

Systemic interconnectedness in the US financial system

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Abstract

This paper constructs and validates measures of interconnectedness in the US banking system, in a 2000-2025 panel dataset of large banks. Using regulatory balance-sheet data, it develops an aggregate interconnectedness index, reflecting a variety of transmission channels for counterparty risk. The index reveals extreme concentration, led by JPM, Citigroup, and BoA. Textual analysis on 10Ks shows that the direct and collateral-stress channels of counterparty risk are mostly responsible for the post-GFC interconnectedness of JPM. An FF5 residual network analysis finds that JPMorgan exhibits high correlations with multiple other systemic banks, indicating elevated potential for shock propagation. Volatility spillover analysis identifies JPM as one of the biggest net transmitters of volatility, and also as exhibiting high sensitivity to external volatility, suggesting potential vulnerability to systemic contagion. Dynamic conditional correlation analysis finds that JPMorgan is highly connected at all times, while banks like Wells Fargo and BoA become disproportionately connected under stress. Overall, the results on interconnectedness degree or ranking remain stable across methods, as does the dynamic evolution of counterparty risk.

Email: marianthimif@gmail.com. I would like to express my deepest gratitude to my thesis advisor, Professor Vasia Panousi, for her exceptional guidance, continuous encouragement, and unwavering support throughout the development of this thesis. Her insightful comments, academic expertise, and patience have been invaluable at every stage of this research. I hereby certify that the work carried out and presented in this submitted thesis is exclusively my own. Any information and material included that has been drawn from other sources has been properly cited in this thesis. Furthermore, I am aware that if it is established that the above declaration is not true, my thesis will be annulled.

1 Introduction

The Global Financial Crisis (GFC) revealed that systemic risk may emerge from the interconnectedness of institutions within the financial system. Banks are linked through dense networks of bilateral obligations, derivative contracts, securities financing transactions, and cross-border exposures. In such an environment, the failure of a single institution may trigger losses and transmit distress through chains of counterparty claims.

Despite post-crisis regulatory reforms, the measurement of interconnectedness and/or counterparty risk remains incomplete. Existing supervisory frameworks identify size, substitutability, complexity, and cross-jurisdictional activity as indicators of systemic importance, but most of these factors are derived from bank reporting without external validation.

This paper is the first study to a variety of distinct methodologies, combining textual and quantitative data with advanced econometric and natural-language processing (NLP) methods, to construct and validate comprehensive measures of systemic interconnectedness. The main findings, which remain qualitatively robust across different approaches, are as follows.

First, using regulatory balance-sheet data, the analysis develops an aggregate interconnectedness index, reflecting a variety of transmission channels for counterparty risk. The index reveals extreme concentration, with JPMorgan accounting for nearly one-fifth of total systemic exposure, followed by Citigroup and Bank of America. Systemic risk therefore appears driven by a small number of interconnected institutions. The elevated interconnectedness index for JPMorgan is nowadays due to OTC derivatives exposure, while Bank of America and Citigroup display stronger contributions from assets and securities, reflecting differences in underlying business models.

Second, textual analysis on 10K reports quantifies a variety of transmission channels of counterparty risk for JPMorgan. Shadow linkages were prominent before the GFC, with the contribution of direct counterparty risk and derivatives increasing in the post-GFC period.

Third, centrality analysis is conducted from the correlation matrix of residuals from a FF5 model. Before the GFC, Bank of America was the most central node of the US banking network. However, after the GFC, JPMorgan emerges as the new center, having acquired Bear Stearns and Washington Mutual. Thus, JPMorgan shows strong connectivity to other systemically important nodes and a high potential for shock propagation.

Fourth, in volatility spillover analysis, Morgan Stanley and JPMorgan emerge the main net transmitters of volatility to other banks. This suggests that disturbances originating from these institutions have the greatest potential to propagate throughout the broader financial system. Additionally, JPMorgan exhibits the highest sensitivity to external volatility shocks, as such shocks account for approximately three-quarters of its forecast-error variance, making it particularly vulnerable to systemic contagion.

Fifth, dynamic conditional correlation analysis finds that JPMorgan maintains elevated co-movement with all major peer institutions throughout the sample, consistent with its dominant position in the Interconnectedness Index and its role as the leading net transmitter of volatility. These correlations are higher in the post-GFC period, compared to the period before, suggesting an upward shift in interdependence following the financial crisis. The results also indicate that system-wide co-movement intensifies markedly during stress episodes. Specifically, all banks display an increase in conditional correlations during crisis episodes, confirming the correlation clustering property of financial markets.

JPMorgan displays a relatively moderate amplification, despite ranking first in average correlation, suggesting that its systemic centrality is persistent rather than driven exclusively by crisis co-movement. In other words, JPMorgan is highly connected at all times, while institutions such as Wells Fargo and Bank of America become disproportionately connected under stress.

2 Literature review

A first strand of related literature studies systemic risk arising from financial interconnectedness. Early contributions emphasize how direct exposures, common asset holdings, and funding dependencies can amplify shocks through the banking system. Acharya et al. (2010) develop a framework for measuring systemic risk based on the expected capital shortfall of financial institutions during crises, later operationalized through the SRISK measure by Brownlees and Engle (2017). Adrian and Brunnermeier (2016) introduce CoVaR, which measures the contribution of an individual institution to system-wide tail risk. These approaches highlight that the systemic importance of a bank depends not only on its size but also on its connections with other institutions.

A second strand of literature examines financial networks using balance-sheet information. Allen and Gale (2000) demonstrate theoretically that the structure of interbank networks plays a crucial role in determining the resilience of the financial system. Subsequent work by Eisenberg and Noe (2001) develops a framework for analyzing contagion through interbank obligations, while Acemoglu, Ozdaglar, and Tahbaz-Salehi (2015) show that network structures can either absorb or amplify shocks, depending on shock magnitude. More recently, Covi, Gorce, and Kok (2019) use granular supervisory data on euro-area banks' large exposures and show that systemic vulnerability depends jointly on network topology and bank-specific characteristics. This literature motivates the construction of balance-sheet-based measures of interconnectedness and highlights the importance of identifying specific transmission channels, including counterparty exposures and collateral-related contagion.

A third strand of literature uses market data to infer interconnectedness among financial institutions. Diebold and Yilmaz (2009, 2012, 2014) develop connectedness measures based on forecast-error variance decompositions from vector autoregressions, providing a framework for quantifying return and volatility spillovers. Their methodology has become one of the most widely used tools for measuring systemic connectedness. Demirer, Diebold, Liu, and Yilmaz (2018) extend this framework to a global sample of large banks and show that interconnectedness varies substantially over time and increases during periods of financial stress. Similarly, Malik and Xu (2017) analyze interconnectedness among global systemically important banks and insurers, finding that market-based connectedness is closely related to broader measures of systemic risk. These studies provide the foundation for the volatility-spillover analysis conducted in this paper.

Related research has also examined directional spillovers and the identification of net transmitters and receivers of risk. Alter and Beyer (2014) analyze spillovers between sovereigns and banks during the European debt crisis, while Adams, Fuess, and Gropp (2014) develop a state-dependent framework showing that spillover effects become substantially stronger during periods of market stress. More recent evidence suggests that connectedness remains an important feature of banking systems even after the post-crisis regulatory reforms. For example, studies of the 2023 US regional banking turmoil find significant increases in volatility spillovers within the banking sector, highlighting the con-

tinued relevance of contagion channels. Altinoglu and Stiglitz (2023) develop a theory of endogenous interbank network formation in which banks strategically choose their degree of interconnectedness, giving rise to collective moral hazard.

A fourth strand of the literature studies the evolution of correlations and contagion over time. Engle’s Dynamic Conditional Correlation (DCC) framework provides a flexible approach for modeling time-varying dependence across financial institutions. DCC-based measures have been widely applied to banking systems to identify periods in which institutions become unusually interconnected and therefore more susceptible to systemic shocks. This literature generally finds that correlations increase sharply during crisis episodes, consistent with the notion that diversification benefits diminish precisely when they are most needed. Studies of banking-sector connectedness during the GFC, the European sovereign debt crisis, and the COVID-19 pandemic document substantial increases in dynamic correlations and systemic risk during periods of heightened uncertainty.

This paper contributes to these literatures in three ways. First, unlike many market-based studies that infer interconnectedness solely from asset prices, it constructs an aggregate interconnectedness index using regulatory balance-sheet information for large U.S. banks over the period 2000–2025. This allows direct examination of multiple counterparty-risk transmission channels and their evolution over time. Second, it combines balance-sheet measures with several complementary market-based methodologies, including residual return networks, volatility-spillover analysis, and dynamic conditional correlations. This multi-method approach permits an assessment of whether different measures identify similar systemic institutions and patterns of risk transmission. Third, the paper provides institution-level evidence on the persistent systemic importance of JPMorgan and the conditions under which other major banks, particularly Bank of America and Wells Fargo, become more central to the network during periods of financial stress. The consistency of the results across methodologies contributes to the growing evidence that systemic importance is a robust and measurable feature of modern banking networks.

3 Data description

This study uses supervisory data obtained from the FR Y-15: Banking Organization Systemic Risk Report, published annually by the Board of Governors of the Federal Reserve System. The FR Y-15 form is submitted by large US bank holding companies, intermediate holding companies, and certain foreign banking organizations. Its purpose is to measure attributes of systemic importance, consistent with the Basel Committee on Banking Supervision (BCBS) and Financial Stability Board (FSB) framework for the identification of global systemically important banks (G-SIBs).

The form is structured into indicator categories that capture systemic risk along several dimensions such as size, interconnectedness, substitutability, complexity, and cross-jurisdictional activity.

The framework encompasses twelve regulatory indicators. Total Exposures represents the aggregate scale of a bank’s financial operations, comprising the comprehensive summation of all on-balance sheet assets and off-balance sheet exposures, and serves as the primary metric for determining an institution’s total systemic magnitude. Intra-Financial System Assets (IFSA) quantify the total value of all credit and capital claims that a reporting bank holds against other financial institutions, capturing its role as a creditor or investor within the financial network and reflecting its direct exposure to the solvency of peer entities, where a higher value indicates greater sensitivity to inward contagion

should a counterparty face distress. Conversely, Intra-Financial System Liabilities (IFSL) represent the total value of financial obligations and debt instruments that the reporting bank owes to other financial entities, characterizing the bank as a debtor or funding recipient and identifying its potential as a primary transmitter of outward systemic risk in the event of its own default.

Securities Outstanding measures a bank’s footprint in securities markets through outstanding debt securities, commercial paper, or other issued financial instruments, while Payments Activity captures the total value of payments sent via major payment systems, reflecting the criticality of a bank as an intermediary in transactional and settlement systems. Assets Under Custody, defined as assets held on behalf of clients, reflects substitutability and the extent to which the financial system depends on the institution for custodial services. Underwriting Activity, measured as the total amount of debt and equity securities underwritten, indicates the bank’s importance in capital market intermediation.

The remaining indicators capture market and cross-border dimensions of interconnectedness. OTC Derivatives reflect gross notional exposure to over-the-counter derivatives contracts, while Trading and Available-for-Sale (AFS) Securities quantify the bank’s involvement in market-based activities. Level 3 Assets, whose valuation relies on unobservable inputs, represent complex, illiquid positions and serve as an indicator of model and valuation risk. Finally, Cross-Jurisdictional Claims and Cross-Jurisdictional Liabilities capture, respectively, claims on foreign counterparties and liabilities to foreign entities, together reflecting the institution’s global financial footprint.

This analysis employed FR Y-15 data for the largest US banking organizations by total assets for the years 2019 through 2024 as depicted in Table 1. These years span both pre- and post-pandemic periods, capturing relevant structural changes in bank interconnectedness. The sample includes JPMorgan Chase & Co., Citigroup Inc., Bank of New York Mellon Corporation, The, State Street Corporation, Bank of America Corporation, Wells Fargo & Company, Goldman Sachs Group, Inc., Morgan Stanley, PNC Financial Services Group, Inc., Northern Trust Corporation, M&T Bank Corporation, U.S. Bancorp, First Citizens Bancshares, Inc., American Express Company, Synchrony Financial, Fifth Third Bancorp, Flagstar Financial, Inc., KeyCorp, Truist Financial Corporation, Charles Schwab Corporation, The, Discover Financial Services, Capital One Financial Corporation, Citizens Financial Group, Inc., Huntington Bancshares Incorporated, Regions Financial Corporation, Ally Financial Inc., UBS Americas Holding LLC, Barclays US LLC, Santander Holdings USA, Inc., DB USA Corporation, DWS USA Corporation, HSBC North America Holdings Inc., Mizuho Americas LLC, BNP Paribas USA, Inc., TD Group US Holdings LLC, RBC US Group Holdings LLC, CIBC Bancorp USA Inc., BMO Financial Corp.

