshous et al. (2015) provide a comprehensive survey of graph-based anomaly detection techniques, highlighting challenges unique to temporal and dynamic network data. Han et al. (2022) review dynamic neural network architectures, emphasizing difficulties such as architecture design, decision-making, and optimization in dynamic settings.

Rossetti and Cazabet (2018) explore dynamic community discovery, categorizing existing methodologies and challenges in tracking evolving community structures over time. Mitra and Paul (2025) further demonstrate how dynamic graph theory addresses noise, missing data, and privacy issues in complex social and financial networks.

These temporal and graph-based approaches represent a frontier in systemic risk analytics, enabling real-time monitoring and early warning capabilities that traditional static analyses cannot provide. Their integration with regulatory frameworks offers potent tools for preemptive financial supervision, improving the detection and management of emerging systemic threats.

3. Data and methodology

3.1 Data acquisition and preprocessing

To assist with the granularity of our study, we employ bank-level datasets sourced from a variety of sources, such as the FDIC BankFind API and FFIEC Call Reports (Consolidated Reports of Condition and Income). We utilize an expansive range of datasets from 1984 Q1 to 2024 Q1 for mid-size and large banks in the U.S. The long and large data range will enhance deep analysis, but it is limited in the extant literature. The selection of banks is based on their total assets and potential dynamic thresholds as identified in the Congress whitepaper.³ We address potential issues such as mergers, acquisitions, and failures that have the potential to compromise our results.

The criteria for “mid-size” and “large” banks based on total assets, potentially dynamic thresholds. We used a variety of variables in accordance with the extant literature (see Section 4.1).

We used data items from Call Reports to infer interbank assets/liabilities (e.g., Fed funds sold/purchased, balances due from depository institutions). Interbank exposure profiles are created by mapping the financial claims and obligations between banks, typically using data on loans, deposits, and other credit instruments exchanged among them. This network representation quantifies the extent and structure of each bank’s direct exposures to other banks within the system.

See Figures A1 to A7 in Appendix A for the bank similarity network depicted by nodes and edges.

³ <https://www.fdic.gov/system/files/2024-06/2023-guidelines-establishing-standards-for-corporate-governance-3064-af94-c-021.pdf>

3.2 Major U.S. regulations from 2014 to 2024

We compile a comprehensive list of major U.S. banking laws and significant regulatory changes from 1984 to 2024 with their enactment/effective dates in Table 1.

Table 1. Comprehensive list of major U.S. banking laws and significant regulatory changes, 1984 to 2024.

Major U.S. Regulations	Main Purpose(s)	Enforcement Date
3.3.1 Financial Institutions Reform, Recovery, and Enforcement Act (FIRREA)	Stricter oversight and capital requirements	1989
3.3.2 Federal Deposit Insurance Corporation Improvement Act (FDICIA)	Mandated risk-based deposit insurance premium	1991
3.3.3 Riegle-Neal Interstate Banking and Branching Efficiency Act (IBBEA)	Created efficient and competitive banking	1994
3.3.4 Gramm-Leach-Bliley Act (GLBA)	Modernize the financial services industry and promote competition	1999
Dodd-Frank Wall Street Reform and Consumer Protection Act (DFA)	Imposed stricter capital and liquidity requirements	2010

Note: For further details on major U.S. regulations, refer to Appendix C.

3.3 Network construction and feature engineering

To avoid the uncertainty of estimating direct loans between banks, our primary method is to construct the network by measuring how similar banks are to each other based on their financial reports. The core idea is that banks with similar business strategies will likely compete for the same customers and be vulnerable to the same economic shocks. This approach is more reliable because it uses actual reported data rather than statistical guesses. Its key advantage is that it captures a critical type of risk beyond direct contagion: the danger that a large group of similar banks could all get into trouble at the same time if the market turns against them (Battiston et al. 2012; Kritzman et al. 2010). This method effectively identifies peer groups and indicates which banks are systemically important, not just because of their size but because their business model is shared by many others, meaning their distress could be felt widely across the system (Billio et al. 2012; Hautsch et al. 2015). Building our network this way allows us to focus on how the strategic landscape of the banking sector has evolved in response to new regulations.

3.4 Temporal analysis of embedding features

The objective of this study is to examine how embedding representations of entities or nodes evolves over time, and to capture dynamic changes in their relationships, behaviors, or attributes. This allows us to better understand temporal patterns, detect anomalies, or improve predictive modeling in time-dependent data.

See Appendix C for detailed temporal analysis of embedding features.

3.5 Network embedding feature calculation (using NetworkX or similar)

We conducted network embedding feature calculations to show how nodes are transformed into low-dimensional vector representations that capture the network’s structural properties and relationships, enabling efficient analysis, visualization, and machine learning tasks.

Table 2: Network embedding feature calculation (using NetworkX or similar).

Embedding feature	Formula
Network density	$d = \frac{2m}{n(n-1)}$
Average triangles per node	$C_i = \frac{\text{number of triangles connected to node } i}{\text{number of triples centered around node } i'}$
Rich-club coefficient	$\phi^w(s) = \frac{2W_{>s}}{\sum_{i s_i>s} S_i (n-1)}$
Normalized tree length	$L(t) = \frac{1}{n-1} \sum_{d_{ij}^t \in T^t} d_{ij}^t$
Average neighbors	$\text{score}(x, y) := \Gamma(x) \cap \Gamma(y) $
Average degree	$\langle k^m \rangle = \left[\left(z \frac{d}{dz} \right)^m g(z) \right]_{z=1}$
Degree assortativity	$r = \frac{\sum_{ij} (A_{ij} - k_i k_j / 2m) k_i k_j}{\sum_{ij} (k_i \delta_{ij} - k_i k_j / 2m) k_i k_j}$
Network transitivity	$C_i = \frac{R_i}{k_i - 1}$
Average clustering coefficient	$C_i = \frac{(\text{number of pairs of neighbors of } i \text{ that are connected})}{(\text{number of pairs of neighbors of } i)}$
Average community size	$\Delta Q = \frac{k_{i,in}}{m} - \gamma \frac{k_i^{out} \cdot \Sigma_{tot}^{in} + k_i^{in} \cdot \Sigma_{tot}^{out}}{m^2}$
Modularity	$Q = \sum_{c=1}^n \left[\frac{L_c}{m} - \gamma \left(\frac{k_c}{2m} \right)^2 \right]$
Average degree centrality	$C_d(v) = d_v / (n - 1)$
Cosine similarity	$k(x, y) = \frac{xy^T}{\ x\ \ y\ }$

4. Results

We provide the results of our study by first showing the summary statistics of all the variables. Second, we present the trajectory of active mid-size and large banks as well as the average number of branches from 1984 to 2024 per quarter. Next is the evolution of the interbank network amidst major regulatory changes followed by the TGNN-based anomaly detection performance. Last, we provide an analysis of anomalies and financial stress.

4.1 Summary statistics

Table 3. Summary statistics of the variables used.

Variable	Mean	Standard Deviation (Std)	Median
Total Assets	8.980E10	2.770E11	2.230E10
Equity Capital	8.830E9	2.690E10	2.170E9
Total Deposit	6.570E10	2.060E11	1.630
Return on Assets (ROA)	0.855	1.502	1.030
Return on Equity (ROEQ)	8.863	34.182	10.660
Interbank Assets (CHBAL)	8.560E9	3.950E10	1.050E9
Interbank Assets (CHBALNI)	1.760E9	4.390E9	5.110E8
Interbank Assets (CHNUS)	2.530E9	1.440	5.250
Interbank Assets (CHUS)	5.350E8	3.220E9	7.890E7
Interbank Assets (FREPO)	3.430E9	2.220E10	5.000E7
Interbank Assets (IFREPOQ)	2.360E7	1.580E8	2.950E5
Interbank Assets (LNDEPAC)	1.080E9	4.600E9	4.430E6
Interbank Liabilities (FREPP)	3.630E9	1.470E10	9.390E10
Interbank Liabilities (EFREPPQ)	2.990E7	1.250E8	4.830E6
Unused Commitments (ABCUBKR)	0.269	2.297	0.000
Unused Commitments (ABCUOTH)	1.070E8	7.220E8	0.000
Unused Commitments (ABCXBK)	1.700E8	1.160E9	0.000
Unused Commitments (ABCXOTH)	1.470E7	2.500E8	0.000
Unused Commitments (LOCFPSBK)	1.330E9	7.680E9	9.020E6
Number of Domestic Offices	436.520	810.960	201.000

On average, the number of mid-size and large banks is 437, and the standard deviation is about 811. In our reported trend, the lowest number of branches/offices is 198, which occurred in 1989, and the highest number of branches is 698, which occurred in 2011. We utilize core profitability and financials, mainly total assets, equity capital, ROA, ROE, etc.

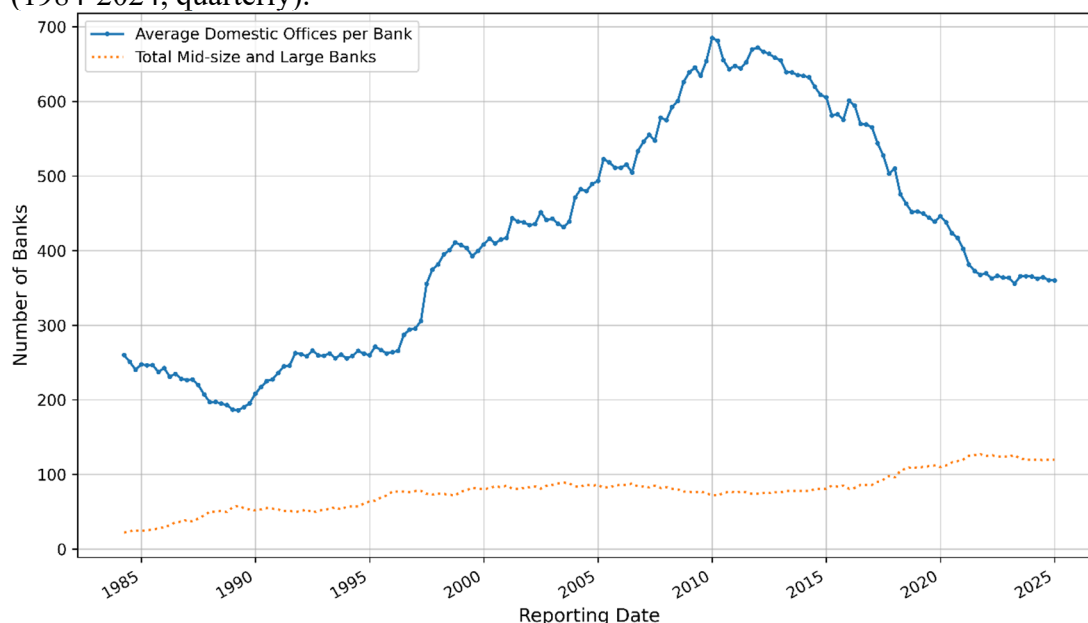
According to the summary statistics, the total assets (TA) of the banks' mean (standard deviation) is 8.980e10 (2.770e11), the mean (standard deviation) of the equity capital (EC) is 8.830e09 (2.69e10), the mean (standard deviation) of return on assets (ROA) is 0.855 (1.502), and the mean (standard deviation) of return of equity (ROE) is 8.86 (34.182), respectively.

We handled data cleaning and transformation by handling the variables' missing values, normalization, and time alignment (quarterly frequency).

Figure 1 shows that the average number of branches per big bank grew enormously from the early 1990s until 2011. This is mainly because large banks bought smaller ones nationwide, absorbing all their locations and creating huge national networks. After 2011, however, this trend flipped dramatically. As people started using online and mobile banking more, banks began closing thousands of their physical branches to save money, causing the average number of locations to drop sharply. Meanwhile, the orange dotted line tells a different story: the total number of banks considered "mid-size and large" has increased slowly. This is because even as some banks merged, others grew big enough organically to join this category, thus leading to more large players today, even if each has fewer branches than they did at their peak. By closing expensive physical branches and moving customers to digital platforms, banks aim to hold onto their massive deposit base and,

thus, their strong liquidity while significantly cutting operational costs. This modernizes their liquidity management, making them less dependent on a physical footprint and more reliant on the strength and appeal of their digital banking services.

Figure 1. Number of active mid-size and large banks and average number of branches (1984-2024, quarterly).



Notes: This graph reports the growth trajectory of mid-size and large banks in the U.S. from 1984 to 2024. The blue line represents active banks, and the orange line represents the average number of bank branches.

4.2 Evolution of the interbank network structure

We show how the various connections and relationships of the interbank network shift in the face of regulatory enforcement and over time. See Appendix B, Figures B1 to B3, for quarterly network trends. Also refer to Figures A1 to A7 in Appendix A for bank similarity structures per quarter.

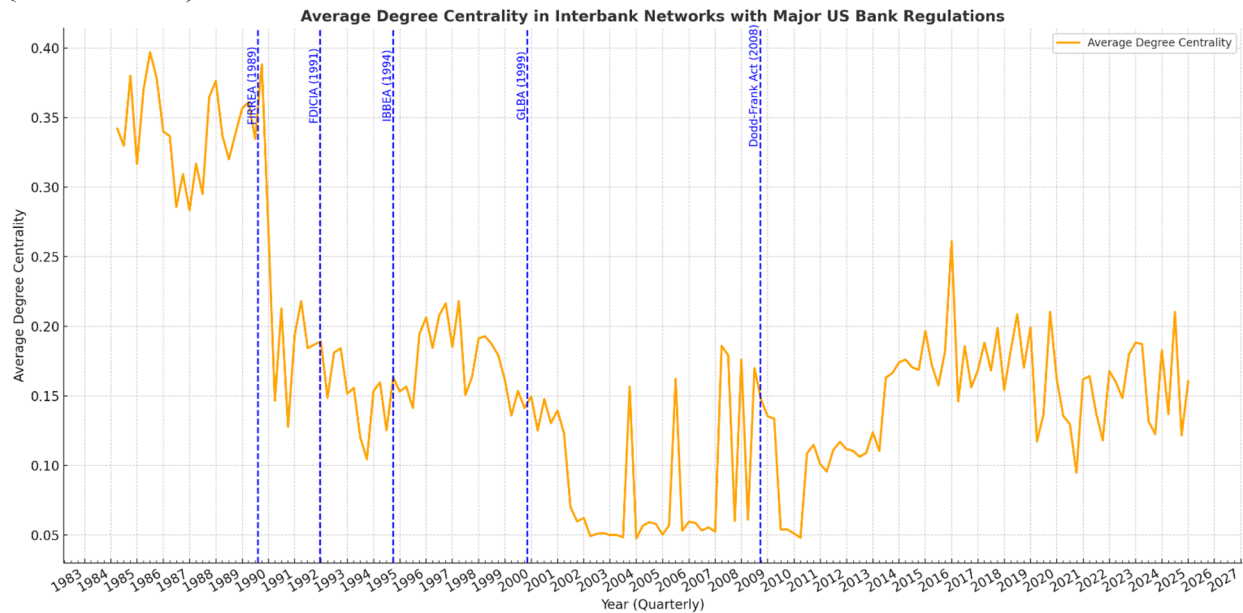
Table 4 shows that the total number of connections often fluctuated wildly, with certain years experiencing a massive spike in interconnectedness that pulled the long-term average up significantly. Despite this volatility in activity, the network’s underlying organizational pattern was very stable. The system consistently broke down into distinct and tightly-knit communities or clusters. In other words, banks didn’t just connect randomly; they formed clear groups, a feature that held true across the entire period. Within these groups, the network was very “cliquey”—meaning if two banks were linked to a common third bank, it was highly probable they were also linked to each other. Furthermore, the analysis reveals a “rich-club” effect: the most influential banks (those with the most connections) had a strong tendency to connect amongst themselves, forming a highly interconnected core at the center of the financial system. While the strength of this “rich-club” core dipped in some years, it remained a persistent feature of the network’s architecture.