4 Interconnectedness index

This section describes the construction of the interconnectedness index from regulatory balance-sheet data for a panel of US banks.

4.1 Framework

Systemic interconnectedness is broadly understood in the literature as the degree to which inter-financial claims and exposures are concentrated within the banking system. Since

bilateral exposure matrices are not directly observable from public data, this paper constructs a market-share-based proxy that captures each institution’s proportional participation across the principal channels of counterparty risk. This section proceeds in two steps, we first derive the index formally, outlining the exposure components and aggregation procedure, and then describe the supervisory data from which these components are drawn.

The index aggregates four regulatory exposure categories, Intra-Financial System Assets (A), Intra-Financial System Liabilities (L), Securities Outstanding (S), and OTC Derivatives (D). These components jointly span direct interbank claims, funding dependencies, market-based balance sheet intermediation, and derivative-linked counterparty chains.

4.2 Definition

Let $i = 1, \dots, N_t$ index banks in year t , and let

$$m \in \mathcal{M} = \{A, L, S, D\}.$$

Denote bank-level exposures by $X_{i,t}^{(m)}$ and aggregate system exposure in category m by

$$X_t^{(m)} = \sum_{i=1}^{N_t} X_{i,t}^{(m)} \quad (1)$$

Define the exposure share:

$$s_{i,t}^{(m)} = \frac{X_{i,t}^{(m)}}{X_t^{(m)}} \quad (2)$$

The Interconnectedness Index is the equally weighted mean share:

$$\mathcal{I}_{i,t} = \frac{1}{|\mathcal{M}|} \sum_{m \in \mathcal{M}} s_{i,t}^{(m)} = \frac{1}{4} \left(s_{i,t}^{(A)} + s_{i,t}^{(L)} + s_{i,t}^{(S)} + s_{i,t}^{(D)} \right) \quad (3)$$

The index is reported in percentage terms:

$$\mathcal{I}_{i,t}^{(\%)} = 100 \cdot \mathcal{I}_{i,t} \quad (4)$$

By construction,

$$\sum_{i=1}^{N_t} \mathcal{I}_{i,t} = 1 \quad (5)$$

so the index redistributes total systemic exposure mass across institutions each year. The index $\mathcal{I}_{i,t}$ measures the average systemic market share of bank i across the four transmission channels, and serves as a proxy for systemic centrality when bilateral exposure matrices are not directly observable. A higher index value indicates that an institution accounts for a disproportionately large share of aggregate inter-financial exposures, implying a greater capacity to spread distress across the system. If a shock hits a single institution, that is, a shock that is specific to that institution and not driven by broader market conditions, the extent to which this shock feeds through into aggregate systemic loss $\mathcal{L}_t$ depends on how large that institution’s exposure share is. Formally, the rate at which a unit shock to institution i amplifies system-wide losses scales with its index value:

$$\frac{\partial \mathcal{L}_t}{\partial \varepsilon_{i,t}} \propto \mathcal{I}_{i,t}. \quad (6)$$

In other words, the larger the share of total exposures an institution holds, the more its distress reverberates through the system. The index therefore serves as a summary measure of each institution’s relative contribution to system-wide risk propagation.

4.3 Descriptive statistics

Table 2 reports the average Interconnectedness Index for the twenty largest US banking organizations, revealing pronounced concentration at the top of the distribution. JPMorgan accounts for nearly one-fifth of total systemic exposure, with Citigroup and Bank of America following. The decline in index values beyond the first five banks which jointly account for more than half of aggregate interconnectedness, points to a clear core–periphery structure in the US banking system, where systemic risk is driven by a small number of interconnected institutions. This is further illustrated in Figure 1, which highlights the extreme right-skewness of the index distribution.

Figure 2 decomposes the average index into its four components intra-financial system assets (A), liabilities (L), securities outstanding (S), and OTC derivatives (D) for the five most interconnected banks. The elevated index for JPMorgan and Goldman Sachs is due to OTC derivatives exposure, while Bank of America and Citigroup display stronger contributions from assets and securities, reflecting differences in underlying business models rather than balance sheet scale alone.

Figure 3 traces the evolution of the index over 2019–2024 for the ten most interconnected banks. The hierarchy remains stable throughout the sample, with JPMorgan consistently near the 20% threshold and the remaining institutions fluctuating within narrow bands, confirming that systemic importance is a persistent structural feature rather than a transitory one.

5 Textual validation: The case of JPMorgan

The FR Y-15 interconnectedness index, constructed from intra-financial assets, liabilities, securities financing transactions, and derivatives exposures, identifies JPMorgan as the most interconnected bank in the US banking system during the most recent five-year window, with an average interconnectedness score of 19.7%. To verify that this finding reflects structural and persistent network centrality rather than short-window dynamics, this section constructs a long-horizon textual proxy of counterparty risk exposure using JPMorgan’s annual Form 10-K filings from 2002 to 2025. If JPMorgan’s interconnectedness is structural, it should be observable not only in regulatory balance-sheet metrics but also in the persistence of counterparty-related disclosures over time.

The annual 10-K filings submitted by JPMorgan for the period 2002–2025 were retrieved and preprocessed. Each document was stripped of HTML markup and converted to lowercase. Let W_t denote the total word count of the filing in year t .

The textual variable reflecting JP Morgan’s counterparty risk is constructed as follows. First, a lexicon is proposed, consisting of five categories, each capturing a transmission channel for counterparty risk, c . These channels are direct counterparty risk, derivatives networks, shadow linkages, systemic contagion, and collateral stress. Direct counterparty risk is the risk that a specific institution on the other side of a JPMorgan contract fails to meet its obligations. Derivatives network is JPMorgan’s web of contractual exposures through financial instruments. Shadow linkages refer to financial activity conducted outside traditional bank balance sheets, such as repurchase agreements. Collateral stress

is related to the assets posted as security against potential losses. Systemic contagion describes a domino effect of spreading financial distress

The terms in each of the five channels are presented Table 3. By sourcing the terms from JPMorgan’s annual 10-K filings, the lexicon ensures that the textual proxy is grounded in real-world institutional reporting. This alignment facilitates a direct conceptual bridge between the qualitative language found in bank disclosures and the balance-sheet-based interconnectedness measures constructed in Section 3.

For channel c in year t , the normalized frequency measure is formally defined as:

$$TI_{c,t} = \frac{\text{Number of keyword matches in category } c \text{ in year } t}{W_t} \times 10,000 \quad (7)$$

This per-10,000-word normalisation controls for variation in document length across the sample, ensuring that observed changes in keyword frequency reflect shifts in disclosure content rather than differences in filing size.

The aggregate textual interconnectedness index for JPMorgan is constructed by summing across all five transmission channels of the counterparty risk lexicon:

$$TI_t = \sum_{c=1}^5 TI_{c,t} \quad (8)$$

yielding a time series of disclosed interconnectedness intensity.

Table 4 reports annual keyword frequencies across the five counterparty risk transmission channels for JPMorgan. Shadow linkages is the dominant category throughout the sample, peaking at 2,017 occurrences in 2011. Its subsequent decline likely reflects post-crisis regulation. Direct counterparty risk and the derivatives network increase from 2009 onward, as JPMorgan absorbed market share vacated by smaller institutions exiting the derivatives business. Collateral stress is negligible before 2010 but increases thereafter, reflecting new margin and clearing requirements introduced by regulation. Lastly, Systemic contagion spikes during the Global Financial Crisis (GFC) and the COVID-19 pandemic, but remains above its pre-2008 baseline throughout, suggesting that awareness of systemic risk has become a permanent feature of JPMorgan’s disclosures rather than an occasional response to acute stress.

Figure 6 presents the aggregate textual interconnectedness index constructed for JPMorgan.

The index rises steadily during the credit expansion period 2002-2007. This coincides with rapid growth in structured credit markets, repo financing, and OTC derivatives activity. At that time, large dealer banks, including JPMorgan, expanded their central role in intermediation. In 2008-2011, i.e. during and in the aftermath of the financial crisis, the index peaks and remains at high levels, consistent with heightened awareness of contagion risk. Subsequently, the index declines and eventually stabilizes at a higher level than in the early 2000s.

Figures 4 and 5 decompose the aggregate textual JPMorgan index into its five channels or components. The shadow linkage channel dominates the pre-crisis and crisis periods, peaking at over 2,000 keyword occurrences in 2011, and reflecting JPMorgan’s extensive exposure to off-balance-sheet vehicles, repo markets, and non-bank financial counterparties. Its subsequent decline after 2014 coincides with regulatory reforms that redirected these activities toward more transparent structures.¹

¹This is consistent with the findings documented by Gorton (2010) and Adrian & Shin (2010).

As shown in Figure 5, the direct counterparty channel becomes textually dominant after 2014. This increase reflects the consolidation of bilateral exposure within large G-SIBs, as smaller intermediaries exited the market following the crisis.

The derivatives component rises sharply between 2008 and 2015 before moderating gradually, in line with the broader recognition of systemic OTC exposure risks. Even after the introduction of central clearing mandates, concern about this risk in disclosures remains above pre-crisis levels.

The contagion channel displays an episodic pattern, with spikes during the GFC and the COVID-19 pandemic. Importantly, the post-2008 baseline remains persistently above its pre-crisis level, indicating that systemic risk awareness has become a more permanent feature of JPMorgan’s institutional disclosure.

The collateral stress channel is the fastest growing counterparty-risk channel. Disclosures in this category are negligible before 2010 and rises steadily thereafter, coinciding with the implementation of Basel III liquidity requirements and margin rules.

Overall, it appears that regulatory tightening has not reduced JPMorgan’s interconnectedness importance. Instead, it has redistributed it across different transmission channels, through collateral and margin channels, rather than unsecured bilateral exposures.

6 Market-based validation

Here, a market-based approach using the Fama–French Five-Factor model is employed to validate the interconnectedness index.

Specifically, the analysis centers on the residuals obtained from the Fama–French Five-Factor asset pricing model. These residuals represent the component of bank stock returns that cannot be explained by common systematic risk factors and therefore capture idiosyncratic shocks, institution-specific information, and potential spillover effects arising from network centrality and counterparty exposures.

The underlying hypothesis is that highly interconnected institutions, due to their central role in financial networks and counterparty relationships, are more exposed to shock propagation and information transmission. Consequently, these banks may exhibit larger or more persistent abnormal-return components, reflecting risks not fully captured by standard systematic factors. In other words, for highly interconnected institutions, idiosyncratic shocks are less likely to remain purely diversifiable and may instead signal latent systemic stress transmission channels.

By examining the magnitude and behavior of model residuals, market-based evidence is provided supporting the systemic importance and interconnectedness rankings derived from regulatory data. This approach helps extend the analysis beyond the limited five-year regulatory sample and incorporate forward-looking information embedded in market prices.

6.1 The Fama–French five-factor model (FF5)

To isolate abnormal return components, an estimation of the FF5 model is used. The model is specified as follows:

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{MKT,i}(R_{M,t} - R_{f,t}) + \beta_{SMB,i}SMB_t + \beta_{HML,i}HML_t + \beta_{RMW,i}RMW_t + \beta_{CMA,i}CMA_t + \varepsilon_{i,t} \quad (9)$$

where $R_{i,t}$ denotes the return of bank i at time t , $R_{f,t}$ is the risk-free rate, and $R_{M,t}$ is the market portfolio return. The factors SMB_t (Small Minus Big), HML_t (High Minus Low), RMW_t (Robust Minus Weak), and CMA_t (Conservative Minus Aggressive) capture the size premium, value premium, profitability factor, and investment factor, respectively. The β coefficients measure the sensitivity of bank returns to systematic risk factors. Finally, α_i represents abnormal performance unexplained by systematic risk, and $\varepsilon_{i,t}$ denotes the residual term. The residual $\varepsilon_{i,t}$ reflects idiosyncratic return variation not captured by systematic risk factors.