Table 4. Summary statistics for network structures: Network density, average community size, average degree centrality, modularity, and other key metrics.

Network Metrics	Mean	Median	Standard Deviation	Kurtosis	Skewness
Number of banks in network	77.713	78	24.836	-0.124	0.003
Number of edges	485.494	411	336.492	0.773	1.203
Average community size	10.318	7.414	5.994	-0.314	0.930
Modularity	0.538	0.551	0.150	-1.122	0.054
Network density	0.168	0.160	0.086	0.465	0.890
Network transitivity	0.800	0.807	0.081	-0.611	-0.214
Average clustering coefficient	0.634	0.628	0.102	-0.903	-0.007
Average neighbors	11.799	11.357	5.161	-0.575	0.336
Degree assortativity	0.673	0.684	0.115	0.636	-0.675
Rich club coefficient	0.192	0.190	0.108	-0.798	0.207
Normalized tree length	0.469	0.446	0.141	-1.017	0.261

Note: The level of activity between these banks was extremely volatile.

Figure 2. Average degree centrality mapped to major U.S. regulations within the sample period (1984 to 2024).



Notes: The orange line represents the average degree centrality among banks from 1984 to 2024. The blue vertical dotted lines are the mapped regulations. Refer to Section 3.2 and Appendix D for the definitions of the regulations and when they were enacted.

The average degree centrality in Figure 2 measures how connected banks are within the interbank network on average, each quarter. Higher values indicate more interconnectedness, while lower values reflect fewer connections or sparser connections.

FIRREA was promulgated in 1989 to stabilize and restructure overnight activities (interbank transactions) in the savings and loan sector after the sector's crisis. Before this regulation, this network topology exhibited moderate fluctuations but trended upward, reflecting gradual increases in interbank connections amid deregulation momentum in the 1980s. After the regulation came into force, there was a slight increase in network connections, indicating the affected banks were gradually building ties while maintaining a tinge of caution under the new overnight structures.

In 1991, FDICIA was enacted with the aim of imposing tighter capital requirements for banks in addition to establishing prompt corrective actions. Before this regulation, the average centrality network displayed a modest upward trend, indicating increasing interconnectivity among banks. However, after the passage of this regulation, the degree of centrality took a nosedive, illustrating that banks maintain interbank linkages while adapting to stricter oversight activities, possibly to manage liquidity more actively under capital pressures.

IBBEA, which came into force in 1994, allows interstate branching, thus removing geographic barriers. Before this regulation, there was moderate centrality with gradual increases. After the act, there was a marked increase in degree centrality, aligning with expanded interbank connections as banks operate across states, taking advantage of branching flexibility to diversify funding sources and liquidity channels.

The GLBA, implemented in 1999, permitted the consolidation of banks, securities, and insurance companies into a single financial institution. Before the regulation, there was steady, higher centrality post-IBBEA, reflecting active network growth. After, centrality remained high with continued mild increases, consistent with further network expansion as banks diversified activities and funding channels under GLBA flexibility.

Dodd-Frank Act of 2008 was enacted to reduce systemic risk post-Global Financial Crisis (post-GFC). Before, there was high and stable centrality, reflecting high interbank connectedness in a low-regulation and high-leverage environment. After, there was a clear decline in degree centrality, consistent with deleveraging, risk aversion, and regulatory tightening, leading to reduced interbank connections as banks became cautious about counterparty exposures under stricter oversight.

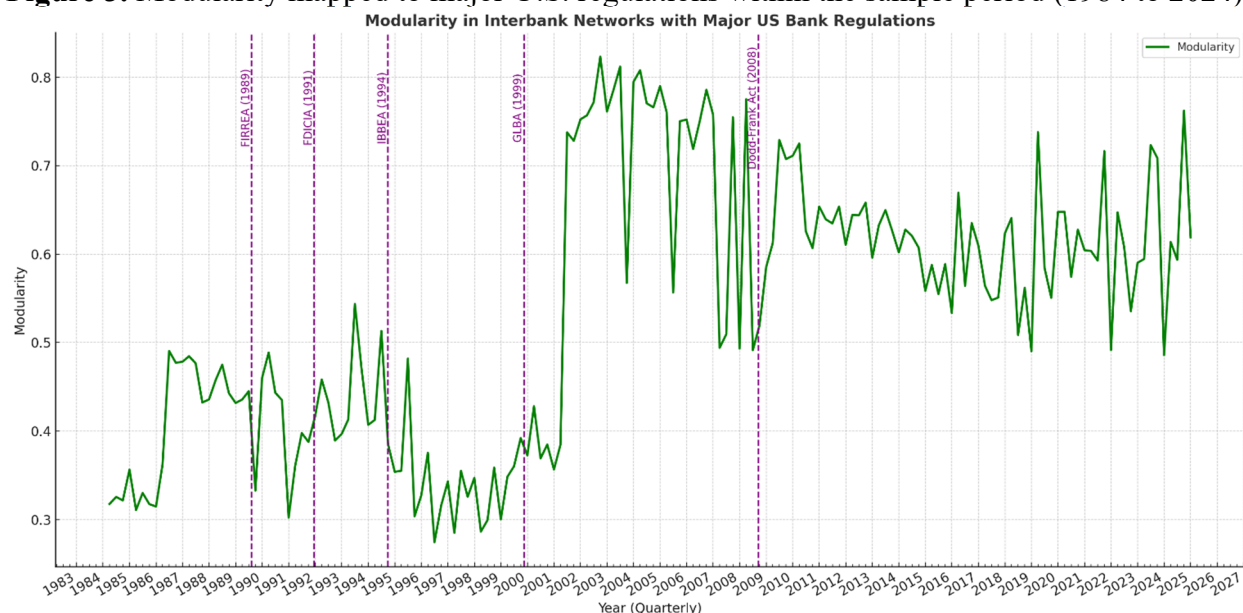
Figure 3 illustrates the modularity in interbank networks, measuring the strength of the division of a network of mid-size and large banks into communities. Higher modularity indicates a network of banks with well-defined, dense communities that are sparsely connected.

FIRREA aimed to stabilize and restructure the overnight activities of the savings and loan sector during the sector's crisis. Before this regulation, this network feature, modularity, exhibited lower stability, generally fluctuating between 0.3 and 0.5. After the regulation, there was an initial brief increase in modularity, followed by variability, and finally settling into a higher range (approximately 0.4 to 0.5), suggesting that FIRREA likely contributed to a more structured network topology.

FDICIA imposed tighter capital requirements for banks, thus putting in place prompt corrective actions. Before the regulation, modularity remained somewhat variable (0.4 to 0.5). After the passage of the regulation, a marked and sustained increase in modularity occurred, surpassing 0.5. This implies that the FDICIA facilitated greater segmentation within interbank networks, likely through stricter capital requirements and oversight.

IBBEA regulation spearheaded interstate branching, removing geographic barriers. Before the enactment of the regulation, modularity displayed volatility within a moderate range (0.4 to 0.6). After its passage, modularity initially declined briefly, then stabilized between 0.4 and 0.5,

Figure 3. Modularity mapped to major U.S. regulations within the sample period (1984 to 2024).



Notes: The green line represents the modularity among banks from 1984 to 2024. The violet vertical dotted lines are the mapped regulations. Refer to Section 3.2 and Appendix D for the definitions of the regulations and when they were enacted.

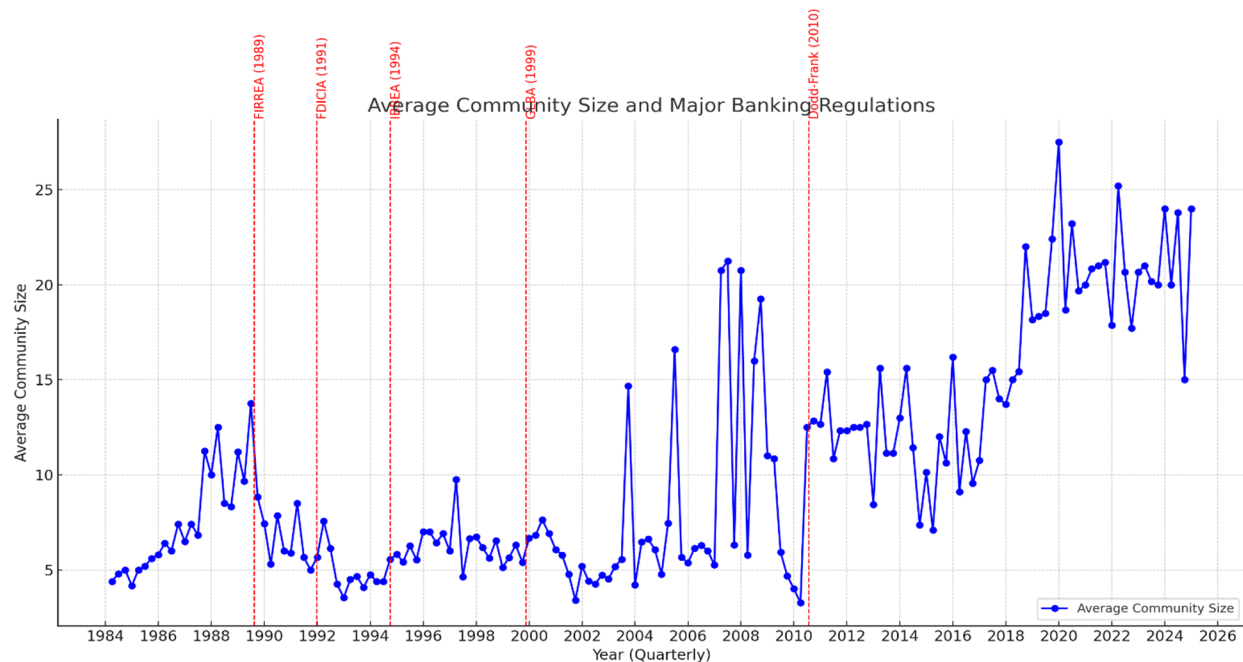
reflecting an increased interconnectedness and reduced segmentation as geographic restrictions eased.

GLBA regulation allowed banks, securities, and insurance companies to combine as one financial institution. Before the regulation, this network feature, modularity, was comparatively stable at around 0.4 to 0.5. Once enacted, there was a pronounced and sharp increase in modularity exceeding 0.7, showing substantial community structuring or fragmentation within the interbank networks. This rise likely reflects the diversification and structural changes in banks' activities as permitted by the GLBA.

The Dodd-Frank regulation was enacted after the 2008-2009 Global Financial Crisis reduced systemic risk. Before the passage of this landmark regulation, modularity was high but fluctuated significantly (0.6 to 0.8), possibly due to the financial crisis dynamics. Once the regulation came into force, modularity displayed a sharp, immediate decline (below 0.6) before recovering somewhat. It maintained high volatility, suggesting continued adjustments and restructuring in response to the comprehensive regulatory changes.

It is worth noting that after analyzing the behavior of banks in the context of these major regulations, we observe the following: First, regulations introducing increased oversight, stricter capital requirements, or greater risk management measures (e.g., FDICIA, GLBA) generally correlated with increases in network modularity, indicating segmentation and clearly delineated community structures. Second, regulations easing geographic and operational restrictions (e.g., IBBEA) tended to initially decrease modularity due to enhanced interconnectedness, though the impact stabilizes over time. Third, comprehensive regulatory changes following financial crises (e.g., FIRREA, Dodd-Frank) demonstrate mixed or volatile effects, suggesting periods of transition and adaptation within interbank networks.

Figure 4: Average community size mapped to major U.S. regulations within the sample period (1984 to 2024).



Notes: The blue line represents the average community size among banks from 1984 to 2024. The red vertical dotted lines are the mapped regulations. Refer to Section 3.2 and Appendix D for the definitions of the regulations and when they were enacted.

Average community size, as shown in Figure 4, is a network metric representing the mean number of nodes (e.g., banks) within identified clusters or groups (communities) in a network. It measures how large, on average, the groups of closely connected banks are. It provides insight into the network's cohesiveness or fragmentation. A high average community size indicates larger, more interconnected groups, whereas lower values suggest smaller, more fragmented clusters.

FIRREA (1989): Before the regulation, the average community size experienced fluctuations with an increasing trend, indicating a growing interconnectedness among banks before FIRREA's enforcement. After its adoption, the average community size showed initial instability, but later a clear increase. This might be due to stricter oversight and capital requirements prompting banks to form more cohesive and stable communities for better risk management.

FDICIA (1991): Before the regulation, the average community size was elevated, reflecting high interconnectedness. Once implemented, a noticeable dip occurred, suggesting tighter regulatory constraints on interbank activities which temporarily reduced community cohesion. Gradually, however, banks adapted, restoring the community size to earlier or even slightly higher levels.

IBBEA (1994): Before this regulation, the average community size was moderately stable, suggesting an established network structure. After its enactment, the average community size surged significantly, indicating that removing interstate banking restrictions enabled banks to more extensively integrate across states, thus increasing network cohesion.

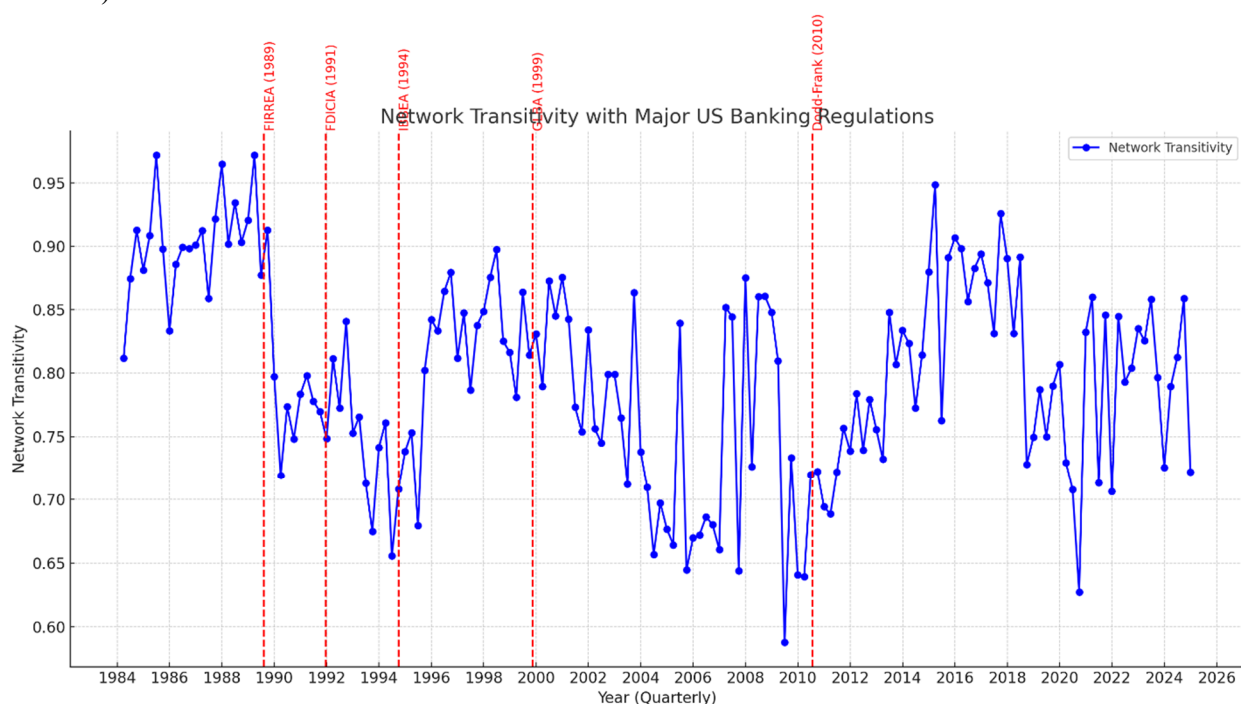
GLBA (1999): Before the regulation, the network was fairly stable with a consistent average community size. Once it entered into force, the average community size increased and exhibited

greater fluctuations, indicating that reduced restrictions on banking, securities, and insurance activities led to dynamic reshaping and greater interconnectedness among banks.

Dodd-Frank (2010): Before this regulation, there was significant volatility in the average community size, likely due to the global financial crisis leading up to the regulation. After its passage, there was a sharp initial decrease in community size, consistent with tighter regulatory scrutiny and increased capital requirements. Eventually, banks adjusted, stabilizing at slightly lower levels, suggesting that regulation aimed at reducing systemic risk effectively diminished overly dense network linkages.

Network transitivity, depicted in Figure 5, measures how interconnected groups within the network are.

Figure 5. Network transitivity mapped to major U.S. regulations within the sample period (1984 to 2024).



Notes: The blue line represents network transitivity among banks from 1984 to 2024. The red vertical dotted lines are the mapped regulations. Refer to Section 3.2 and Appendix D for the definitions of the regulations and when they were enacted.

FIRREA (1989): Before the regulation, network transitivity was very high (~0.90 to 0.95), indicating a highly interconnected and clustered banking network. After its passage, there was a significant drop in the network, falling to around 0.80, reflecting the impact of stricter oversight and restructuring that reduced tightly-knit interbank clusters.

FDICIA (1991): Before the regulation (after FIRREA), transitivity stabilized but remained lower than pre-1989 levels (~0.80). After, FDICIA led to a further decline (~0.75), showing increased regulatory pressure constrained interbank clustering, likely due to enhanced capital requirements and risk controls.

IBBEA (1994): Before, transitivity hovered around 0.75, reflecting a modestly clustered network. After IBBEA enforcement, there was a modest recovery or stabilization in clustering, suggesting that the removal of interstate branching restrictions allowed some re-expansion of network connectivity.

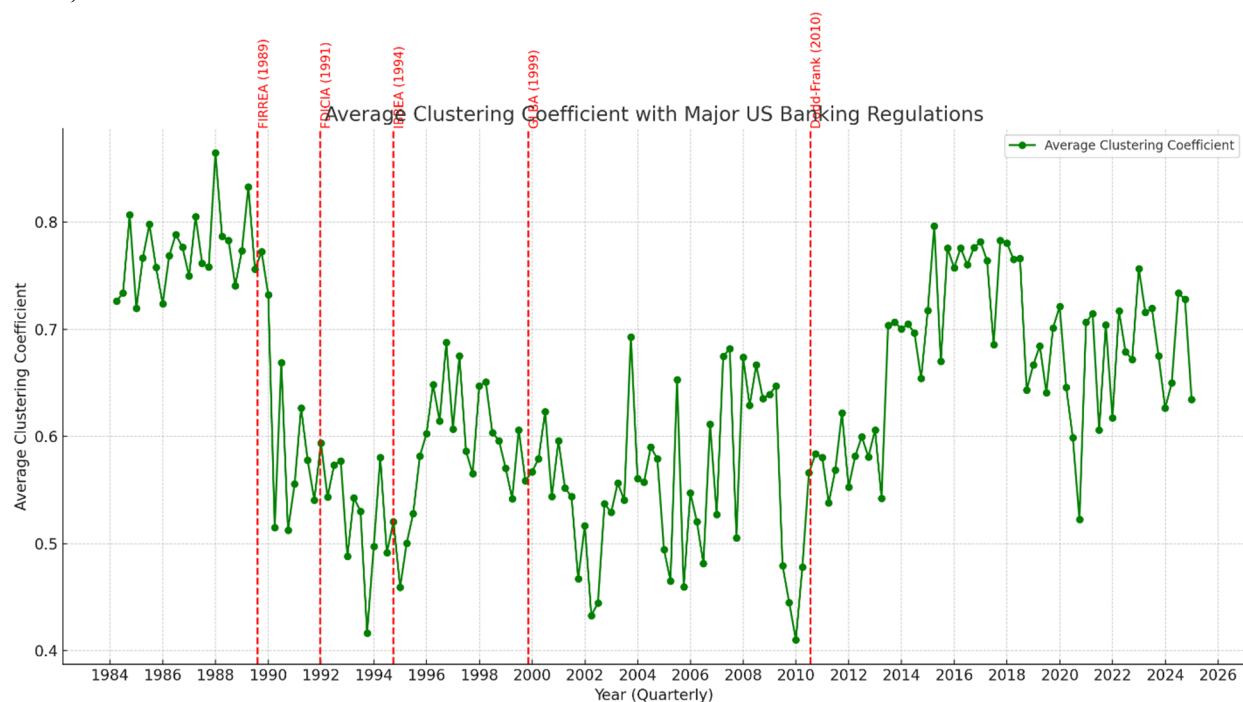
GLBA (1999): Before the regulation, network transitivity was relatively stable at around 0.75. After GLBA implementation, the metric fluctuated but generally declined, reaching around 0.65, reflecting dynamic restructuring as banks adapted to new consolidations (freedoms) and competitive pressures in integrated financial markets.

Dodd-Frank (2010): Before, transitivity was moderately low (~0.65 to 0.70), indicating reduced local clustering relative to earlier decades. Post-Dodd-Frank, a further decline occurred with short-term volatility, dipping below 0.65 at times, indicating that enhanced post-crisis regulations caused banks to significantly reduce tightly clustered connections for risk management.

In all, the figure shows that major regulatory events typically led to a reduction in network clustering immediately after enforcement, reflecting a tightening of interbank connections to comply with stricter rules. Some regulations, like IBBEA, temporarily stabilized or slightly increased clustering by easing restrictions, while others, like Dodd-Frank, caused sharp declines and volatility, illustrating adaptive restructuring in response to systemic risk concerns.

In Figure 6, the average clustering coefficient indicates local interconnectedness among banks.

Figure 6: Average clustering mapped to major U.S. regulations within the sample period (1984 to 2024).



Notes: The green line represents the average clustering coefficient among banks from 1984 to 2024. The red vertical dotted lines are the mapped regulations. Refer to Section 3.2 and Appendix D for the definitions of the regulations and when they were enacted.

FIRREA (1989): Before this regulation, the average clustering coefficient was high, approximately around ~ 0.75 to 0.85 , indicating strong local interconnections among banks. After, there was a notable decline, dropping to ~ 0.60 , reflecting the effect of regulatory restructuring and heightened oversight, thus reducing tight local bank clusters.

FDICIA (1991): Before this regulation, the average clustering coefficient had somewhat stabilized around ~ 0.60 after the enforcement of FIRREA (post-FIRREA). After FDICIA, the average clustering coefficient decreased further to ~ 0.50 , reflecting more restrictive capital requirements and a trend toward more cautious interbank relationships.

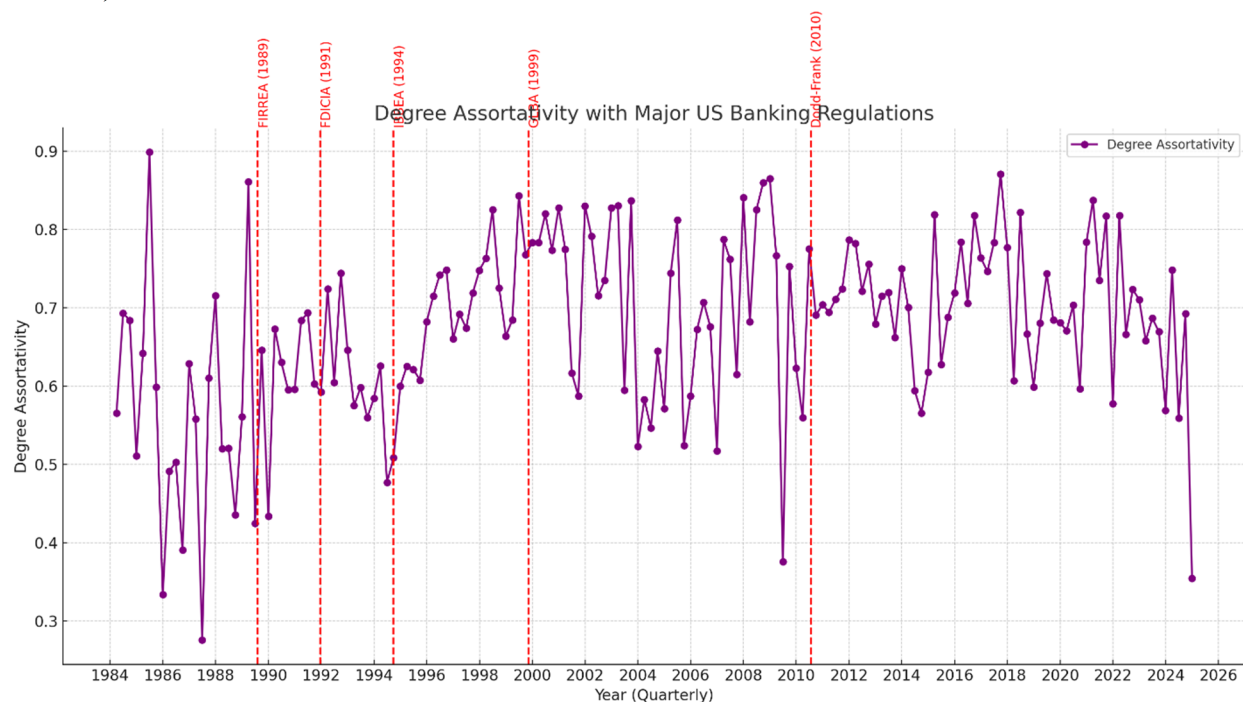
IBBEA (1994): Before the passage of this regulation, the average clustering coefficient remained low and stable (~ 0.50). Once enforced, the metric showed a mild rebound, suggesting interstate banking liberalization allowed banks to rebuild some local clustering within the expanded network.

GLBA (1999): Before 1999, the average clustering coefficient hovered around ~ 0.55 to 0.60 . After the passage of the GLBA, the coefficient increased modestly, reflecting enhanced integration across financial sectors after deregulation and consolidation.

Dodd-Frank (2010): Before the global financial crisis, the average clustering coefficient was relatively high (~ 0.60). After the crisis and enforcement of the Dodd-Frank Act, the metric dropped sharply to ~ 0.40 , highlighting banks' reactions to increased regulatory stringency post-crisis and leading to significant network restructuring as well as less tight local clustering. Some partial recovery followed, but it remained below pre-Dodd-Frank levels.

Degree assortativity is the extent to which similar banks connect to each other (see Figure 7).

Figure 7. Degree assortativity mapped to major U.S. regulations within the sample period (1984 to 2024).



Note: The violet line represents the degree assortativity among banks from 1984 to 2024. The red vertical dotted lines are the mapped regulations. Refer to Section 3.2 and Appendix D for the definitions of the regulations and when they were enacted.

FIRREA (1989): Before this act, degree assortativity was moderately volatile, fluctuating roughly between 0.4 and 0.7, indicating inconsistent patterns in how similar banks connected. Post-FIRREA, assortativity trends stabilized and increased slightly, suggesting banks began preferring connections with others of similar connectivity or size, possibly reflecting risk management responses to new regulations.

FDICIA (1991): Before the passage of this regulation, degree assortativity was on a rising trajectory and relatively stable near 0.6 to 0.7. After, the metric continued to increase and stabilize at around 0.7, implying that banks strengthened their homophilous connections, aligning more closely with similar peers under enhanced regulatory frameworks.