Banks with greater systemic centrality may therefore exhibit residual dynamics consistent with heightened exposure to shock transmission mechanisms. Accordingly, the statistical properties of $\varepsilon_{i,t}$ are analyzed to assess whether market-based abnormal return behavior aligns with regulatory measures of interconnectedness.

Daily adjusted closing prices are obtained from Yahoo Finance from January 2003 to December 2025. Adjusted closing prices are used to ensure that stock splits and dividend distributions are incorporated into the return series. Daily simple returns are computed as:

$$R_{i,t} = \frac{P_{i,t} - P_{i,t-1}}{P_{i,t-1}} \quad (10)$$

where $P_{i,t}$ denotes the adjusted closing price of bank i at time t . Missing observations are preserved, in order to retain institutions with shorter trading histories. Only the first observation, which mechanically produces missing values due to return differencing, is removed. The model is estimated using Ordinary Least Squares (OLS) separately for each bank.² Figure 7 presents the cumulative return indices for the sample banks, constructed by compounding daily returns.

Table 5 reports the estimation results of the FF5 model. The FF5 explain a substantial proportion of return variation across sample banks, with R^2 values ranging from 0.56 to 0.74. The comparatively lower explanatory power observed for Mizuho Financial Group ($R^2 = 0.30$) likely reflects differences in market structure, trading hours, and currency exposure. JPMorgan exhibits the highest R^2 (0.741), indicating that its returns are linked to systematic risk factors. This finding is consistent with its central role in financial markets and broad exposure to macro-financial conditions. The estimated intercepts (α_i) are economically small across institutions, as expected in an efficient market setting. Nevertheless, JPMorgan displays the largest positive abnormal return component, suggesting persistent return dynamics not fully captured by standard risk factors.

6.2 Residual interconnectedness and centrality analysis

Subsequently, a network of banking interconnectedness is constructed using the correlation structure of abnormal return innovations from the FF5 model estimation. Because these residuals are purged of systematic risk factors, the resulting network reflects institution-specific co-movements potentially driven by balance sheet interdependencies, common counterparties, and contagion dynamics.

The Pearson correlation matrix for the FF5 residuals is computed as follows:

²To preserve data integrity and maximize sample utilization, missing observations are removed on a bank-specific basis. This approach avoids unnecessary loss of information while maintaining consistent factor alignment.

$$\rho_{ij} = \text{Corr}(\varepsilon_{i,t}, \varepsilon_{j,t}) \quad (11)$$

and it measures the degree to which idiosyncratic shocks co-move across institutions. The resulting matrix defines the weighted adjacency matrix of an undirected financial network.

To quantify systemic importance within the network, eigenvector centrality is computed. Unlike simple degree measures, eigenvector centrality assigns greater importance to nodes connected to other highly connected nodes, thereby capturing recursive influence within the financial system. Formally, centrality scores c_i satisfy:

$$c_i = \frac{1}{\lambda} \sum_j \rho_{ij} c_j \quad (12)$$

where λ denotes the dominant eigenvalue of the adjacency matrix. This measure is particularly appropriate for systemic risk analysis because it incorporates both direct and indirect channels of shock transmission. Banks with higher eigenvector centrality are more deeply embedded in the shock transmission network and may act as amplifiers of financial stress. Consequently, centrality provides a market-based proxy for systemic importance derived from abnormal return co-movements.

Table 6 presents the interconnectedness rankings derived from the residual correlation network over the full sample period 2003–2025. Bank of America (BoA) emerges as the most central institution in the network, with a centrality score of 0.41, followed closely by JPMorgan (0.38) and Wells Fargo (0.37).

The dominance of BoA during the full period likely reflects its extensive retail banking strategy, large deposit base, mortgage exposure, and significant involvement in credit markets, all of which increase sensitivity to common funding conditions and household credit cycles. Since the GFC, BoA has absorbed balance sheet stress, including mortgage-related losses and the integration of Merrill Lynch, reinforcing its central role in shock transmission dynamics. JPMorgan ranks second but remains highly central, consistent with its role as a major derivatives dealer, clearing bank, and global liquidity provider. Wells Fargo and Citigroup also exhibit strong centrality. By contrast, Mizuho Financial Group exhibits very low centrality, likely due to differences in geographic exposure, trading hours, currency denomination, and limited overlap with US funding and counterparty networks. These findings suggest that, when considering the entire 2003–2025 period, the residual shock transmission network is dominated by institutions most exposed to household credit cycles and crisis-era balance sheet stress.

Figure 8 shows the matrix of residual correlations of abnormal returns. Several economically meaningful clusters emerge based on shared business models. For example, Goldman Sachs and Morgan Stanley show a high residual correlation of 0.51, indicating that they share firm-specific shocks. A similar comovement is observed between universal banks like BoA and Citigroup (0.44), and between custody banks like Bank of New York Mellon and State Street (0.45). In contrast, Mizuho Financial Group exhibits near-zero correlations with the US institutions, reflecting geographic segmentation, currency differences, and distinct funding markets.

Figure 9 visualizes the residual shock transmission in a network context. BoA occupies the most central position, connecting with both commercial banking institutions and market-based intermediaries. Its position suggests a bridging role, linking consumer credit exposure with wholesale funding and capital market activities. JPMorgan appears as a secondary hub with extensive connections across investment banking and liquidity provision channels. The Goldman Sachs–Morgan Stanley cluster reflects strong co-movement

driven by capital market activity and trading operations. The custody banks Bank of New York Mellon and State Street form a tightly connected substructure, reflecting shared exposure to asset flows and institutional liquidity management.

Table 7 reports the eigenvector centrality rankings for the period after January 2009. Now, JPMorgan emerges as the most central institution, surpassing BoA, which dominated the full-sample network. This finding indicates that systemic influence within the US banking network is not static, but it evolves in response to crisis-driven developments. Specifically, during the financial crisis, JPMorgan executed strategic acquisitions that significantly expanded its systemic footprint. The acquisition of Bear Stearns, supported by government facilitation, provided immediate scale in investment banking. Additionally, the acquisition of Washington Mutual’s assets following its collapse, granted JPMorgan a vast retail banking network, particularly on the US West Coast, expanding its deposit base and geographic reach.

Figure 10 presents the correlation matrix of FF5 residuals in the post-2009 period. Several patterns emerge. First, strong residual correlations persist among large US universal banks, particularly BoA (0.46) and BAC–WFC (0.45), likely reflecting shared exposure to household credit and mortgage markets. Second, the strongest dependence is observed between GS and MS (0.52), consistent with their similar investment banking and trading business models. Third, JPMorgan exhibits elevated correlations with multiple systemic institutions (BAC 0.39, GS 0.36, WFC 0.38, MS 0.32), reinforcing its role as a central conduit for risk transmission. Custody banks (BK, STT) display moderate connectivity, while MFG remains weakly integrated, indicating limited direct spillover within the US-centric network. Overall, the post-crisis residual dependence structure suggests that systemic interconnectedness remains concentrated among large universal and investment banks.

Figure 11 exhibits a clear hierarchy. JPMorgan occupies the most central position, recording the highest eigenvector centrality (0.41), indicating strong connectivity to other systemically important nodes and a high potential for shock propagation. BoA follows as a major hub, reflecting its integration in household credit and mortgage markets. A dense capital-markets cluster is formed by Goldman Sachs and Morgan Stanley, consistent with their shared dependence on trading and market-making activities. Meanwhile, financial infrastructure institutions such as Bank of New York Mellon and State Street occupy intermediate but structurally important positions due to their roles in custody, clearing, and settlement services.

6.3 Rolling-window centrality analysis

To capture the time-varying nature of systemic importance, the interconnectedness network is estimated using a rolling-window framework. Instead of constructing a single static network, the residual correlation network via Pearson correlations and eigenvalue centrality, is re-estimated over successive time windows of fixed length.

The window is moved forward one period at a time, producing a time series that captures the evolution of systemic relevance. Figure 12 presents the rolling eigenvector centrality of JPMorgan relative to its peer group from 2010 to 2025. The solid line represents JPMorgan’s centrality, the dashed line shows the peer-group average (excluding JPM), while the shaded band denotes the range between the minimum and maximum centrality values of the remaining banks. Three key findings emerge. First, JPMorgan’s centrality remains consistently above the peer-group average, indicating a dominant po-

sition within the shock transmission network. Second, temporary spikes coincide with stress episodes, notably during the COVID-19 pandemic in 2020 and the regional banking turmoil in 2023, suggesting heightened network dependence on JPMorgan during periods of instability. Third, the persistent differential between JPMorgan and the peer range, implies a non-transitory hierarchy in systemic influence rather than cyclical fluctuations.

7 Volatility spillover validation

The previous sections assessed systemic importance in the US banking system using balance-sheet exposures, network interconnectedness metrics, and market-based factor sensitivities. Across all three approaches, JPMorgan consistently emerged as the most systemically important institution.

To further validate these findings using a dynamic market-based framework, this section employs the Diebold and Yilmaz (2012) volatility spillover methodology. Unlike static interconnectedness measures, this approach captures how shocks to risk perceptions propagate across financial institutions through volatility transmission. Specifically, their framework measures how shocks to the volatility of one institution contribute to the forecast error variance of others, thereby capturing the directional flow of systemic risk.

By examining volatility spillovers among major US banks, one can identify which institutions act as net transmitters or receivers of systemic risk. This provides an additional layer of evidence regarding systemic relevance, as institutions that consistently transmit volatility shocks play a central role in the amplification of financial instability.

7.1 Volatility measurement

Daily volatility is estimated using the Garman–Klass range-based estimator³, which exploits intraday price information:

$$\sigma_t^2 = \frac{1}{2} \left(\ln \frac{H_t}{L_t} \right)^2 - (2 \ln 2 - 1) \left(\ln \frac{C_t}{O_t} \right)^2, \quad (13)$$

where H_t , L_t , O_t , and C_t denote the high, low, open, and close prices respectively. This estimator provides an efficient and low-noise measure of daily realized volatility.

7.2 VAR Representation

Let $\mathbf{v}_t$ denote the vector of volatilities for N banks. The dynamics are modeled using a VAR(p):

$$\mathbf{v}_t = \sum_{i=1}^p A_i \mathbf{v}_{t-i} + \varepsilon_t, \quad (14)$$

where ε_t is a vector of innovations with covariance matrix Σ .

³The Garman–Klass estimator uses the daily high, low, opening and closing prices to estimate volatility more efficiently than simple close-to-close measures. By incorporating intraday price ranges, it captures more information about market fluctuations during the trading day.

7.3 Generalized forecast error variance decomposition (FEVD)

Using the generalized variance decomposition of Koop, Pesaran, and Shin (1996), the contribution of shocks in bank j to the H -step-ahead forecast error variance of bank i is:

$$\theta_{ij}^{(H)} = \frac{\sum_{h=0}^{H-1} (e'_i A_h \Sigma e_j)^2 / \sigma_{jj}}{\sum_{h=0}^{H-1} (e'_i A_h \Sigma A'_h e_i)}. \quad (15)$$

where rows are normalized to sum to one to ensure interpretability.

7.3.1 Spillover measures

From the variance decomposition matrix, several systemic risk measures are constructed. First, the Total Spillover Index (TSI) is constructed as:

$$TSI = \frac{\sum_{i \neq j} \theta_{ij}}{N} \times 100, \quad (16)$$

measuring overall system-wide connectedness. Second, directional spillovers (S) are constructed as:

$$S_{i \leftarrow \bullet} = \sum_{j \neq i} \theta_{ij} \quad (\text{received}), \quad (17)$$

$$S_{i \rightarrow \bullet} = \sum_{j \neq i} \theta_{ji} \quad (\text{transmitted}). \quad (18)$$

Third, net spillovers (NS), are:

$$NS_i = S_{i \rightarrow \bullet} - S_{i \leftarrow \bullet}. \quad (19)$$

where positive values indicate that a bank is a net transmitter of volatility shocks, while negative values indicate a net receiver.

7.4 Rolling windows

To capture time variation in systemic risk transmission, the spillover measures are computed using a rolling window VAR. This allows the identification of periods during which specific institutions intensify or absorb systemic risk, particularly during episodes of financial stress.