IBBEA (1994): Before its enactment, degree assortativity remained elevated and stable around 0.7. After, there was a slight increase and stabilization at higher values (~0.7 to 0.75), reflecting more homogenous interbank connections, possibly due to interstate expansion enabling more strategic, similarity-based ties.

GLBA (1999): After the expansionary regulation of IBBEA in 1994, degree assortativity was high and stable (~0.7 to 0.75). After, the metric maintained high levels with some fluctuations, indicating a persistent preference for similar banks to connect, consistent with consolidation and sector integration trends.

Dodd-Frank (2010): Before the passage of this regulation, degree assortativity remained relatively high but volatile, averaging around 0.7. After, the metric showed increased volatility with occasional sharp dips (below 0.4 at times), indicating a significant restructuring of bank linkages as institutions adapted to the stringent post-crisis regulatory environment. The pattern reflects a period of instability with banks reassessing traditional connectivity preferences.

At this juncture, we examine the social network of mid-size and large banks in terms of the trends at the node level. The topologies we focus on to explain the behaviors of these financial institutions in the context of major U.S. bank regulations are average neighbor, rich club coefficient, and normalized tree length.

Figure 8 maps average neighbors, which is the average number of direct connections each bank has in the network. This is identical to the “Avg. Degree” from the system-level trend and reflects overall network connectivity.

FIRREA (1989): Before the regulation, average neighbors hovered around 7 to 8, indicating moderate connectivity among banks. After, there was a distinct drop in the average neighbors, reflecting banks reducing direct links, likely due to regulatory tightening and risk management.

FDICIA (1991): Before its passage, the metric remained low following FIRREA’s impact. After the regulation, further reduction took place, suggesting increased caution and regulatory constraints continued to limit interbank connections.

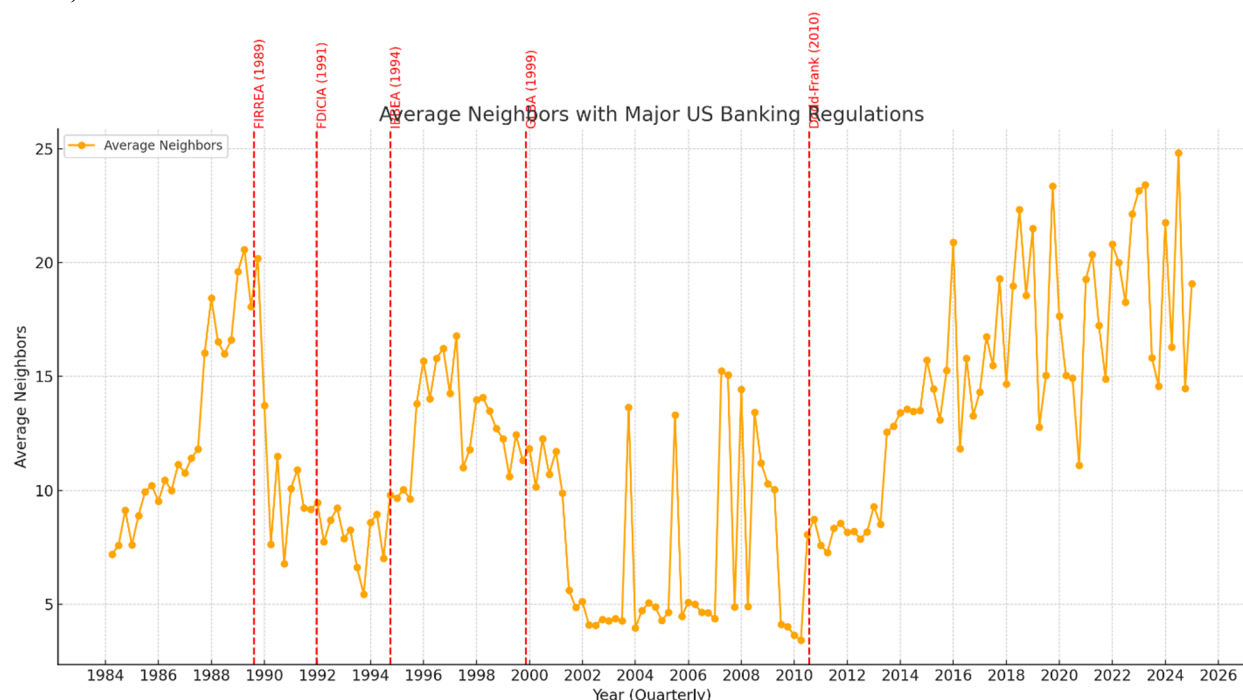
IBBEA (1994): Before IBBEA, average neighbors were low but stable. After the regulation, the metric stabilized and even showed a slight upward trend, indicating that easing interstate banking restrictions facilitated more network connections.

GLBA (1999): Before the GLBA, average neighbors hovered around 5 to 6. After its enactment, a gradual increase followed, reflecting deregulation’s effect in promoting interbank integration and network expansion.

Dodd-Frank (2010): Before the regulation, average neighbors were moderately high (~7 to 8), reflecting a relatively interconnected network. After Dodd-Frank, a sharp decline ensued, showing that post-crisis regulations led banks to substantially reduce direct interbank relationships for safety and compliance. The network connectivity partially recovered afterward, but it remained cautious.

Overall, the figure illustrates that regulatory changes strongly influenced how interconnected banks were, with initial tightening phases causing declines in connections and deregulation phases encouraging growth in network connectivity.

Figure 8. Average neighbors mapped to major U.S. regulations within the sample period (1984 to 2024).



Notes: The orange line represents the average neighbors among banks from 1984 to 2024. The red vertical dotted lines are the mapped regulations. Refer to Section 3.2 and Appendix D for the definitions of the regulations and when they were enacted.

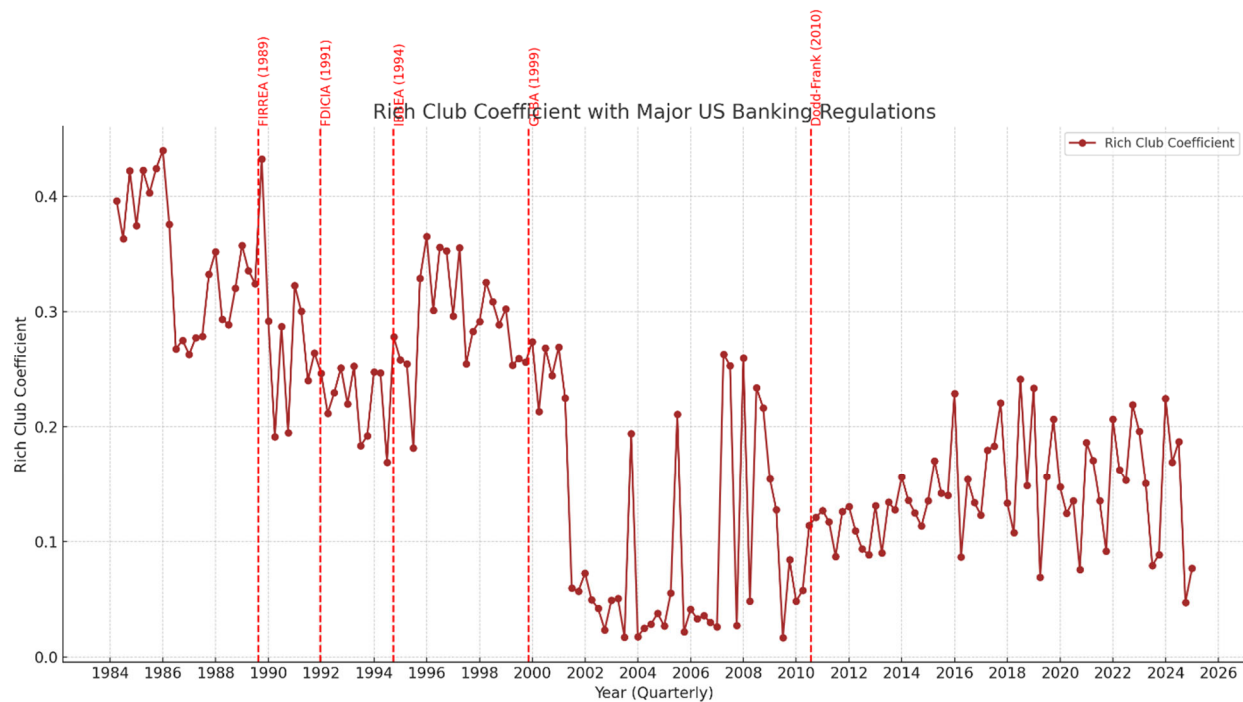
The rich club coefficient in Figure 9 measures the tendency of high-degree nodes (“rich” nodes) or systemically important banks to be more densely connected amongst themselves than to lower-degree nodes or smaller or less important banks. A high coefficient indicates a “rich club” phenomenon where the most connected banks form a tight core.

FIRREA (1989): Before the regulation, the rich club coefficient was relatively high (~ 0.4 to 0.45), indicating strong interconnections among the most connected banks, implying a tightly-knit elite core. A noticeable decline occurred soon after FIRREA, suggesting that regulatory pressures weakened the dominance or connectivity concentration among the top-tier banks.

FDICIA (1991): Before its enactment, the rich club coefficient was stable but lower than pre-FIRREA levels (~ 0.4). After FDICIA, a further decline ensued (~ 0.35), consistent with the ongoing regulatory tightening that disrupted concentrated core banking ties.

IBBEA (1994): Before, the coefficient had stabilized somewhat near ~ 0.35 . After the regulation, it remained stable or increased slightly, implying that easing interstate banking restrictions may have supported some reformation or stabilization of core bank connectivity.

Figure 9. Rich club coefficient mapped to major U.S. regulations within the sample period (1984 to 2024).



Note: The deep red line represents the rich club coefficient among banks from 1984 to 2024. The red vertical dotted lines are the mapped regulations. Refer to Section 3.2 and Appendix D for the definitions of the regulations and when they were enacted.

GLBA (1999): Before the act, the metric showed a modest recovery, around ~ 0.35 to 0.4 . After this regulation, the rich club coefficient fluctuated but generally trended downward, reflecting a more dynamic, competitive environment with less concentrated core banking networks.

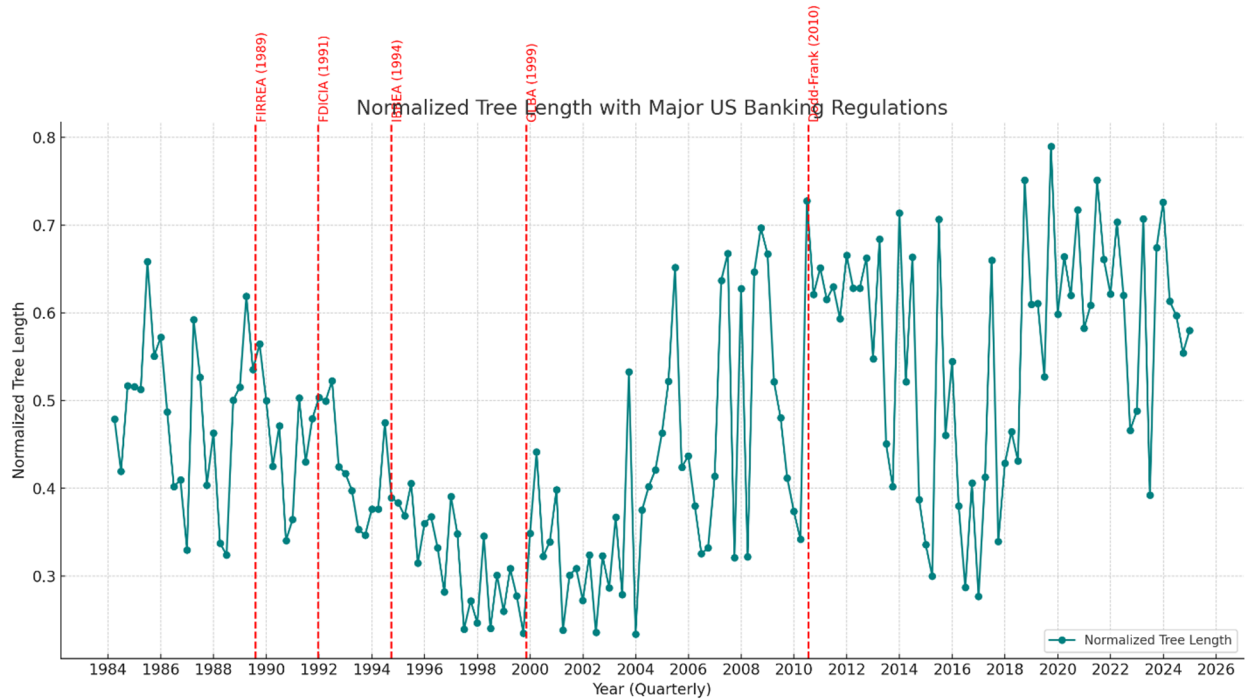
Dodd-Frank (2010): Before its passage, the rich club coefficient was moderately low and variable (~ 0.3 to 0.4). Once the act entered into force, a sharp drop followed, going below 0.3 at times, indicating a substantial weakening of concentrated connectivity among the elite banks, likely due to post-crisis regulatory reforms aimed at reducing systemic risk.

Figure 10 tracks the normalized tree length. “Tree length” in network analysis refers to characteristics of spanning trees or path lengths within tree-like substructures. A lower normalized tree length implies more efficient connections or a more compact core structure. Large banks are at the core and connected to smaller banks in the periphery.

FIRREA (1989): Before this regulation, the normalized tree length was relatively low and stable, indicating a compact and efficient network with shorter average paths between nodes. Following FIRREA, there was a gradual increase in tree length, suggesting the network became less compact and possibly more fragmented as banks adjusted to tighter regulations.

FDICIA (1991): Before this act, tree length continued to increase post-FIRREA, reflecting growing fragmentation. After 1991, the upward trend continued, implying a further loosening of the tight network structure and longer average paths, likely due to additional regulatory constraints.

Figure 10. Normalized tree length mapped to major U.S. regulations within the sample period (1984 to 2024).



Note: The green line represents the normalized tree length among banks from 1984 to 2024. The red vertical dotted lines are the mapped regulations. Refer to Section 3.2 and Appendix D for the definitions of the regulations and when they were enacted.

IBBEA (1994): Before this expansionary regulation, the normalized tree length was moderately high, showing a more spread-out network. After, there was a slight stabilization or modest decrease, indicating that easing interstate banking restrictions may have allowed some network consolidation.

GLBA (1999): Before this consolidation regulation, the metric remained stable or showed minor declines. After the GLBA, tree length fluctuated but generally increased, consistent with ongoing network restructuring due to deregulation and expansion.

Dodd-Frank (2010): Before the global financial crisis, tree length had increased significantly, reflecting a fragmented, less efficient network. After the metric peaked near the Dodd-Frank enforcement date, it gradually declined, suggesting an initial network disruption followed by a reorganization as banks adapted to stringent post-crisis rules.

4.3 TGNN-based anomaly detection performance

The objective of TGNN-based anomaly detection performance is that using TGNN helps detect anomalies more accurately by leveraging their network structures and time dynamics. The model's anomaly detection performance reveals a high score for large banks, particularly JPMorgan Chase (Bank CERT # 628). The bank appears multiple times in the anomaly detection from 2014_Q1 to 2024. See Table 5 for details of the scores and their corresponding bank certificates.

Table 5. TGNN-based anomaly detection performance.

Quarter	Highest Anomalous Score	Bankid (CERT)	Quarter	Highest Anomalous Score	Bankid (CERT)
2014 Q1	0.1828	628	2019 Q3	0.1592	3510
2014 Q2	0.193	13074	2019 Q4	0.2403	9396
2014 Q3	0.1557	6548	2020 Q1	0.1727	6989
2014 Q4	0.1752	31628	2020 Q2	0.2251	28088
2015 Q1	0.0904	12441	2020 Q3	0.2193	28892
2015 Q2	0.1939	8728	2020 Q4	0.1686	12368
2015 Q3	0.1721	867	2021 Q1	0.1735	628
2015 Q4	0.1719	7946	2021 Q2	0.2118	17838
2016 Q1	0.1327	7888	2021 Q3	0.1486	803
2016 Q2	0.1341	4297	2021 Q4	0.1916	7230
2016 Q3	0.1652	18221	2022 Q1	0.1855	628
2016 Q4	0.1356	24045	2022 Q2	0.1432	4988
2017 Q1	0.1402	6672	2022 Q3	0.1742	6600
2017 Q2	0.1834	6989	2022 Q4	0.1903	803
2017 Q3	0.1743	110	2023 Q1	0.1966	20234
2017 Q4	0.1899	35583	2023 Q2	0.1354	7946
2018 Q1	0.2004	8273	2023 Q3	0.2001	27237
2018 Q2	0.1636	7213	2023 Q4	0.2437	11813
2018 Q3	0.2242	628	2024 Q1	0.1747	803
2018 Q4	0.1441	3510	2024 Q2	0.1995	628
2019 Q1	0.2536	58978	2024 Q3	0.174	17491
2019 Q2	0.1364	57053	2024 Q4	0.2006	12368

Note: For brevity and limited space, we limited the TGNN-based anomaly score to this range from 2014Q1 to 2024Q4.

4.3.1 Analysis of anomalies and financial stress

Many factors could have driven the high anomaly score of JP Morgan. The chief factor is regulatory pressures because of fines and financial settlement agreements reached with regulators by JPMorgan. Also, the bank is a globally systemically important financial institution with many connections and plays a central role in the global interbank market of lending and derivatives. Hence, any unusual position in the interbank market, for example, large overnight positions, will require substantial collateral, which will in turn create liquidity issues in the network and significantly amplify the anomaly detection score. This connotes the idea of too-big-to-fail (Acharya et al. 2014) and the core-periphery model (Craig and von Peter 2014; Fricke and Lux 2015).

Another bank that recorded the highest anomaly score is First Horizon, and this is because it acquired Iberiabank Corporation (the parent company of IberiaBank) in a merger that closed on July 1, 2020. After the merger, all IberiaBank branches in Louisiana were rebranded as First Horizon Bank. This significantly expanded First Horizon's footprint in the state, making it one of the largest banks operating in Louisiana.

4.4 Robustness checks

Table 6: Summary of robustness tests of the TGNN model for mid-size and large U.S. banks from 1984 to 2024 anomaly detection in interbank network on system-level consistency (Pearson correlation coefficients) and node-level consistency (average Jaccard index).

run	Hyperparameters				Interbank Network		
	hd	od	lr	epochs	pce	p_value	aji
1	32	16	0.01	50	0.830	3.17E-12	0.800
2	32	16	0.005	30	0.918	1.86E-18	0.844
3	32	16	0.005	50	0.843	7.46E-13	0.828
4	32	8	0.01	30	0.883	2.21E-15	0.831
5	32	8	0.01	50	0.896	2.02E-16	0.829
6	32	8	0.005	30	0.822	8.22E-12	0.823
7	32	8	0.005	50	0.911	8.63E-18	0.842
8	32	32	0.01	30	0.847	4.49E-13	0.811
9	32	32	0.01	50	0.860	7.34E-14	0.817
10	32	32	0.005	30	0.862	5.79E-14	0.843
11	32	32	0.005	50	0.815	1.71E-11	0.793
12	16	16	0.01	30	0.856	1.27E-13	0.827
13	16	16	0.01	50	0.894	2.87E-16	0.828
14	16	16	0.005	30	0.867	2.93E-14	0.824
15	16	16	0.005	50	0.869	2.00E-14	0.826
16	16	8	0.01	30	0.854	1.80E-13	0.825
17	16	8	0.01	50	0.895	2.65E-16	0.852
18	16	8	0.005	30	0.744	7.05E-09	0.762
19	16	8	0.005	50	0.865	3.73E-14	0.821
20	16	32	0.01	30	0.848	3.94E-13	0.834
21	16	32	0.01	50	0.867	2.86E-14	0.813
22	16	32	0.005	30	0.760	2.18E-09	0.763
23	16	32	0.005	50	0.854	1.68E-13	0.813
24	64	16	0.01	30	0.876	7.15E-15	0.835
25	64	16	0.01	50	0.881	2.96E-15	0.842
26	64	16	0.005	30	0.774	6.94E-10	0.774
27	64	16	0.005	50	0.667	7.68E-07	0.708
28	64	8	0.01	30	0.785	2.85E-10	0.797
29	64	8	0.01	50	0.712	6.01E-08	0.667
30	64	8	0.005	30	0.816	1.56E-11	0.832
31	64	8	0.005	50	0.914	4.66E-18	0.843
32	64	32	0.01	30	0.913	6.35E-18	0.846
33	64	32	0.01	50	0.818	1.22E-11	0.828
34	64	32	0.005	30	0.906	2.88E-17	0.861
35	64	32	0.005	50	0.846	5.12E-13	0.810

Notes: hd—hidden dimension of the TGNN model; od—output dimensions of the TGNN model; lr—learning rate of the TGNN model; pce—Pearson correlation coefficients; aji—average Jaccard index value.

A series of robustness tests was conducted to evaluate the stability and reliability of the TGNN model for identifying anomalous nodes in the quarterly U.S. interbank networks. The primary goal of these tests was to ensure that the model's ability to detect anomalies is consistent and not overly sensitive to the choice of hyperparameters. The evaluation was performed on two levels: system-level consistency and node-level consistency. The model was trained 35 times with varying hyperparameters, including hidden dimension (hd), output embedding dimension (od), learning rate (lr), and the number of training epochs.

The stability of the results was measured in two ways. First, the overall ranking of anomalous banks was compared between runs, showing a strong agreement with an average Pearson correlation (pce), often exceeding 0.85 and sometimes reaching as high as 0.918. The statistical significance of these high correlations is confirmed by the extremely low p-values (e.g., $1.86E-18$), meaning the consistency is not due to chance. Second, the groups of top anomalous banks identified in each run were compared, revealing a high degree of overlap. The average Jaccard index (aji), which measures this overlap, was consistently above 0.80, with several runs achieving 0.844 and 0.842, respectively. This means that, on average, over 84% of banks flagged as the most vulnerable were the same across different model configurations. This result confirmed that the TGNN model is a robust and reliable tool, repeatedly identifying similar systemic risk patterns and the same specific institutions as potential vulnerabilities, regardless of minor changes in its setup.

5. Discussion

5.1 Implications of network structure on systemic risk

The structural properties of interbank networks—density, modularity, and centrality—play pivotal roles in shaping systemic risk and financial stability. High network density and average degree indicate tightly interconnected banks, which can enhance liquidity distribution and operational efficiency. Such interconnectedness facilitates rapid liquidity transmission and capital allocation, critical for normal functioning. However, this same connectivity increases systemic vulnerability by enabling faster contagion of financial distress across institutions (Allen and Gale 2000; Eisenberg and Noe 2001; Gai et al. 2011).

Conversely, lower density reduces the likelihood of contagion by limiting interbank exposures, but at the cost of potential inefficiencies in liquidity allocation (Acemoglu et al. 2015). Modularity, which measures the segmentation of the network into distinct communities, is a critical factor for resilience. Networks with higher modularity localize shocks within communities, reducing systemic spillovers and mitigating contagion risk (Battiston et al. 2012; Craig and von Peter 2014). Decreasing modularity signals increased interconnectedness across clusters, which may amplify the spread of financial shocks (Elliott et al. 2014; Glasserman and Young 2016).

Centrality measures identify banks that serve as key hubs within the network. High centrality nodes facilitate efficient liquidity flows but simultaneously represent points of systemic vulnerability. Distress or failure of these core banks can disproportionately trigger contagion, given their extensive connections (Dasgupta 2004; Freixas et al. 2000). Lower centrality can reduce individual bank risk but might impair overall market efficiency and liquidity distribution (Acemoglu et al. 2015).

Additional network features like the rich club coefficient highlight core-periphery structures where highly connected banks form elite clusters. While this can improve transactional efficiency,

it concentrates systemic risk within a small group, necessitating careful regulatory oversight (Dasgupta 2004; Elliott et al. 2014). Overall, the interplay between these network metrics suggests that both excessive interconnectedness and fragmentation pose risks, requiring a balanced network topology for systemic resilience.

5.2 Regulation impacts

Major U.S. banking regulations from 1984 to 2024 have significantly influenced interbank network structures. The enactment of FIRREA in 1989 and FDICIA in 1991, with their emphasis on stricter capital requirements and regulatory oversight, corresponded with a reduction in direct interbank connections and network density, while modularity increased. These changes reflect banks' more cautious liquidity management in response to heightened regulatory scrutiny ((Madura and Wiley 2000; Mansur and Elyasuani 1994).

In 1994, the Riegle-Neal Interstate Banking and Branching Efficiency Act (IBBEA) relaxed geographic restrictions, enabling interstate banking and branch expansion. This deregulation increased network centrality, community sizes, and interconnectedness, promoting efficiency and diversification of liquidity sources (Carlson and Mitchener 2006; Johnson and Rice 2008).

The Gramm-Leach-Bliley Act (GLBA) in 1999 further deregulated the banking sector by allowing financial conglomerates via the combination of banking, securities, and insurance activities. This deregulation induced higher modularity and clustering, reflecting the fragmentation of the network into distinct but concentrated financial groups (Chen et al. 2025; Zhao and He 2014).

In contrast, the 2010 Dodd-Frank Act, enacted post-Global Financial Crisis, aimed to reduce systemic risk through stringent oversight and increased capital requirements. Its implementation led to lower network centrality and interconnectivity, signaling a shift towards a more cautious and less dense interbank environment (Acharya 2012; Gao et al. 2018).

These regulatory cycles demonstrate how periods of stringent oversight tend to fragment network structures, raising modularity and lowering density, while deregulation periods encourage integration and network centrality. The interbank network's adaptive responses highlight the need for regulations that balance risk containment with liquidity efficiency.

5.3 Policy implications

Our findings underscore the importance of regulatory frameworks that maintain an optimal level of interconnectedness within interbank networks. Regulators should aim to foster diversified network connections that mitigate systemic vulnerabilities without compromising liquidity efficiency (Allen and Gale 2000; Gai et al. 2011). Policies should discourage an excessive concentration of exposures within a “rich club” of systemically important banks, which can amplify contagion risk.

Dynamic regulatory assessments informed by network analytics can help ensure regulations evolve alongside structural market changes, preventing unintended consequences such as risk concentration or network fragility (Acharya 2012; Madura and Wiley 2000). Transparent and detailed reporting of interbank exposures enhances the fidelity of systemic risk models and supports proactive risk management (Battiston et al. 2012; Eisenberg and Noe 2001).

Furthermore, promoting modular network structures, characterized by distinct communities, can localize shocks and prevent widespread contagion. Encouraging diversification in banks'

business models and funding sources contributes to this resilience (Battiston et al. 2012; Craig and von Peter 2014; Haldane and May 2011).