To summarise the rolling-window evidence into a single cross-institutional comparison, the mean net spillover is computed for each bank across all estimation windows. This measure is defined as the difference between the total volatility a bank transmits to the rest of the system and the total it receives from it. A persistently positive value identifies a net transmitter, namely an institution whose shocks disproportionately propagate outward, while a negative value identifies a net receiver, one that predominantly absorbs externally generated stress.

7.5 Results

Table 8 presents the directional volatility spillover matrix estimated via the FEVD framework over the full 2003–2024 sample period. The diagonal elements represent own-variance

shares, while the off-diagonal elements measure cross-bank spillovers, i.e. the percentage contribution of idiosyncratic shocks from one bank to the forecast error variance of another. The rightmost “FROM” column captures the total volatility an institution receives from the network, while the bottom “TO” and “NET” rows quantify transmitted spillovers and identify systemic roles.

The Total Spillover Index (TSI) of 77.90% indicates a highly interconnected banking system in which the majority of volatility is transmitted across institutions. The net spillover measures, explicitly ranked in Table 9, reveal asymmetries in systemic risk transmission. An hierarchy emerges in the financial architecture, with Morgan Stanley (12.63%) and JPMorgan (10.60%) standing as the paramount net transmitters of volatility. This suggests that disturbances originating within these institutions have the greatest potential to propagate throughout the broader financial system. Wells Fargo (7.55%), Bank of America (6.91%), and Citigroup (6.82%) also act as significant net transmitters, reflecting their central roles in credit intermediation and broad funding markets.

In contrast, specialized trust and custodial institutions function as significant net receivers of volatility. State Street (-25.88%) and Bank of New York Mellon (-15.53%) exhibit negative net spillover values, indicating they are primarily absorbers of systemic shocks transmitted by the network rather than primary sources of contagion. Interestingly, Goldman Sachs also registers as a slight net receiver (-3.10%), distinguishing its systemic risk profile from that of its closest peer, Morgan Stanley, over the full sample period.

For the post-crisis 2009-2024 period, the TSI is estimated at 78.55%, representing a marginal increase from the full-sample baseline. This indicates that despite regulatory reforms, systemic interconnectedness remains a defining feature of the US banking system. The results suggest that such reforms have not eliminated cross-institutional dependencies but have instead reshaped the channels through which volatility propagates.

The “FROM” column in Table 10 illustrates that, for the majority of banks, external shocks account for approximately three-quarters of their forecast error variance. This confirms that individual bank volatility is predominantly driven by system-wide dynamics rather than firm-specific idiosyncratic events. Notably, JPMorgan (80.44%) and Bank of New York Mellon (80.09%) exhibit the highest sensitivity to external volatility, suggesting they are particularly vulnerable to systemic contagion. Conversely, the “TO” row identifies the primary engines of volatility propagation. During this period, Bank of America (87.95%), Wells Fargo (87.21%), and JPMorgan (86.26%) emerge as the most significant transmitters of volatility to the rest of the network, highlighting the systemic influence of the large-scale commercial and retail-oriented banking sector.

Table 11 ranks the institutions by their net systemic contribution, revealing a significant reallocation of risk roles compared to the full sample. Bank of America (+10.12%) and Wells Fargo (+9.20%) now lead as the dominant net transmitters of volatility. The biggest structural repositioning is observed in Goldman Sachs (GS). While previously categorized as a marginal net receiver in the full-sample results, in the post-crisis era, it has become the system’s largest net receiver (-17.06%). This negative net spillover, alongside the continued receiver status of custodial banks like BNY Mellon (-10.94%) and State Street (-4.59%), suggests that these institutions now act as significant absorbers of systemic shocks.

Overall, interconnectedness remains extremely high in both periods, but the identity of the main net transmitter changes. In the full sample, MS is the leading net transmitter, whereas in the post-crisis period BoA assumes the dominant role. Third, GS transitions from a mild net receiver in the full sample to the largest net receiver in the post-crisis

period.

Table 13 presents the full-sample hierarchy. JPMorgan emerges as the dominant net transmitter at +9.87%, well ahead of its nearest competitors Bank of America (+5.47%), Citigroup (+4.55%), and Morgan Stanley (+3.12%). Goldman Sachs, Wells Fargo, Bank of New York Mellon, and State Street all record negative values, confirming their structural role as net receivers of system-wide volatility shocks.

Table 15 further confirms that JPMorgan’s dominance is not episodic: it occupied the first-rank position in 43.3% of all rolling windows, more than twice the frequency of any peer institution. Table 14 extends this analysis across six macroeconomic sub-periods, reporting the mean net spillover, the TSI, and the frequency of top-rank occupancy. Figure 13 illustrates these dynamics. The net spillover series surges at each major stress event, namely the Lehman Brothers collapse, the COVID-19 pandemic, and the SVB-triggered regional banking turmoil, before returning to a moderate but persistently positive baseline between crises. Figure 14 corroborates this at the network level. There, pronounced TSI spikes at each of these events confirm that JPMorgan’s transmission intensity and system-wide interconnectedness are mutually reinforcing.

8 Dynamic conditional correlation

The four methodologies employed in the preceding sections converge on a consistent finding: JPMorgan occupies a structurally dominant position within the US banking system, whether measured through regulatory balance-sheet exposures, idiosyncratic return comovements, or directional volatility transmission. Nevertheless, a shared limitation of these frameworks is their inability to capture the continuous, daily evolution of pairwise interdependencies. The FR Y-15 index is observed at annual frequency, the Fama–French residual network is estimated over fixed sub-periods, and the Diebold–Yilmaz spillover measures, while dynamic, rely on rolling windows of fixed length.

To address this limitation, the Dynamic Conditional Correlation (DCC) model of Engle(2002) is employed. This model allows pairwise correlations between institutions to evolve continuously at daily frequency. This is particularly relevant in the context of systemic risk, where interconnectedness is known to intensify non-linearly during stress episodes. The DCC framework thus serves a specific validation purpose: if the systemic importance rankings derived from time-varying market correlations align with those obtained from regulatory data and volatility spillovers, this constitutes multi-layer evidence that the identified institutional hierarchy reflects a structural feature of the US banking system rather than a measurement artifact.

8.1 Univariate GARCH(1,1)

First, daily log returns for the banks in the sample, $r_{i,t}$, are purged from institution-specific conditional heteroskedasticity via the univariate GARCH(1,1) model:

$$\begin{cases} r_{i,t} = \mu_i + \varepsilon_{i,t} & (20a) \\ \varepsilon_{i,t} = \sigma_{i,t} z_{i,t}, \quad z_{i,t} \sim \mathcal{N}(0, 1) & (20b) \\ \sigma_{i,t}^2 = \omega_i + \alpha_i \varepsilon_{i,t-1}^2 + \beta_i \sigma_{i,t-1}^2 & (20c) \end{cases}$$

where $\sigma_{i,t}^2$ is the conditional variance, $\omega_i > 0$ is the long-run variance component, $\alpha_i \geq 0$ captures the sensitivity of volatility to recent shocks (ARCH effect), and $\beta_i \geq 0$ measures the persistence of past conditional variance (GARCH effect). The standardized residuals $\hat{z}_{i,t} = \varepsilon_{i,t}/\hat{\sigma}_{i,t}$ are retained for the DCC estimation in the following step. Table 16 reports the estimated parameters for all eight institutions.

The estimated parameters are consistent across all banks and in line with the established empirical properties of financial return volatility. The ARCH coefficient $\hat{\alpha}$ ranges from 0.05 to 0.09, indicating that volatility responds moderately but significantly to new market shocks. The GARCH coefficient $\hat{\beta}$ is uniformly high, ranging from 0.89 to 0.95, confirming that conditional volatility is highly persistent.

The volatility persistence measure $\hat{\alpha} + \hat{\beta}$ is close to unity for all institutions, ranging from 0.98 (Bank of New York Mellon) to 1 (Wells Fargo). This near-integrated behaviour is a well-documented characteristic of financial institutions, and implies that volatility shocks have long-lasting effects on the conditional variance process. Importantly, the high persistence estimates are consistent with the volatility observed during the GFC and the pandemic. These results confirm that each return series exhibits significant time-varying volatility that must be accounted for prior to estimating dynamic correlations. Crucially, the persistence measure remains strictly below unity for all institutions, ensuring covariance stationarity, a necessary condition for the consistency of the DCC estimator employed in the following step.

8.2 DCC estimation and dynamic correlation structure

Second, having extracted the standardized residuals from the univariate GARCH(1,1) models, the DCC model is estimated. The estimator recovers a daily time series of 8×8 conditional correlation matrices by allowing pairwise correlations to evolve as a function of past standardized shocks. The dynamic correlation matrix R_t is derived from the auxiliary process:

$$Q_t = (1 - a - b)\bar{Q} + a\hat{z}_{t-1}\hat{z}_{t-1}' + bQ_{t-1} \quad (21)$$

$$R_t = \text{diag}(Q_t)^{-1/2}Q_t\text{diag}(Q_t)^{-1/2} \quad (22)$$

where $\bar{Q}$ is the unconditional covariance matrix of the standardized residuals, $a \geq 0$ governs the sensitivity of correlations to recent joint shocks, and $b \geq 0$ controls their persistence. The estimated parameters are reported in Table 17.

The estimated parameters are economically meaningful and consistent with the DCC literature for financial institutions. The low value of $\hat{a} = 0.05$ indicates that pairwise correlations adjust gradually to new joint shocks, while the high persistence $\hat{b} = 0.96$ confirms that, once correlations become elevated, as happens during crisis episodes, they remain elevated for extended periods.

8.3 Results

While the TSI measures the directional transmission of volatility shocks across institutions capturing how risk propagates through the system, the average DCC correlation measures the degree of simultaneous co-movement among banks. These are conceptually distinct dimensions of systemic risk: the former reflects contagion dynamics, while the latter reflects structural interdependence. As illustrated in Figure 14, the TSI peaks sharply

during the GFC, the pandemic, and the SV banking turmoil, the same episodes during which the average DCC correlation reaches its highest values.

The DCC estimation yields a daily time series of conditional correlation matrices for the full sample period 2003–2024. The analysis next examines the dynamic evolution of these correlations through two complementary representations: the bilateral correlations between JPMorgan and each peer institution, and the average system-wide pairwise correlation, which serves as a daily indicator of aggregate systemic stress.

Figure 15 presents the time-varying conditional correlations between JPMorgan and four systemically important peers: Bank of America, Citigroup, Goldman Sachs, and Morgan Stanley. Several patterns emerge consistently across all pairs. First, unconditional mean correlations are high, ranging from 0.73 (JPM–MS) to 0.79 (JPM–BAC), confirming that JPMorgan maintains elevated co-movement with all major peer institutions throughout the sample. This is consistent with its dominant position in the Interconnectedness Index and its role as the leading net transmitter of volatility. Second, all four pairs exhibit a decline in conditional correlations during the early phase of the GFC, followed by an increase as the crisis intensified. Third, correlations remain elevated in the post-crisis period relative to the pre-2007 sample, suggesting a upward shift in interdependence following the crisis, consistent with the increased systemic footprint of large US banks documented in Section 5.

Figure 16 plots the average pairwise DCC correlation across all institution pairs, constructed as the daily average of the upper triangle of R_t . This series serves as a market-implied indicator of aggregate systemic stress, capturing the degree to which the banking system moves as a unified block on any given day.

The unconditional mean of 0.69 confirms a high baseline level of systemic co-movement across the sample. Three distinct spikes are again clearly visible for the three crisis events in the sample. The pre-crisis period is characterized by lower and more volatile average correlations, likely reflecting institutional heterogeneity during tranquil market conditions. The post-2010 period displays a permanently higher correlation floor, consistent with the structural consolidation of the US banking sector and the increased systemic importance of the surviving large institutions documented in the preceding sections.

Taken together, these results establish two key findings. First, JPMorgan is the most correlated institution within the peer group, reinforcing its systemic centrality across all measurement frameworks employed in this study. Second, system-wide co-movement intensifies markedly during stress episodes, confirming that the US banking system exhibits the correlation clustering property that renders diversification ineffective precisely when it is most needed.

8.4 Validation and comparisons

This section translates the DCC estimated time-varying correlation structure into systemic importance rankings and evaluates their consistency with the findings of the preceding sections. Three complementary results are reported: the DCC-based systemic ranking, the amplification of correlations during crisis periods, and a formal comparison with the FR Y-15 Interconnectedness Index.

Table 18 ranks all eight institutions by their average conditional correlation with the rest of the system across the full sample period. This measure captures the degree to which each institution moves in tandem with the broader banking system on a daily basis, and serves as a market-implied proxy for systemic centrality. JPMorgan ranks first, with an

average conditional correlation of 0.73, consistent with its dominant position across all preceding methodologies. BoA and Citigroup follow in second and third place, reflecting their large balance sheets and broad exposure to common macro-financial conditions.

Table 19 reports the average conditional correlation for each institution separately during good and bad times, together with the amplification measure defined as the difference between the two. Crisis periods are defined as June 2007 – June 2009, February 2020– December 2020, and March 2023 – June 2023). All institutions display an increase in conditional correlations during crisis episodes, confirming the correlation clustering property of financial markets. Wells Fargo exhibits the largest amplification ($\Delta = 0.089$), followed by BoA ($\Delta = 0.087$), reflecting their strong exposure to household credit and mortgage markets, sectors particularly vulnerable to systemic stress. Notably, JPMorgan displays a relatively moderate amplification ($\Delta = 0.061$) despite ranking first in average correlation, suggesting that its systemic centrality is structural and persistent rather than driven exclusively by crisis co-movement. Hence, JPMorgan is highly connected at all times, while institutions such as Wells Fargo and Bank of America become disproportionately connected under stress.

Table 20 presents a direct comparison between the FR Y-15 Interconnectedness Index rankings and the DCC-based rankings. The rank difference column quantifies the degree of disagreement between the two methodologies. The two rankings are very similar. The Spearman rank correlation of $\rho = 0.95$ ($p < 0.001$) confirms a statistically significant correspondence between the balance-sheet-based FR Y-15 measure and the market-implied DCC ranking. JPMorgan, Wells Fargo, Bank of New York Mellon, and State Street occupy similar positions in both rankings.

The three methodologically distinct approaches, i.e. regulatory balance-sheet exposures (FR Y-15), residual shock networks (FF5), and directional volatility spillovers (DCC), have consistently identified JPMorgan as the most interconnected and, therefore, potentially systemically important institution in the US banking system. The DCC analysis now provides a fourth and independent confirmation of this hierarchy, derived entirely from the daily dynamics of market-implied correlations. The convergence of these four frameworks, each capturing a distinct dimensions of systemic interconnectedness, provides strong multi-layer evidence that the identified institutional ranking reflects a structural and persistent feature of the US banking system.

9 Conclusions

This paper constructs and validates a comprehensive measure of systemic interconnectedness within the US banking system using multi-layer evidence from regulatory, textual, and market-based sources. The main findings are as follows.

First, using regulatory balance-sheet data, the analysis develops an aggregate interconnectedness index, reflecting a variety of transmission channels for counterparty risk. The index reveals extreme concentration, with JPMorgan accounting for nearly one-fifth of total systemic exposure, followed by Citigroup and Bank of America. Systemic risk therefore appears driven by a small number of interconnected institutions. The elevated interconnectedness index for JPMorgan is nowadays due to OTC derivatives exposure, while Bank of America and Citigroup display stronger contributions from assets and securities, reflecting differences in underlying business models.

Second, textual analysis on 10K reports quantifies a variety of transmission channels of counterparty risk for JPMorgan. Shadow linkages were prominent before the GFC, with

the contribution of direct counterparty risk and derivatives increasing in the post-GFC period.

Third, centrality analysis is conducted from the correlation matrix of residuals from a FF5 model. Before the GFC, Bank of America was the most central node of the US banking network. However, after the GFC, JPMorgan emerges as the new center, having acquired Bear Stearns and Washington Mutual. Thus, JPMorgan shows strong connectivity to other systemically important nodes and a high potential for shock propagation.

Fourth, in volatility spillover analysis, Morgan Stanley and JPMorgan emerge the main net transmitters of volatility to other banks. This suggests that disturbances originating from these institutions have the greatest potential to propagate throughout the broader financial system. Additionally, JPMorgan exhibits the highest sensitivity to external volatility shocks, as such shocks account for approximately three-quarters of its forecast-error variance, making it particularly vulnerable to systemic contagion.

Fifth, dynamic conditional correlation analysis finds that JPMorgan maintains elevated co-movement with all major peer institutions throughout the sample, consistent with its dominant position in the Interconnectedness Index and its role as the leading net transmitter of volatility. These correlations are higher in the post-GFC period, compared to the period before, suggesting an upward shift in interdependence following the financial crisis. The results also indicate that system-wide co-movement intensifies markedly during stress episodes. Specifically, all banks display an increase in conditional correlations during crisis episodes, confirming the correlation clustering property of financial markets. JPMorgan displays a relatively moderate amplification, despite ranking first in average correlation, suggesting that its systemic centrality is persistent rather than driven exclusively by crisis co-movement. In other words, JPMorgan is highly connected at all times, while institutions such as Wells Fargo and Bank of America become disproportionately connected under stress.

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Tables and Figures

Interconnectedness Index

#	Financial Institution	#	Financial Institution
1	JPMorgan Chase & Co.	20	Charles Schwab Corporation, The
2	Citigroup Inc.	21	Discover Financial Services
3	Bank of New York Mellon	22	Capital One Financial Corp.
4	State Street Corporation	23	Citizens Financial Group, Inc.
5	Bank of America Corporation	24	Huntington Bancshares Inc.
6	Wells Fargo & Company	25	Regions Financial Corporation
7	Goldman Sachs Group, Inc.	26	Ally Financial Inc.
8	Morgan Stanley	27	UBS Americas Holding LLC
9	PNC Financial Services	28	Barclays US LLC
10	Northern Trust Corporation	29	Santander Holdings USA, Inc.
11	M&T Bank Corporation	30	DB USA Corporation
12	U.S. Bancorp	31	DWS USA Corporation
13	First Citizens Bancshares	32	HSBC North America Holdings
14	American Express Company	33	Mizuho Americas LLC
15	Synchrony Financial	34	BNP Paribas USA, Inc.
16	Fifth Third Bancorp	35	TD Group US Holdings LLC
17	Flagstar Financial, Inc.	36	RBC US Group Holdings LLC
18	KeyCorp	37	CIBC Bancorp USA Inc.
19	Truist Financial Corp.	38	BMO Financial Corp.

Table 1: *Constituent banking organizations and intermediate holding companies subject to the Federal Reserve’s FR Y-15 Systemic Risk Report, representing the population of institutions evaluated for global systemic importance and regulatory capital surcharges. See discussion in section 3*

Table 2: **Top U.S. Banks by Average Interconnectedness Index (%)**

Bank	Interconnectedness Index (%)
JPMorgan Chase & Co.	19.72
Citigroup Inc.	13.40
Bank of America Corporation	11.56
Goldman Sachs Group, Inc.	10.70
Morgan Stanley	9.09
Wells Fargo & Company	7.28
Bank of New York Mellon Corporation	4.78
State Street Corporation	4.11
Mizuho Americas LLC	1.79
HSBC North America Holdings Inc.	1.52
PNC Financial Services Group, Inc.	1.40
U.S. Bancorp	1.38
Capital One Financial Corporation	1.29
BMO Financial Corp.	1.11
Charles Schwab Corporation	1.05
American Express Company	1.04
Truist Financial Corporation	0.80
Northern Trust Corporation	0.78

Table 2 reports the average Interconnectedness Index for the twenty largest U.S. banking organizations over the period 2019–2024. See discussion in section 3

Table 3: Full Enriched Counterparty Risk Lexicon. See discussion in Section 5

Category	All Lexicon Terms
Direct Counterparty Risk	counterparty risk; counterparty credit risk; default risk; counterparty default; obligor default; non-performance risk; settlement risk; pre-settlement risk; current exposure; potential future exposure; PFE; credit valuation adjustment; CVA; debit valuation adjustment; DVA; cross-default; bilateral exposure; credit risk mitigation; credit enhancement; netting agreement; unsecured exposure; replacement cost
Derivatives Network	over-the-counter derivatives; OTC derivatives; interest rate swaps; credit default swaps; CDS; total return swaps; swaption; notional amount; gross notional; net notional; bilateral netting; multilateral netting; master netting agreement; ISDA master agreement; rehypothecation; substitution of collateral; novation; clearing member; central clearing; derivative instruments; exchange-traded derivatives; compression; notional value
Shadow Linkages	unfunded lending commitments; letters of credit; financial guarantees; special purpose vehicle; SPV; variable interest entity; VIE; conduit; securitization; structured investment vehicle; SIV; repo; repurchase agreements; reverse repo; securities lending; off-balance sheet; liquidity facilities; credit support; securities financing transactions; SFT; asset-backed; mortgage-backed
Systemic Contagion	interconnectedness; interdependencies; systemic risk; contagion; spillover effect; network risk; concentration risk; financial infrastructure; too big to fail; SIFI; G-SIB; resolution plan; living will; cross-border exposure; interbank market; prime brokerage; correspondent banking; wrong-way risk; correlation risk; macroprudential; financial stability; fire sale; market disruption

Category	All Lexicon Terms
Collateral Stress	margin call; variation margin; initial margin; collateral dispute; haircut; liquidity call; collateral exhaustion; posted collateral; received collateral; central counterparty; CCP; clearing house; high quality liquid assets; HQLA; encumbered assets; unencumbered; collateral management; margin requirements; collateral eligibility; repledged; valuation haircuts; liquidity coverage ratio; LCR; net stable funding ratio; NSFR; collateral transformation; collateral optimization; eligible collateral; collateral buffer

Keyword Frequencies by Category: JPMorgan 10-K Filings (2002–2025)

Year	Direct Counterparty Risk	Derivatives Network	Shadow Linkages	Systemic Contagion	Collateral Stress
2002	33	30	471	54	5
2003	57	58	646	80	4
2004	56	62	887	74	3
2005	69	66	947	75	5
2006	65	62	966	71	6
2007	52	60	1060	95	6
2008	72	90	1264	158	7
2009	114	125	1585	169	8
2010	127	145	1687	193	9
2011	142	140	2017	187	21
2012	188	154	1793	168	35
2013	162	137	1845	156	32
2014	201	179	1772	171	96
2015	247	182	1457	186	103
2016	202	170	1400	159	109
2017	200	149	1370	154	127
2018	190	142	1366	155	139
2019	216	149	1175	159	160
2020	203	141	1130	161	144
2021	210	138	1127	223	177
2022	206	134	1056	147	164
2023	215	133	1056	143	165
2024	228	137	1069	148	170
2025	224	146	1103	129	177

Table 4: *Longitudinal distribution of systemic risk proxies and financial network densities (2002–2025). The data delineate the structural evolution of inter-institutional linkages, specifically highlighting the divergence between shadow banking conduits, derivative-based counterparty exposures, and the historical escalation of collateral-driven stress over the observation period. For a granular analysis of these trends and their macroeconomic implications, see Section 5.*

Fama–French Five-Factor Model: Estimation Results (2003–2025)

Bank	R^2	α	Observations
BAC	0.713	0.000060	5,785
BK	0.628	0.000045	5,785
C	0.640	-0.000199	5,785
GS	0.644	0.000201	5,785
JPM	0.741	0.000290	5,785
MFG	0.301	-0.000292	4,814
MS	0.598	0.000085	5,785
STT	0.563	0.000021	5,785
WFC	0.673	0.000120	5,785

Table 5: *Estimation results for the Fama–French five-factor model applied to the daily returns of major banking institutions. The R^2 values indicate the model’s explanatory power, while α represents the risk-adjusted excess returns; bold entries signify the leading performance and statistical fit within the peer group. See discussion in Section 6*

Eigenvector Centrality Rankings: Full Sample (2003–2025)

Bank	Centrality Score
BAC	0.4069
JPM	0.3847
WFC	0.3663
C	0.3462
BK	0.3440
GS	0.3374
STT	0.3235
MS	0.3036
MFG	0.0578

Table 6: *Mean network centrality rankings derived from residual correlations over the 2003–2025 period. Higher scores denote greater systemic importance and interconnectedness within the financial ecosystem, with Bank of America (BAC) emerging as the most central node in the correlation network. See discussion in Section 6*