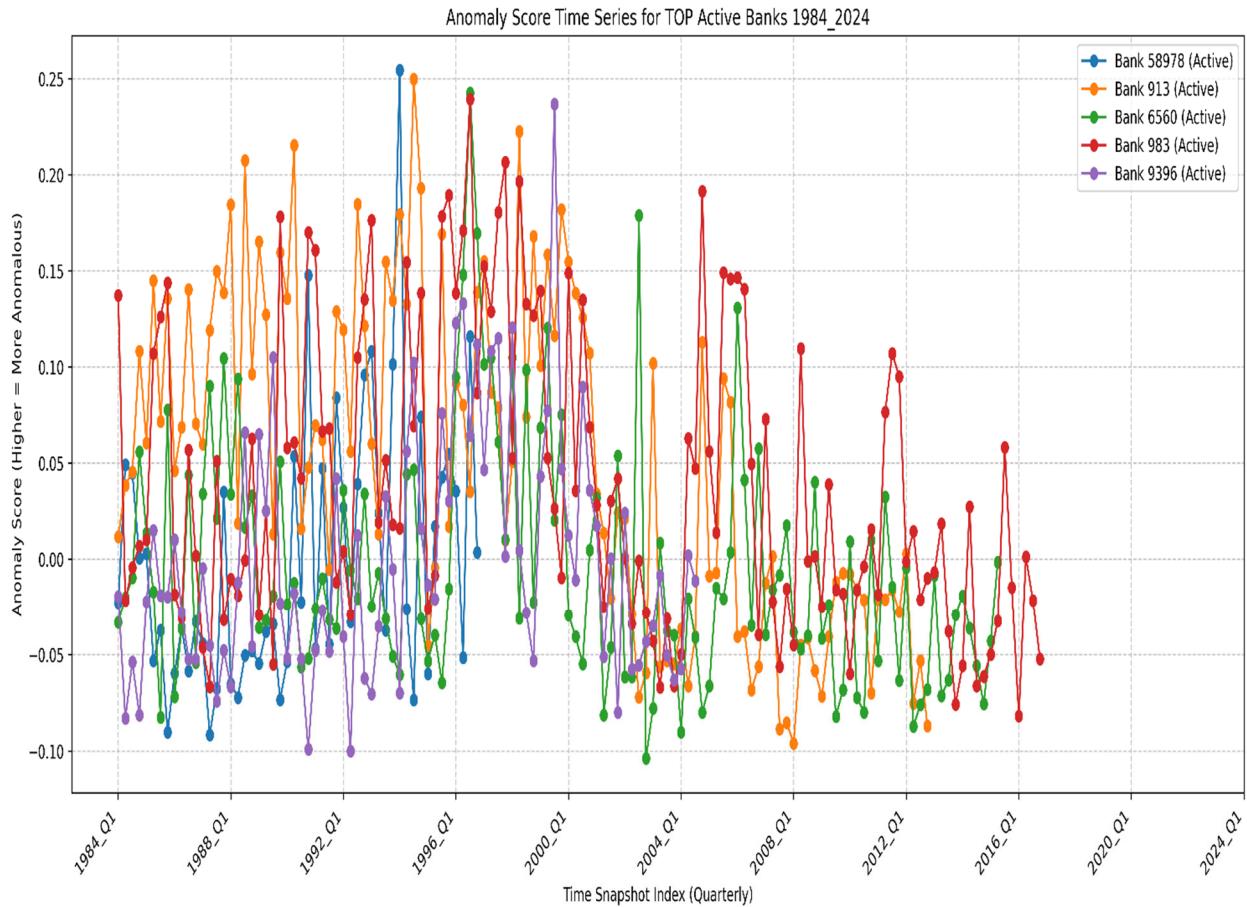
5.4 Significance of detected anomalies and TGNN potentials

The application of temporal graph neural networks (TGNNs) in this study highlights their significant potential in systemic risk surveillance. TGNN-based anomaly scores detect structural and behavioral irregularities in interbank networks that traditional risk metrics, such as value-at-risk (VaR), may miss or detect only ex post (Acemoglu et al. 2015; Battiston et al. 2012).

These models identify critical nodes exhibiting abnormal temporal patterns, enabling regulators to monitor systemically important banks and mitigate the risk of “too-big-to-fail” scenarios (Acharya et al. 2014). The TGNN approach facilitates near-real-time monitoring of dynamic interbank interactions, providing early warning signals and actionable insights to support timely supervisory interventions (Cai et al. 2021; Jiang et al. 2023).

Scalability and adaptability make TGNNs well-suited for the evolving financial landscape, capable of integrating with regulatory frameworks to automate systemic risk detection and reduce reliance on reactive measures (Faloutsos 2009; Ranshous et al. 2015).

Figure 11. TGNN-based anomaly score time series for top active banks (1984 to 2024).



6. Limitations and future research directions

This study relies on inferred interbank relationships using the cosine similarity of balance sheets due to limited granular exposure data, which may affect network accuracy and anomaly detection. Additionally, focusing on mid-size and large banks excludes smaller institutions, limiting the generalizability of the findings. Finally, while causal links between regulations and network changes are challenging to establish definitively, the associations identified provide valuable insights into evolving interbank dynamics.

7. Conclusion

Our study sheds light on a comprehensive exploration of the U.S. mid-size and large interbank network evolution from 1984 to 2024. Our key findings include significant structural shifts in the interbank network driven by major regulatory events, including FIRREA (in 1989), FDICIA (in 1991), IBBEA (in 1994), GLBA (in 1999), and Dodd-Frank (in 2010). We show that the interbank network exhibited adaptive behaviors, which are revealed as fluctuations in centrality, modularity, and clustering metrics in response to regulatory changes. Regulatory constraints generally increased network modularity and decreased interbank centrality, suggesting a distinct and fragmented market structure to mitigate systemic risks. Conversely, expansionary regulation led to enhanced interconnectedness, creating highly centralized “rich club” structures, thereby increasing efficiency but potentially heightening systemic vulnerability (Acharya 2012; Battiston et al. 2012; Carlson and Mitchener 2006).

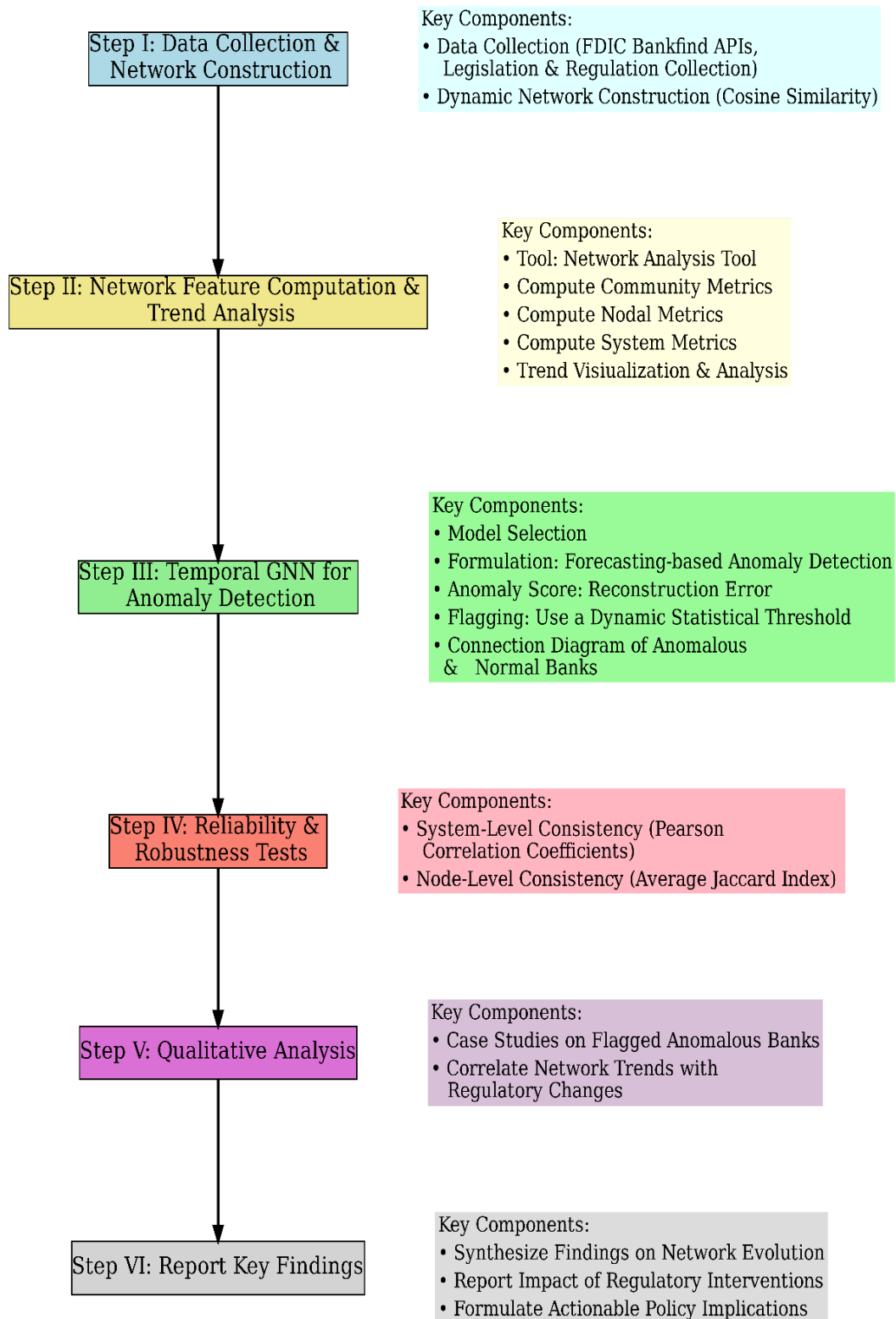
Moreover, temporal graph neural networks (TGNNs) effectively detected anomalies that correlated significantly with historical periods of financial distress and bank-specific stress events. Our study also shows that TGNN anomaly scores provided valuable early-warning signals of financial stress, identifying vulnerabilities on the horizon, specifically several quarters ahead of traditional metrics. This provides insights into the utility of TGNN-detected anomalies as a proactive monitoring tool (Battiston et al. 2012; Eisenberg and Noe 2001; Gong et al. 2019).

Our research makes several novel contributions to extant literature. First and foremost, to the best of our knowledge, this study offers an extensive temporal analysis of the interbank network across four decades, bridging a significant gap in historical and systemic risk literature. Second, our research provides empirical insights into key financial regulations’ effectiveness and unintended consequences as we systematically mapped significant U.S. regulations on interbank network topologies. Third, we expanded the application of machine learning techniques in financial stability research, as shown in our usage of advanced TGNN methods, such as EvolveGCN or TGN, in anomaly detection within financial networks.

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Figure 12. Flowchart of the interbank analysis research on mid-size and large banks.



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Appendix A: Bank similarity network

Bank Similarity Network (NetworkX) - 1991_Q4 (51 N, 241 E)

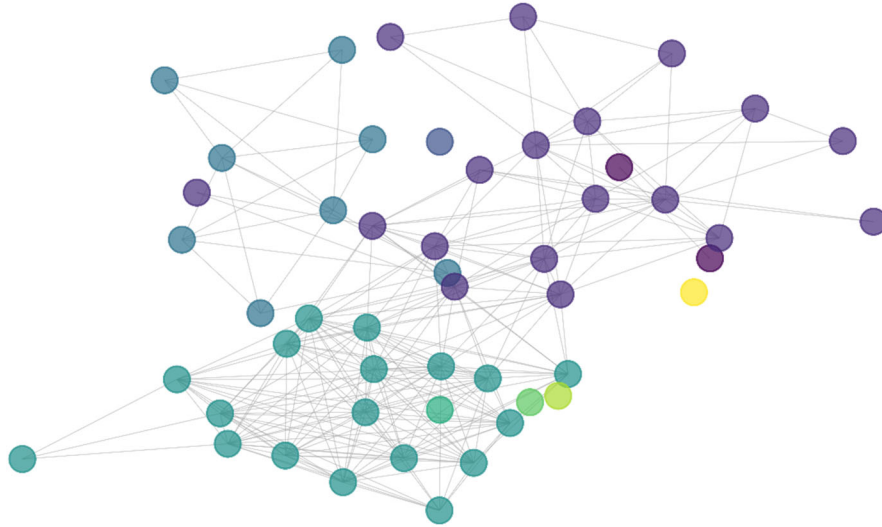


Figure A1. Network reveals a segmented but interconnected interbank system during this period. It involves 51 banks (nodes) and 241 connections.

Bank Similarity Network (NetworkX) - 1999_Q4 (80 N, 473 E)

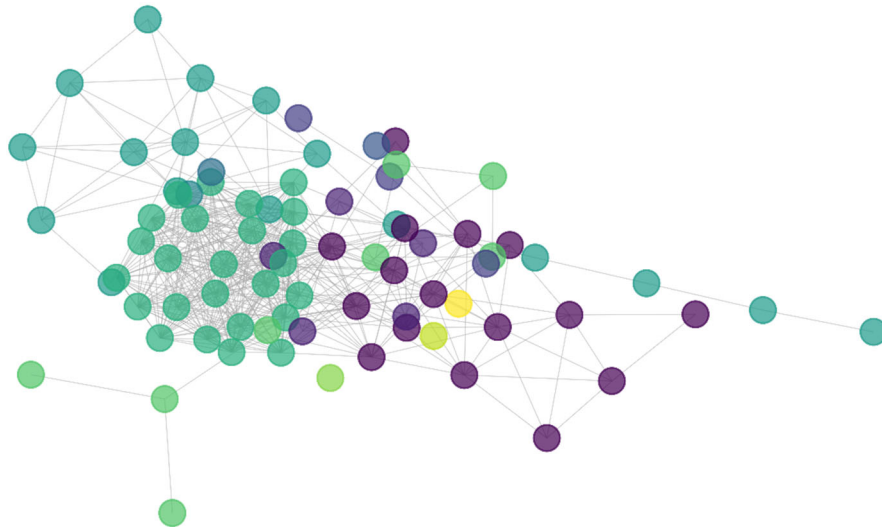


Figure A2. The network reflects an expanded and more integrated interbank system with richer connectivity and evolving structural complexity by 1999. It involves 80 banks (nodes) and 473 connections.

Bank Similarity Network (NetworkX) - 2008_Q4 (77 N, 396 E)

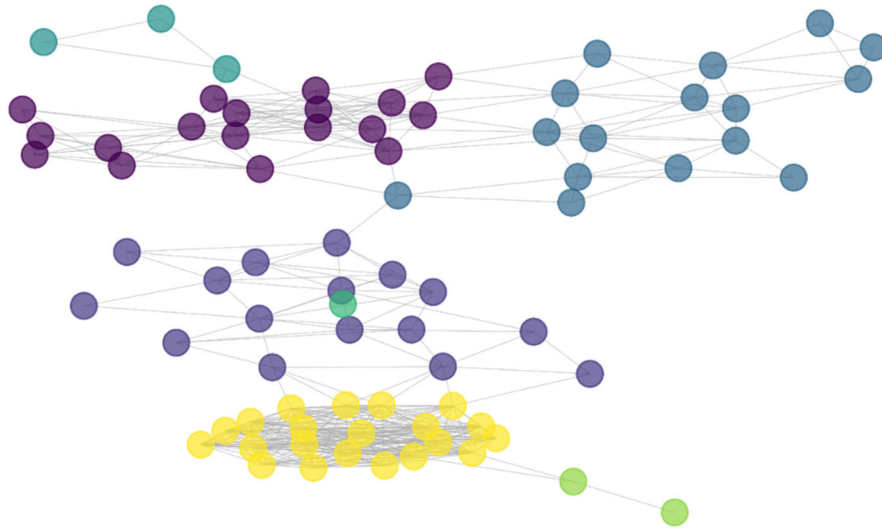


Figure A3. The network shows a modular and less densely interconnected system. It involves 77 banks (nodes) and 396 connections.

Bank Similarity Network (NetworkX) - 2010_Q4 (76 N, 288 E)

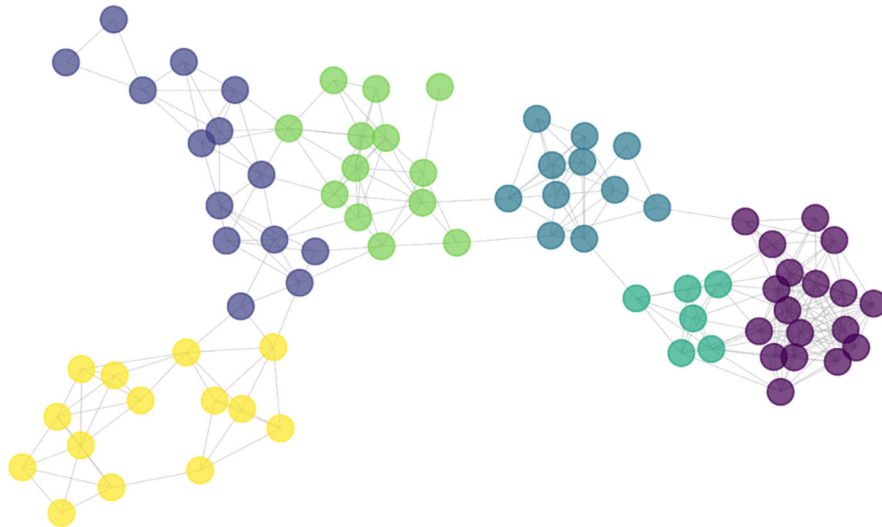


Figure A4. The network exhibits multiple distinct clusters with relatively strong internal connectivity and sparse links between groups. It involves 76 banks (nodes) and 288 connections.

Bank Similarity Network (NetworkX) - 2018_Q4 (109 N, 1172 E)

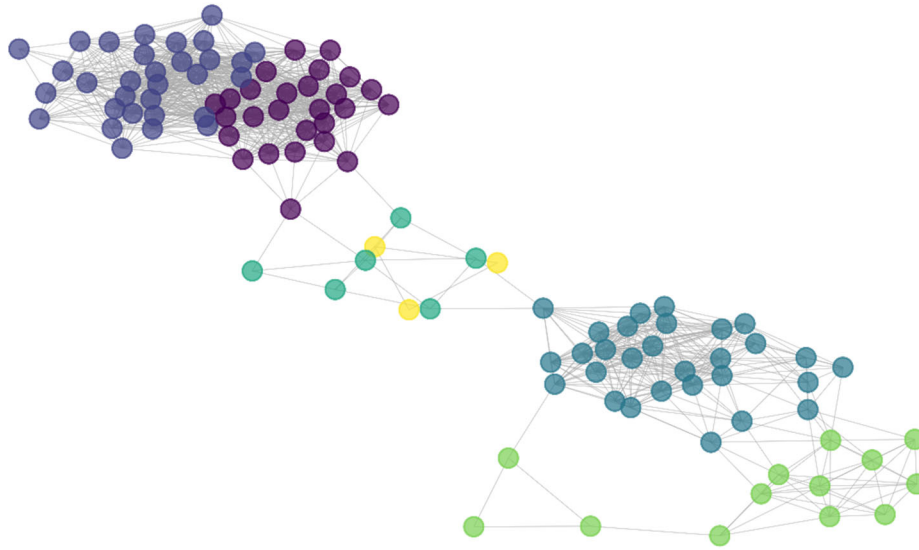


Figure A5. The network displays multiple large, densely connected clusters with strong intra-cluster connectivity, indicating groups of banks with high similarity in their balance sheets. It involves 109 banks (nodes) and 1172 connections.

Bank Similarity Network (NetworkX) - 2020_Q4 (120 N, 1156 E)

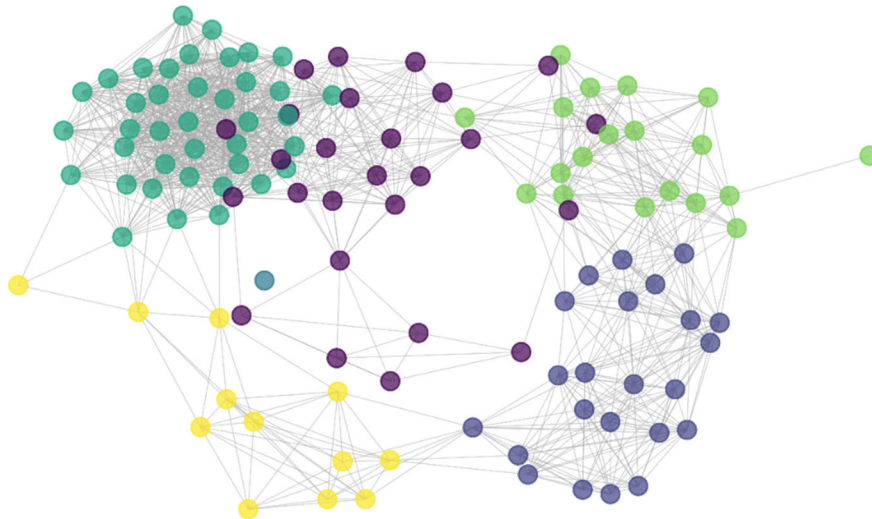


Figure A6. The network features several large, densely connected clusters with strong internal cohesion, reflecting groups of banks with similar balance sheet profiles. It involves 120 nodes (banks) and 1156 connections.

Bank Similarity Network (NetworkX) - 2024_Q4 (120 N, 1145 E)

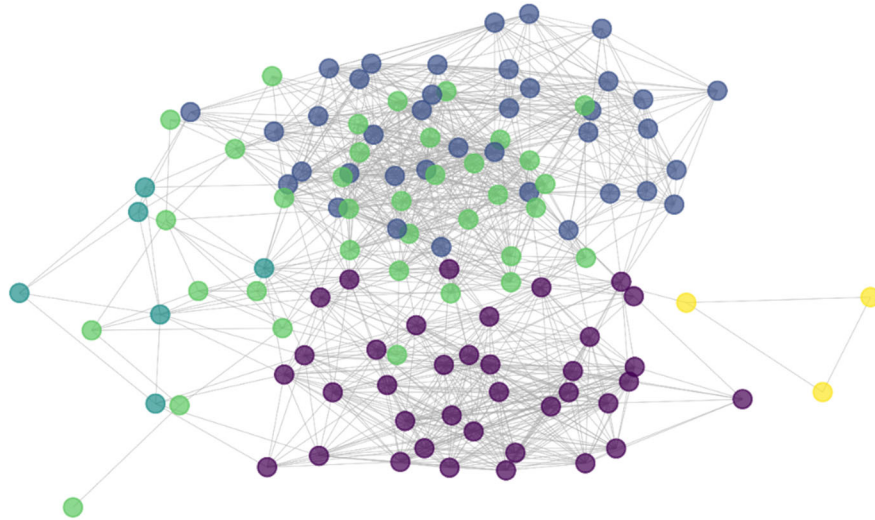


Figure A7. The network appears highly integrated with dense connections spanning most nodes, resulting in less distinct clustering and fewer isolated groups. It involves 120 banks (nodes) and 1145 connections.

Appendix B: Evolution of the interbank network structure

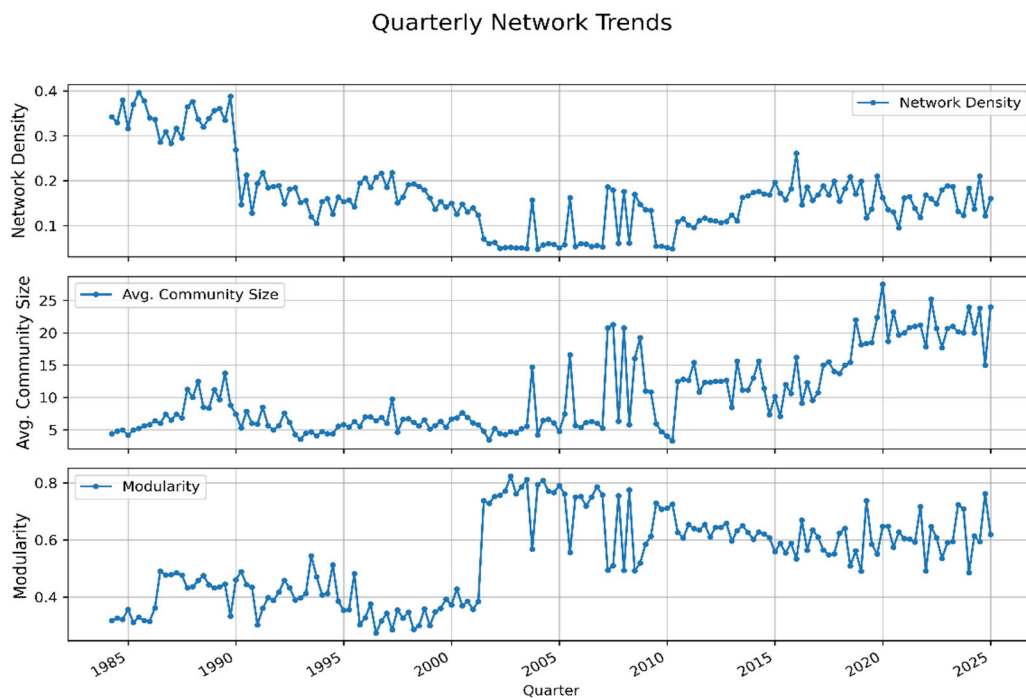


Figure B1. Quarterly network trends – modularity, average community, and network density.

Initially, the network was a dense, interconnected web, but the Riegle-Neal Act of 1994 began encouraging mergers. The most dramatic transformation came with the Gramm-Leach-Bliley Act of 1999, which allowed for the creation of financial “supermarkets.” This is visible in the charts as a sudden, massive spike in modularity, where the system abruptly reorganized from a single tangled web into a collection of distinct and separate banking communities. In the modern era, following the 2008 financial crisis, the Dodd-Frank Act and the Volcker Rule further solidified this structure while making the communities themselves much larger. As crisis-driven consolidation continued and stricter rules favored the largest institutions, these powerful ecosystems grew by absorbing more firms, causing the average community size to skyrocket in recent years. This transformed the banking system from a broadly interconnected network into a landscape dominated by a few massive, internally focused banking groups.

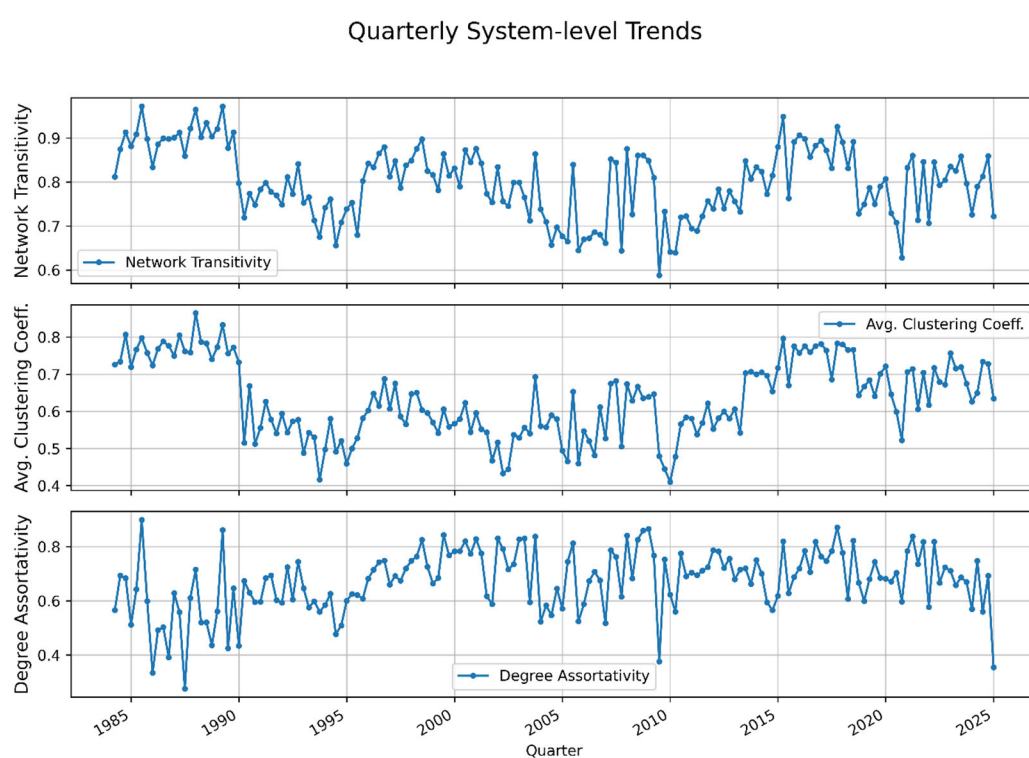


Figure B2. Quarterly system-level trends – degree assortativity, average clustering coefficient, and network transitivity (1984 to 2024).

This figure illustrates how banking regulations reshaped the very fabric of how banks interact, essentially creating and then solidifying a “rich club” of powerful institutions. In the early years, before major deregulation, the banking system was highly “cliquey,” with many local banks forming tight-knit groups, as shown by the very high network transitivity and clustering. The Riegle-Neal Act of 1994, which allowed for interstate mergers, began to change this by breaking up those local cliques, causing the overall “cliquey-ness” to drop. At the same time, this consolidation started building a “rich club” effect, where the newly powerful banks connected more among themselves, a trend visible in the rising degree assortativity. This was supercharged

by the Gramm-Leach-Bliley Act, where the network was extremely tight-knit, but the savings and loan (S&L) crisis (Wang 2025) and subsequent regulations like FIRREA and FDICIA in the early 1990s temporarily broke down these close relationships, as seen in the clear dip in both transitivity and clustering. As the system recovered and the Riegle-Neal Act of 1994 fueled a wave of mergers, the network “re-clustered” into new, stable groups. The Gramm-Leach-Bliley Act of 1999 then strengthened the “rich club” effect, allowing for the creation of massive financial conglomerates that became even more central and interconnected with each other, pushing assortativity to a new, higher level. The most dramatic event is the 2008 financial crisis, which caused all three metrics to plunge as trust evaporated and relationships shattered; the especially sharp drop in assortativity shows the “rich club” itself fracturing under the strain. The subsequent Dodd-Frank Act reshaped the system, and as it recovered, a new, more heavily regulated version of this “cliquey,” “rich club” structure re-emerged, demonstrating a resilient but sensitive architecture that bends during crises but ultimately returns to its core form.