Table: Eigenvector Centrality Rankings

Bank	Centrality Score
JPM	0.4087
BAC	0.3859
MS	0.3598
GS	0.3419
BK	0.3374
WFC	0.3330
STT	0.3239
C	0.3230
MFG	0.0611

Table 7: *This table ranks the institutions by Eigenvector Centrality(2009-2025), which measures a node’s influence by accounting for both the quantity and the quality of its connections; a high score indicates the bank is linked to other highly central nodes within the network. In the post-crisis era (2009–2025), JPMorgan Chase (JPM) and Bank of America (BAC) maintain the highest scores, cementing their status as the structural ‘core’ of the financial system. The relatively uniform scores among the top eight banks suggest a highly integrated domestic network where idiosyncratic shocks are likely to propagate quickly. Conversely, the exceptionally low score for MFG (0.0611) suggests that its residual movements are largely decoupled from the US banking core, indicating it operates on the network’s periphery with minimal systemic ‘hidden’ influence compared to its peers. See discussion in Section 6*

Volatility Spillover Matrix: Full Sample (2003–2024)

	JPM	BAC	C	GS	MS	WFC	BK	STT	FROM (%)
JPM	21.39	13.29	13.64	10.53	11.06	14.04	9.22	6.82	78.61
BAC	13.01	23.73	15.90	7.87	9.27	15.64	7.64	6.94	76.27
C	13.47	15.92	23.59	8.68	9.72	14.19	7.48	6.95	76.41
GS	13.24	9.39	10.61	22.39	17.48	10.11	9.41	7.37	77.61
MS	11.92	9.45	9.71	15.70	25.54	9.22	10.08	8.37	74.46
WFC	13.65	15.73	13.21	8.73	9.44	22.08	9.14	8.02	77.92
BK	13.03	9.74	10.22	11.53	14.88	11.04	18.98	10.57	81.02
STT	10.89	9.66	9.93	11.44	15.25	11.23	12.53	19.08	80.92
TO (%)	89.21	83.18	83.23	74.50	87.09	85.47	65.50	55.04	
NET (%)	10.60	6.91	6.82	-3.10	12.63	7.55	-15.53	-25.88	
Total Spillover Index (TSI) = 77.90%									

Table 8: *This table reports the directional volatility spillover matrix estimated via the Diebold–Yilmaz (2012) generalized forecast error variance decomposition (FEVD) framework. The ij -th entry represents the percentage contribution to the H -step-ahead forecast error variance of bank i arising from idiosyncratic shocks to bank j . The ‘FROM’ column captures the total volatility received by an institution from the rest of the network, while the ‘TO’ row quantifies the total volatility transmitted. The ‘NET’ row identifies systemic roles, where positive values highlight net transmitters of risk (e.g., MS at 12.63% and JPM at 10.60%) and negative values signify net receivers (e.g., STT at -25.88% and BK at -15.53%). The Total Spillover Index (TSI) of 77.90% reflects a high degree of cross-institutional interdependence, suggesting that nearly 78% of individual bank volatility is driven by systemic linkages rather than firm-specific events over the 2003–2024 sample period. See discussion in Section 7*

Net Volatility Spillover Rankings: Full Sample (2003–2024)

Rank	Bank	NET (%)	
1	MS	+12.63	← Net Transmitter
2	JPM	+10.60	← Net Transmitter
3	WFC	+7.55	← Net Transmitter
4	BAC	+6.91	← Net Transmitter
5	C	+6.82	← Net Transmitter
6	GS	-3.10	
7	BK	-15.53	
8	STT	-25.88	

Table 9: *This table ranks the selected financial institutions based on their net volatility spillover contributions, calculated as the difference between the volatility transmitted ‘To’ the network and the volatility received ‘From’ the network. Positive values identify net transmitters of risk such as Morgan Stanley (MS) and JPMorgan Chase (JPM), which export idiosyncratic shocks to the rest of the banking sector. Negative values identify net receivers, most notably the custodial banks State Street (STT) and Bank of New York Mellon (BK). See discussion in Section 7*

Volatility Spillover Matrix: Post-Crisis Period (2009–2024)

	JPM	BAC	C	GS	MS	WFC	BK	STT	FROM (%)
JPM	19.56	12.62	11.62	9.89	12.54	13.30	10.40	10.07	80.44
BAC	11.71	22.17	15.19	6.66	10.87	13.91	8.71	9.78	77.83
C	11.32	15.88	23.67	6.99	10.64	13.47	8.17	9.85	76.33
GS	13.05	10.62	10.19	21.80	14.70	10.45	9.43	9.74	78.20
MS	12.73	11.80	11.41	11.77	21.43	10.55	9.82	10.49	78.57
WFC	12.56	14.57	12.26	7.71	9.59	21.99	10.13	11.18	78.01
BK	13.19	10.94	10.41	8.83	11.40	12.10	19.91	13.23	80.09
STT	11.68	11.52	10.72	8.29	10.81	13.42	12.48	21.08	78.92
TO (%)	86.26	87.95	81.80	61.14	80.54	87.21	69.15	74.33	
NET (%)	5.82	10.12	5.48	-17.06	1.97	9.20	-10.94	-4.59	
Total Spillover Index (TSI) = 78.55%									

Table 10: *This table presents the post-crisis (2009–2024) directional volatility spillover matrix estimated using the Diebold–Yilmaz (2012) framework. The ij -th entry represents the percentage contribution of shocks from bank j to the forecast error variance of bank i . The Total Spillover Index (TSI) of 78.55% indicates a continued high level of systemic interconnectedness in the post-crisis era. During this period, Bank of America (BAC, 10.12%) and Wells Fargo (WFC, 9.20%) emerge as the most prominent net transmitters of volatility. Notably, Goldman Sachs (GS) shifts to a significant net receiver position (-17.06%), while custodial banks like BK (-10.94%) continue to primarily absorb systemic shocks from the network. See discussion in Section 7*

Net Volatility Spillover Rankings: Post-Crisis Period (2009–2024)

Rank	Bank	NET (%)	
1	BAC	+10.12	← Net Transmitter
2	WFC	+9.20	← Net Transmitter
3	JPM	+5.82	← Net Transmitter
4	C	+5.48	← Net Transmitter
5	MS	+1.97	← Net Transmitter
6	STT	-4.59	
7	BK	-10.94	
8	GS	-17.06	

Table 11: *This table ranks the selected financial institutions by their net volatility spillover contributions during the post-crisis period (2009–2024). Net spillovers are calculated as the difference between volatility transmitted to and received from the network. In a significant shift from the full-sample results, Bank of America (BAC) and Wells Fargo (WFC) emerge as the leading net transmitters of systemic risk. Conversely, Goldman Sachs (GS) has transitioned into the role of the system’s largest net receiver (-17.06%), followed by the custodial bank Bank of New York Mellon (BK). These rankings illustrate a reallocation of systemic influence toward large commercial and retail-oriented banks in the post-crisis financial architecture. See discussion in Section 7*

Mean Net Volatility Spillover Rankings: Full Sample (2004–2024)

Rank	Bank	Mean NET (%)	
1	JPM	+9.87	← Dominant Transmitter
2	BAC	+5.47	← Net Transmitter
3	C	+4.55	← Net Transmitter
4	MS	+3.12	← Net Transmitter
5	GS	-0.74	
6	WFC	-2.93	
7	BK	-8.42	
8	STT	-10.92	

Table 12: Hierarchical ranking of selected financial institutions based on mean net volatility spillover indices. Positive values signify net transmitters of systemic volatility to the network, whereas negative values denote net receivers. See discussion in Section 7

Mean Net Volatility Spillover Rankings: Full Sample (2004–2024)

Rank	Bank	Mean NET (%)	
1	JPM	+9.87	← Dominant Transmitter
2	BAC	+5.47	← Net Transmitter
3	C	+4.55	← Net Transmitter
4	MS	+3.12	← Net Transmitter
5	GS	-0.74	
6	WFC	-2.93	
7	BK	-8.42	
8	STT	-10.92	

Table 13: Hierarchical ranking of selected financial institutions based on mean net volatility spillover indices. Positive values signify net transmitters of systemic volatility to the network, whereas negative values denote net receivers. See discussion in Section 7

JPMorgan Net Spillover Analysis Across Macroeconomic Regimes

Period	Mean NET (%)	TSI (%)	Rank #1 Freq. (%)	Role
Full (2004–2024)	+9.87	83.4	43.3	Net Transmitter
Pre-GFC (2004–2007)	+11.15	82.6	61.2	Net Transmitter
GFC (2007–2009)	+16.80	93.4	54.3	Net Transmitter
Post-GFC (2010–2019)	+7.35	78.1	35.2	Net Transmitter
COVID-19 (2020)	+11.36	100.0	31.4	Net Transmitter
Post-COVID (2021–2024)	+9.61	84.1	38.8	Net Transmitter

Table 14: *Sub-period sensitivity analysis of JPM’s net directional connectedness. This table decomposes the bank’s systemic footprint across distinct macroeconomic regimes, reporting the Mean Net Spillover, the Total Spillover Index (TSI), and the relative frequency of JPM acting as the system’s dominant volatility transmitter. Positive net values across all horizons underscore the institution’s persistent role as a primary source of systemic risk propagation. See discussion in Section 7*

Rolling-Window Net Spillover Rankings: Full Sample (2004–2024)

Rank	Bank	Mean NET (%)	Rank #1 (% of windows)	
1	JPM	+9.870	43.3	← JPM
2	BAC	+5.466	15.7	
3	C	+4.555	16.0	
4	MS	+3.122	15.6	
5	GS	-0.741	3.5	
6	WFC	-2.929	4.2	
7	BK	-8.420	1.3	
8	STT	-10.922	0.4	

Table 15: *Hierarchical ranking of systemic importance based on mean net directional volatility spillovers over the full sample period (2004–2024). Mean Net (%) denotes the difference between the volatility transmitted to and received from the network; positive values identify net transmitters of shocks, while negative values characterize net receivers. The ‘Rank #1’ column reports the percentage of rolling-window observations in which each institution emerged as the dominant transmitter, underscoring JPM’s persistent role as a primary conduit of systemic risk. See discussion in Section 7*

GARCH(1,1) Parameter Estimates and Volatility Persistence (2003–2024)

Bank	$\hat{\omega}$	$\hat{\alpha}$	$\hat{\beta}$	Persistence ($\hat{\alpha} + \hat{\beta}$)
JPMorgan Chase	0.0417	0.0820	0.9063	0.9882
Bank of America	0.0385	0.0790	0.9138	0.9928
Citigroup	0.0292	0.0907	0.9068	0.9975
Goldman Sachs	0.0601	0.0720	0.9118	0.9838
Morgan Stanley	0.0738	0.0839	0.9015	0.9854
Wells Fargo	0.0143	0.0735	0.9265	1.0000
Bank of NY Mellon	0.0834	0.0854	0.8893	0.9747
State Street	0.0187	0.0460	0.9532	0.9991

Table 16: *GARCH(1,1) Parameter Estimates and Volatility Persistence.* Notes: This table reports the maximum likelihood estimates of the conditional variance parameters ($\hat{\omega}$, $\hat{\alpha}$, and $\hat{\beta}$) for the daily returns of eight major U.S. financial institutions. The Persistence metric, defined as the sum of the ARCH ($\hat{\alpha}$) and GARCH ($\hat{\beta}$) coefficients, quantifies the rate at which volatility shocks dissipate over time. Values approaching unity imply a highly persistent volatility process, which is a stylized fact characteristic of financial asset returns. See discussion in Section 8

DCC-GARCH Model Estimation Results (2003–2024)

Parameter	Estimate
$\hat{a}$ (shock sensitivity)	0.0447
$\hat{b}$ (persistence)	0.9551
Persistence ($\hat{a} + \hat{b}$)	0.9997
Sample period	2003–2024
Observations	5,535
Correlation matrices recovered	$5,535 \times 8 \times 8$

Table 17: *Estimation Results for the Dynamic Conditional Correlation (DCC) Model.*
Notes: This table reports the system-wide parameters for the DCC-GARCH framework. The coefficient $\hat{a}$ captures the innovation impact, representing the sensitivity of the conditional correlations to recent shocks in standardized residuals. The coefficient $\hat{b}$ represents the smoothing parameter, which dictates the persistence of the correlation process. The sum $\hat{a} + \hat{b} < 1$ ensures that the process is mean-reverting, although the proximity to unity indicates highly persistent co-movements within the financial sector over the 2003–2024 sample period. See discussion in Section 8