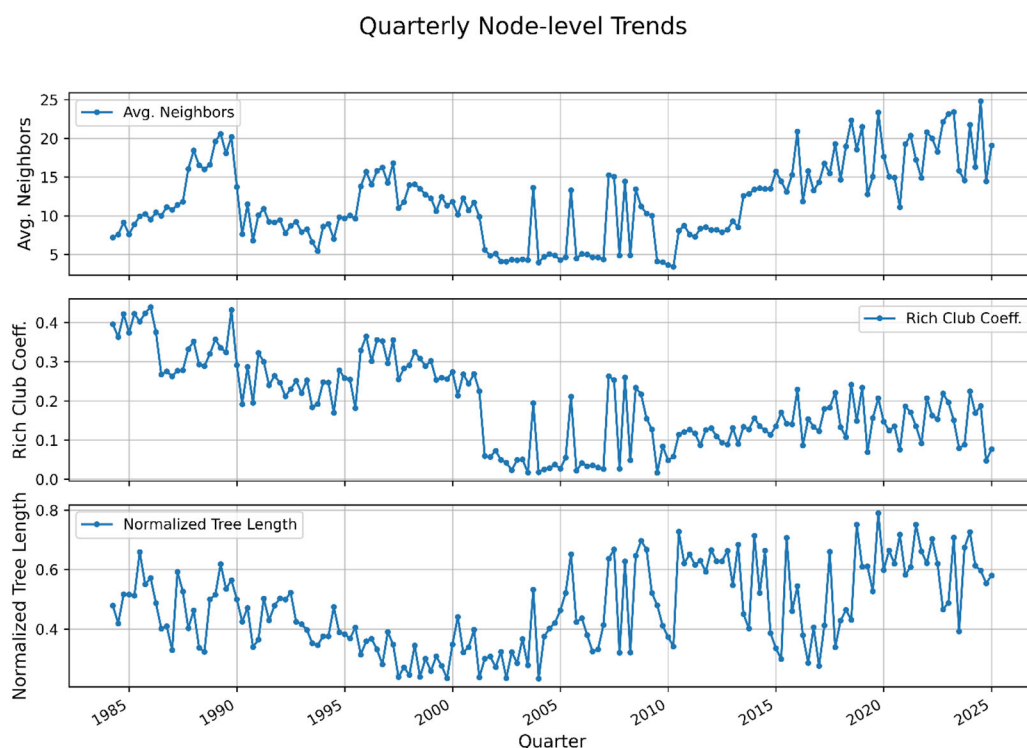


Figure B3. Quarterly node-level trends – average neighbors, rich club coefficient, and normalized tree length (1984 to 2024).

This figure illustrates how regulations and crises directly impacted the power dynamics of the banking system, particularly the formation and behavior of a “rich club” of the most connected banks. In the early 1990s, the S&L crisis (Wang 2025) and regulations like FIRREA caused a temporary breakdown in relationships, seen in the sharp dip in both the average number of bank connections and the internal cohesion of the “rich club.” The subsequent Riegle-Neal and Gramm-Leach-Bliley Acts then fueled the creation of massive, centralized “super-banks.” This is clearly

visible as the network’s efficiency increased (a lower “tree length”), but it also led to a more insular system where these giants focused inward, causing a temporary drop in the “rich club” coefficient as they reorganized. The 2008 financial crisis is marked by a dramatic shattering of the system: trust evaporated, banks disconnected from each other (plummeting “average neighbors”), the “rich club” itself fractured (a collapsing coefficient), and the network’s structure became highly inefficient (a spiking “tree length”). In the post-crisis era, the heavy compliance costs of the Dodd-Frank Act favored the largest institutions, making them more central than ever. This is shown by the steady and dramatic rise in the average number of connections per bank, as smaller firms increasingly had to link up with the few remaining behemoths to operate, cementing the dominance of a reformed, but highly sensitive, “rich club.”

Appendix C: Temporal analysis of embedding features

Node level: Examples of the network structure at the node-level are degree centrality, betweenness centrality, closeness centrality, PageRank, local clustering coefficient, and initial node embeddings (if used as an input to TGNN). The node-level analysis will assist regulators with their oversight responsibilities of monitoring the temperature of the financial system and fashioning policy interventions to curtail any systemic risk and identify individual bank vulnerabilities in assessing localized systemic risks.

Metric	Description in banking
Degree centrality	Measures how many direct lending/borrowing relationships a bank has in the interbank network. This topology is used in Cont, Moussa, and Santos (2013), which explores how this network topology plays a role in shock propagation.
Betweenness centrality	Measures how often a bank acts as a bridge in interbank transactions or payment flows. A high level of this topology indicates a potential channel or a stymie to liquidity flow, which is important in systemic risk analysis. In the literature, Soramäki et al. (2007) find that this network topology has a low average path length and low connectivity.
Closeness centrality	Measures how quickly a bank can reach all other banks through interbank connections. High closeness indicates efficient access to liquidity and information within the network. According to Minoiu and Reyes (2013), financial connectedness expands and contracts with the cycle of global capital flow. It emphasizes that the 2008-2009 global financial crisis is the largest unusual perturbation to the global banking network.
PageRank	Measures the importance of a bank in the network, accounting for the quality of counterparties. It indicates key providers of liquidity or vulnerable nodes that go beyond the simple degree. Battiston et al. (2012) introduce debt rank as a new measure of systemic impact motivated by the feedback-centrality. They find that banks (22) that received the FED emergency loans formed a strongly connected graph where each node became systemically important at the height of the global financial crisis.
Local clustering coefficient	Measures the tendency of a bank’s counterparties to also trade among themselves. High clustering indicates a localized liquidity pool or risk of concentration. Iori et al. (2008) studied network topology, such as clustering coefficients and centrality, on the Italian overnight interbank market.

Community level: Detection algorithm (e.g., Louvain), number of communities, average community size, and distribution of community sizes. This level of analysis provides insights into how regulators identify troubled banks for interventions and prevent systemic risk. Similarly, it facilitates policy design and interventions tailored to specific banking community structures, enhancing financial stability.

Community metric	Explanation and literature
Community detection	It efficiently identifies communities within large networks and optimizes modularity, a measure that quantifies the density of connections within communities compared to connections between communities. Battiston et al. (2012) used the Louvian algorithm on the interbank network to uncover community structures that show systemic vulnerabilities. They also identify a cluster of financial institutions with similar risk profiles, which assist regulators in detecting potential contagion pathways.
Number of communities	It refers to the total clusters in a community network structure, providing insights into the network's fragmentation and integration, showing organizational patterns and interdependence among the nodes. Empirical support for this community structure is the work of Craig and von Peter (2014), who provide evidence of a tiered structure in the interbank market of the German banking system.
Average community size	It is the mean number of nodes per community. It indicates how network entities organize themselves, informing whether interactions typically occur within small, tightly-knit groups or larger, loosely-connected clusters. Fricke and Lux (2015) studied interbank lending networks using community detection algorithms and highlighted the average community size. Smaller community sizes corresponded to a fragmented interbank market, whereas larger sizes suggested greater systemic interdependencies.
Distribution of community sizes	Examining how community sizes vary across a network reveals the heterogeneity of network structures. It indicates whether a network comprises similarly sized communities or exhibits skewed distributions (many small communities with a few large ones). PÃ©rez (2014) examined community size distributions in interbank payment networks in Colombia. They found highly skewed distributions indicating a few large communities dominated by major financial institutions and numerous smaller peripheral communities.

System level (global): System-level analysis is essential for capturing interbank relationships' complex interdependencies and feedback loops, enabling more effective risk management and policymaking to safeguard financial stability. Examples are below: network density, average degree, global clustering coefficient, modularity, characteristic path length, and diameter.

Feature	Description
Network density	Measures how connected the network of mid-size and large banks is relative to the maximum possible connections.
Average community size	If the network of mid-size and large banks is divided into communities, this is the average number of banks per community.

Modularity	Measures the strength of dividing a network of mid-size and large banks into communities. Higher modularity indicates a network of banks with well-defined, dense, sparsely connected communities.
Network transitivity	Measures the overall tendency for nodes (active mid-size and large banks) to cluster together. Higher transitivity means a more “cliquish” or tightly knit network of banks.
Average clustering coefficient	For each node (active bank), it measures how connected its neighbors are to each other. It’s a local measure of cliquishness.
Degree assortativity	Measures the preference for nodes (active banks) to attach to others similar in degree (number of connections).
Average neighbors	The average number of direct connections each bank has in the network. This is identical to the “average degree” from the system-level chart and reflects overall network connectivity.
Rich club coefficient	It measures the tendency of high-degree nodes (“rich” nodes) or systemically important banks to be more densely connected amongst themselves than lower-degree nodes or smaller or less important banks. A high coefficient indicates a “rich club” phenomenon where the most connected banks form a tight core.
Normalized tree length	“Tree length” in network analysis refers to characteristics of spanning trees or path lengths within tree-like substructures. A lower normalized tree length implies more efficient connections or a more compact core structure. Large banks are at the core and connected to smaller banks at the periphery.

Appendix D: Major U.S. regulations from 2014 to 2024

D1. Financial Institutions Reform, Recovery, and Enforcement Act (FIRREA) - 1989

This regulation was promulgated in response to the savings and loan crisis. FIRREA restructured the federal savings and loan regulatory system. It established the Resolution Trust Corporation to manage insolvent thrifts and transferred regulatory authority to the Office of Thrift Supervision. The act also introduced stricter oversight and capital requirements for savings institutions, and the enforcement date was 1989.

D2. Federal Deposit Insurance Corporation Improvement Act (FDICIA) -1991

FDICIA enhanced the FDIC’s authority, mandated risk-based deposit insurance premiums, and introduced prompt corrective action provisions. It also imposed stricter capital requirements and limited certain activities of insured state banks, and its enforcement date was 1991.

D3. Riegle-Neal Interstate Banking and Branching Efficiency Act (IBBEA) - 1994

This act allowed bank holding companies to acquire banks in any state and permitted interstate branching. It aimed to create a more efficient and competitive banking system by reducing geographic restrictions and came into force in 1994.

D4. Gramm-Leach-Bliley Act (GLBA) - 1999

GLBA repealed parts of the Glass-Steagall Act, allowing commercial banks, investment banks, and insurance companies to consolidate. It aimed to modernize the financial services industry and promote competition. The enforcement date was 1999.

D5. Dodd-Frank Wall Street Reform and Consumer Protection Act - 2010

Dodd-Frank introduced comprehensive financial regulatory reforms in response to the 2008 financial crisis. It established the Consumer Financial Protection Bureau, imposed stricter capital and liquidity requirements, and introduced the Volcker Rule, which restricted proprietary trading by banks.

The Volcker Rule is a key provision of the Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010, enacted in response to the 2007–2009 financial crisis. Named after former Federal Reserve Chairman Paul Volcker, the rule aims to reduce excessive risk-taking by banks and safeguard the financial system from speculative activities that do not benefit customers or the broader economy. It was enforced in 2010.

Appendix E: Significance of detected anomalies and TGNN capacity to provide early warning signals

E1. Significance of detected anomalies

The bank behavior and events captured by the temporal graph neural network (TGNN)-detected anomalies are first, regulatory pressure, and legal events. To explain, banks under significant regulatory scrutiny or involved in major financial settlements and compliance issues exhibit high anomaly scores. For instance, JP Morgan recorded a high anomaly score associated with regulatory pressures, fines, and settlements due to its central role in interbank lending and derivatives markets, amplifying its interbank risk exposure (Acharya et al. 2014; Strahan 2013).

Another important TGNN-detected anomaly is eventful and significant mergers and acquisitions within the interbank relationships. The anomalies captured by TGNN include periods of substantial organizational restructuring, such as mergers or acquisitions. First Horizon Bank, which exhibited a notably high anomaly score, reflects such an event due to its acquisition of IberiaBank Corporation. This significantly changes its interbank market footprint and connectivity (Carlson and Mitchener 2005; Hassan and Giouvris 2021; Johnson and Rice 2008).

Moreover, the TGNN-detected anomaly captures systemically important financial activities such as large overnight interbank positions or other alternative market transactions indicative of potential liquidity stress or systemic risks. Banks labeled as “too-big-to-fail” or involved in substantial interconnectedness record an elevated anomaly score (Battiston et al. 2012; Craig and von Peter 2014; Fricke and Lux 2015).

Lastly, the anomalies detected by TGNN reflect significant expansions or contractions in a bank's geographic or market footprint. This causes shifts in their position and interconnectedness in the interbank network. This can arise from strategic expansions when there is regulatory

relaxation or contraction due to regulatory tightening (Avery et al. 1999; Chen et al. 2025; Rice and Davis 2007).

E2. How early can TGNN-detected anomalies provide warning signals?

TGNN-generated anomaly scores offer proactive early warning signals of financial stress, often several quarters in advance: Anomaly signals consistently precede recognized financial stress or distress events several quarters ahead. Historical anomalies that identified JP Morgan and First Horizon emerged significantly prior to known mergers, regulatory events, and/or publicly reported financial stress. This implies, therefore, that the model's ability to provide timely early warnings is plausible.

Moreover, this dynamic time-series model (TGNN) has the capacity to identify nuance changes in banks' interbank relationships that precede broader financial stress and invariably provides crucial lead-time advantages. This helps regulators proactively intervene to mitigate systemic risks and manage potential contagion (Acemoglu et al. 2015; Eisenberg and Noe 2001; Gai and Kapadia 2010).

Lastly, it has been shown that high anomaly scores strongly correlate with elevated financial stress periods documented. This correlation enhances the credibility and usage of TGNN-based anomaly detection as a surveillance tool. This emphasizes the model's efficacy in preemptively signaling financial vulnerabilities (Battiston et al. 2012; Gong et al. 2019; Wang et al. 2017).

In summary, the anomalies detected by TGNN provide valuable and timely signals concerning bank behaviors associated with regulatory pressures, significant mergers, systemic financial activities, and shifts in banking footprint. Also, these anomalies offer substantial advance warning signals (often several quarters ahead) regarding potential systemic risks or financial distress, emphasizing TGNN's utility as a proactive regulatory monitoring tool.