Systemic Importance Rankings by Average DCC Correlation (2003–2024)

Rank	Bank	Avg. DCC Correlation
1	JPMorgan Chase	0.725
2	Bank of America	0.715
3	Citigroup	0.701
4	Morgan Stanley	0.698
5	Goldman Sachs	0.687
6	Wells Fargo	0.673
7	Bank of NY Mellon	0.660
8	State Street	0.645

Table 18: *Ranking of Financial Institutions by Mean Systemic Interconnectedness (2003–2024).* This table establishes a hierarchy of systemic importance based on the time-series average of dynamic conditional correlations (DCC) between each specific institution and the remaining firms in the sample. Banks at the top of the ranking, notably JPMorgan Chase and Bank of America, exhibit the highest degree of co-movement with the broader financial system. From a macroprudential perspective, these results suggest that institutions with higher average correlations serve as central nodes in the financial network, potentially acting as primary conduits for the propagation of systemic risk and sectoral contagion during periods of market stress. See discussion in Section 8

DCC Correlation Amplification: Tranquil vs. Crisis Periods

Bank	Tranquil	Crisis	Amplification (Δ)
Wells Fargo	0.660	0.749	0.089
Bank of America	0.702	0.789	0.087
Bank of NY Mellon	0.649	0.729	0.081
State Street	0.635	0.701	0.066
Citigroup	0.692	0.756	0.063
JPMorgan Chase	0.717	0.777	0.061
Goldman Sachs	0.678	0.738	0.059
Morgan Stanley	0.691	0.741	0.050

Table 19: *Empirical analysis of Dynamic Conditional Correlation (DCC) estimates, documenting the transition from tranquil market states to periods of systemic financial distress. The amplification factor (Δ) serves as a quantitative metric for the intensification of inter-bank dependencies, providing statistical evidence of heightened contagion risks and the breakdown of asset diversification during crisis regimes. See discussion in Section 8*

Systemic Importance Rankings: FR Y-15 and DCC-GARCH Comparison

Bank	FR Y-15 Score (%)	FR Y-15 Rank	DCC Corr.	DCC Rank	$ \Delta \text{ Rank} $
JPMorgan Chase	19.72	1	0.725	1	0
Citigroup	13.40	2	0.701	3	1
Bank of America	11.56	3	0.715	2	1
Goldman Sachs	10.70	4	0.687	5	1
Morgan Stanley	9.09	5	0.698	4	1
Wells Fargo	7.28	6	0.673	6	0
Bank of NY Mellon	4.78	7	0.660	7	0
State Street	4.11	8	0.645	8	0
Spearman rank correlation: $\rho = 0.952$, $p\text{-value} = 0.0003$					

Table 20: *Comparative analysis of systemic importance rankings derived from the regulatory FR Y-15 framework and the market-based Dynamic Conditional Correlation (DCC-GARCH) model. The table contrasts accounting-based systemic scores with average conditional correlations to evaluate the consistency between regulatory indicators and market-perceived risk. The reported Spearman rank correlation ($\rho = 0.952$) provides robust statistical evidence of the high degree of alignment between these disparate methodologies, suggesting that market-based interdependence measures effectively capture the fundamental systemic footprint identified by banking regulators. See discussion in Section 8*

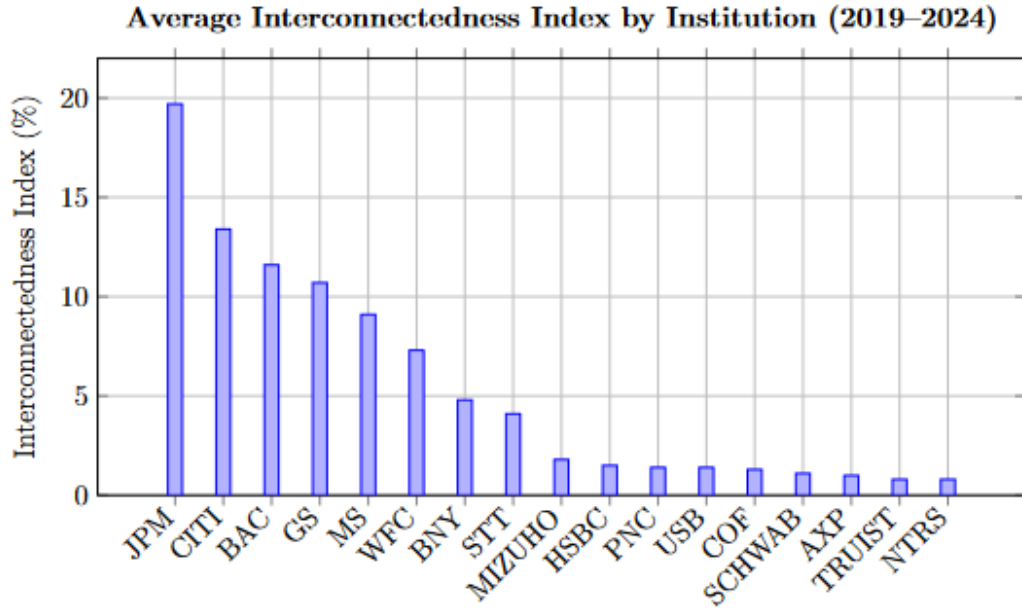


Figure 1: *This figure illustrates the distribution of the Average Interconnectedness Index across seventeen leading financial institutions. The data reveals a highly concentrated network structure, with JPMorgan Chase (19.7%) and Citigroup (13.4%) acting as primary nodes of systemic exposure. A detailed analysis of the underlying network metrics and their implications for financial stability is provided in Section 3.*

Interconnectedness Index: Component Decomposition by Institution

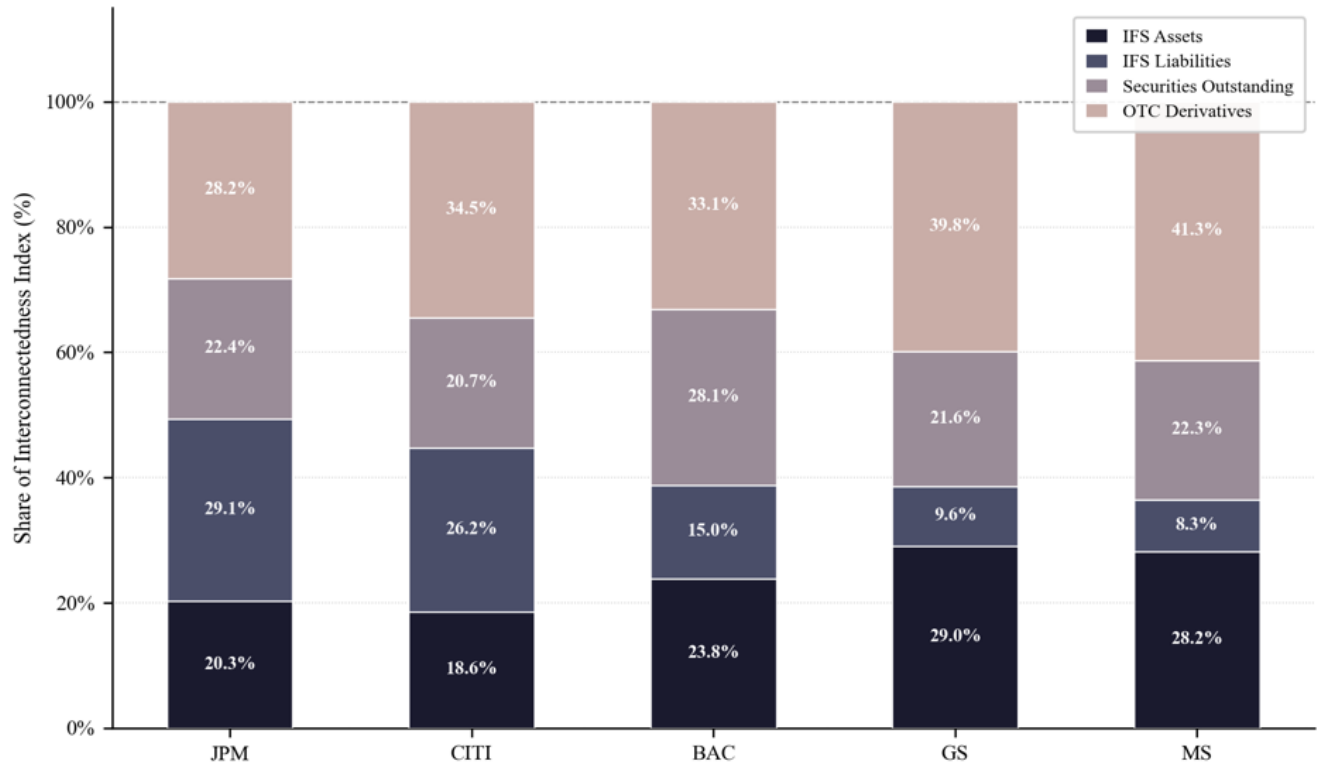


Figure 2: Bars represent the cumulative index value, partitioned by asset and liability classes. This decomposition reveals the heterogeneous nature of bank connectivity, with varying reliance on OTC derivative markets and intra-financial system (IFS) positions. Discussion regarding the implications of this variance can be found in Section 3.

Interconnectedness Index: Longitudinal Evolution by Institution (2019–2024)

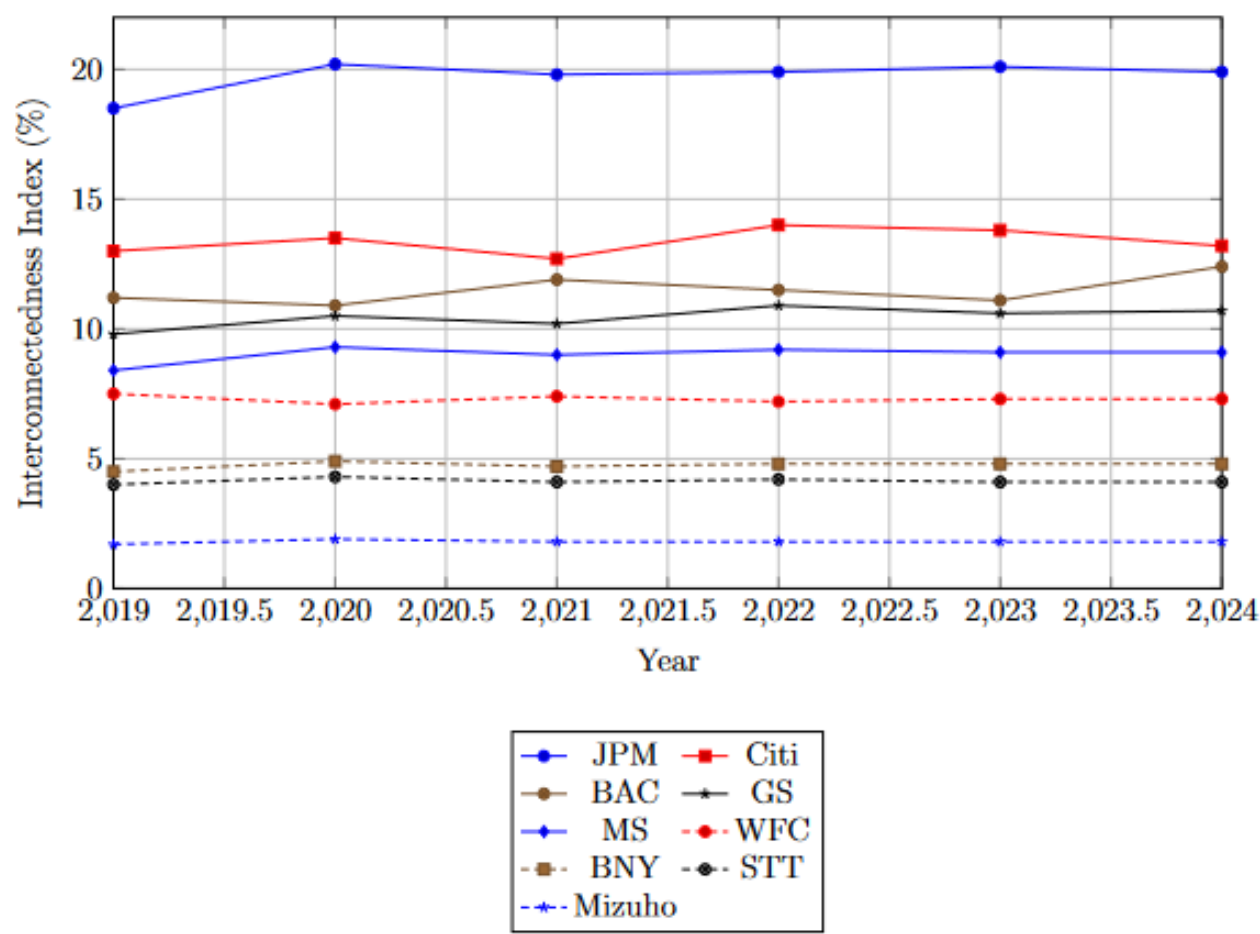


Figure 3: This figure tracks the longitudinal evolution of interconnectedness indices for a cohort of ten major financial institutions. Despite the macroeconomic volatility of the 2020–2023 period, the data exhibits a persistent structural hierarchy, with JPMorgan Chase and Citigroup maintaining consistently high levels of systemic integration. The relative stability of these metrics suggests that interbank network positions are deeply rooted in institutional business models. Further analysis of these trends is provided in Section 3.

JPMorgan - Normalized Growth Index (Base Year 2002 = 1.0)

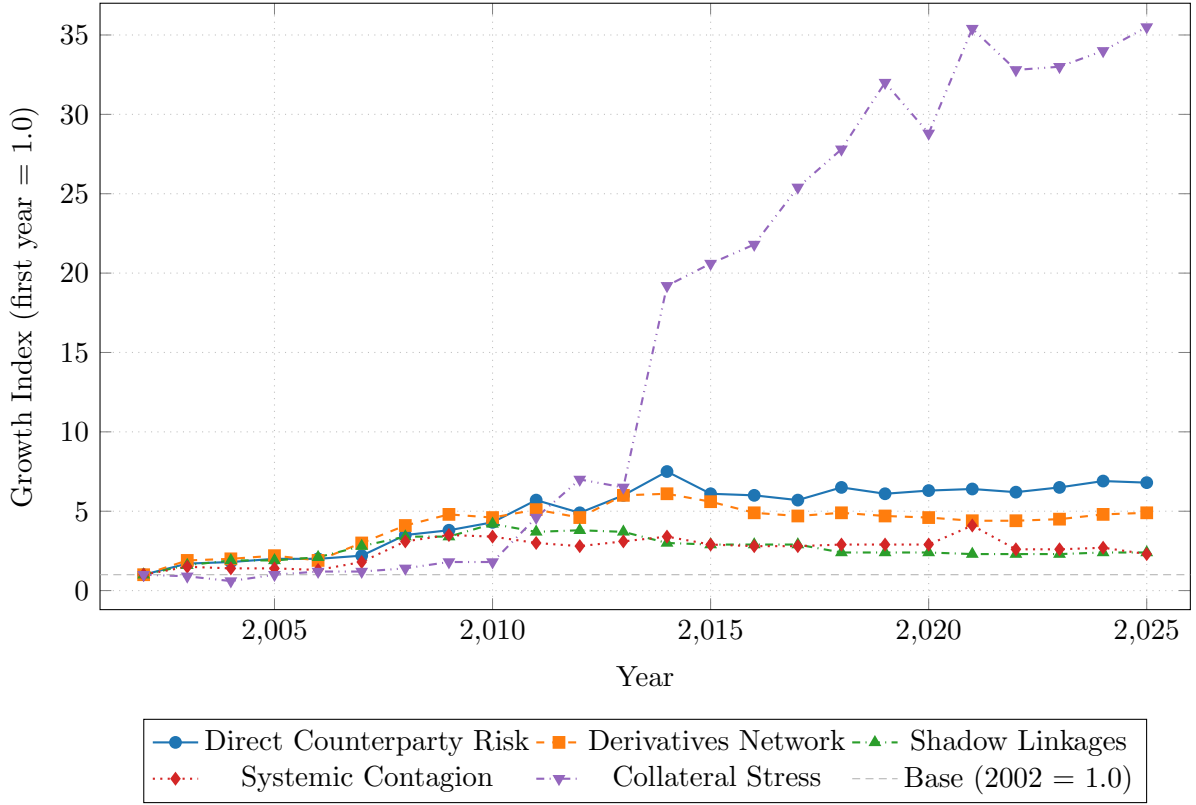


Figure 4: *Longitudinal evolution of category-specific systemic risk disclosures within JPMorgan’s textual corpora, measured as term frequency per 10,000 words over the 2002–2025 period. Leveraging an enriched, domain-specific systemic risk lexicon, the analysis disaggregates overarching risk sentiment into five core structural dimensions: Direct Counterparty Risk, Derivatives Network, Shadow Linkages, Systemic Contagion, and Collateral Stress. The temporal dynamics capture significant shifts in the institutional risk narrative, notably the historical dominance and subsequent secular moderation of Shadow Linkages post-Global Financial Crisis, alongside the steady emergence and escalation of Collateral Stress concerns in the post-2010 regulatory environment. See Section 5 for a detailed empirical discussion and methodological framework.*

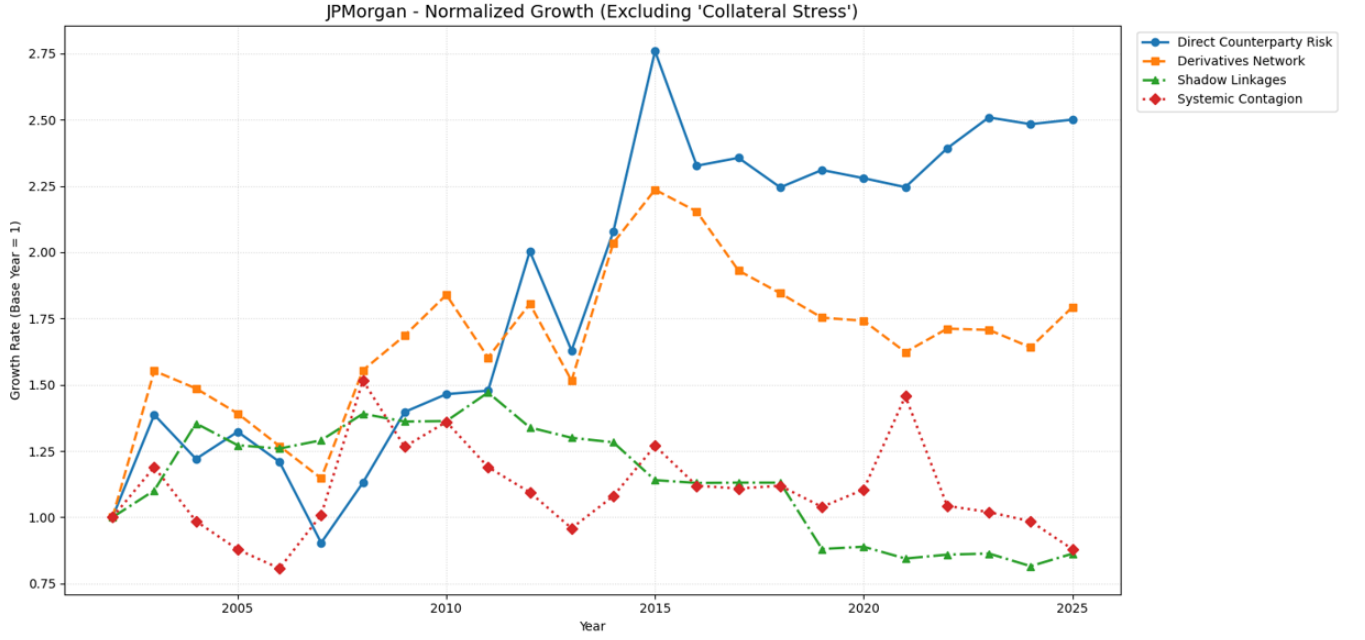


Figure 5: *Detailed longitudinal evolution of category-specific systemic risk disclosures within JPMorgan’s textual corpora (2002–2025), excluding the ‘Collateral Stress’ dimension. By removing the dominant scaling effect of Collateral Stress which reaches an index value of approximately 35 by 2025 this disaggregated view isolates the dynamics of the remaining four structural dimensions. Post-2014, Direct Counterparty Risk emerges as the primary driver of the risk narrative, while the Derivatives Network exhibits a post-crisis peak in 2015 followed by gradual moderation. Conversely, Shadow Linkages demonstrate a decline post-2011, dropping below the baseline, while Systemic Contagion displays spikes notably during the Great Financial Crisis (2008) and the 2021 period. See Section 5 for a detailed empirical discussion and methodological framework.*

Aggregate Interconnectedness Index: JPMorgan 10-K Filings (2002–2025)

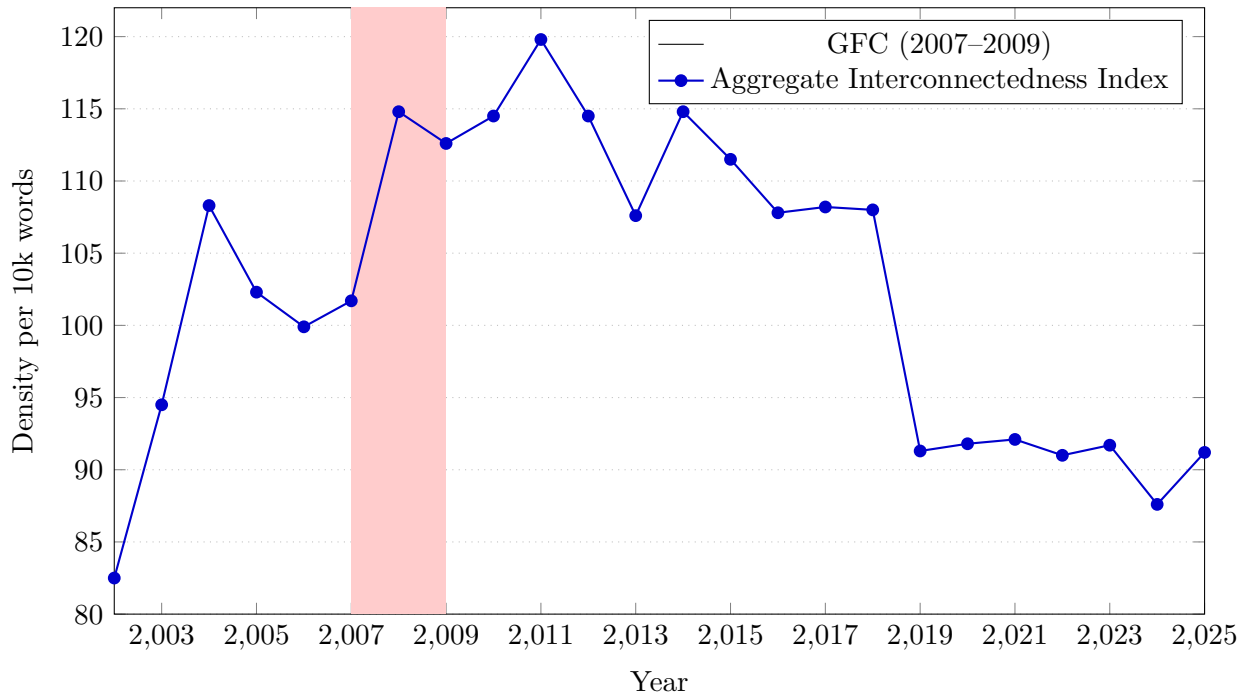


Figure 6: *Longitudinal trajectory of the Aggregate Interconnectedness Index for JPMorgan, spanning the 2002–2025 period. Expressed as cumulative term density per 10,000 words, this composite metric aggregates disclosures across all constituent dimensions of the enriched systemic risk lexicon to provide a holistic measure of institutional exposure to systemic vulnerabilities. The shaded area delineates the Global Financial Crisis (GFC) of 2007–2009, highlighting an acute structural escalation in interconnectedness discourse. Notably, this heightened sensitivity persists through the subsequent phase of intensive macroprudential regulatory reform (circa 2010–2012) prior to a sustained, secular normalization in more recent reporting cycles. A comprehensive empirical evaluation of these aggregate trends is provided in Section 5.*

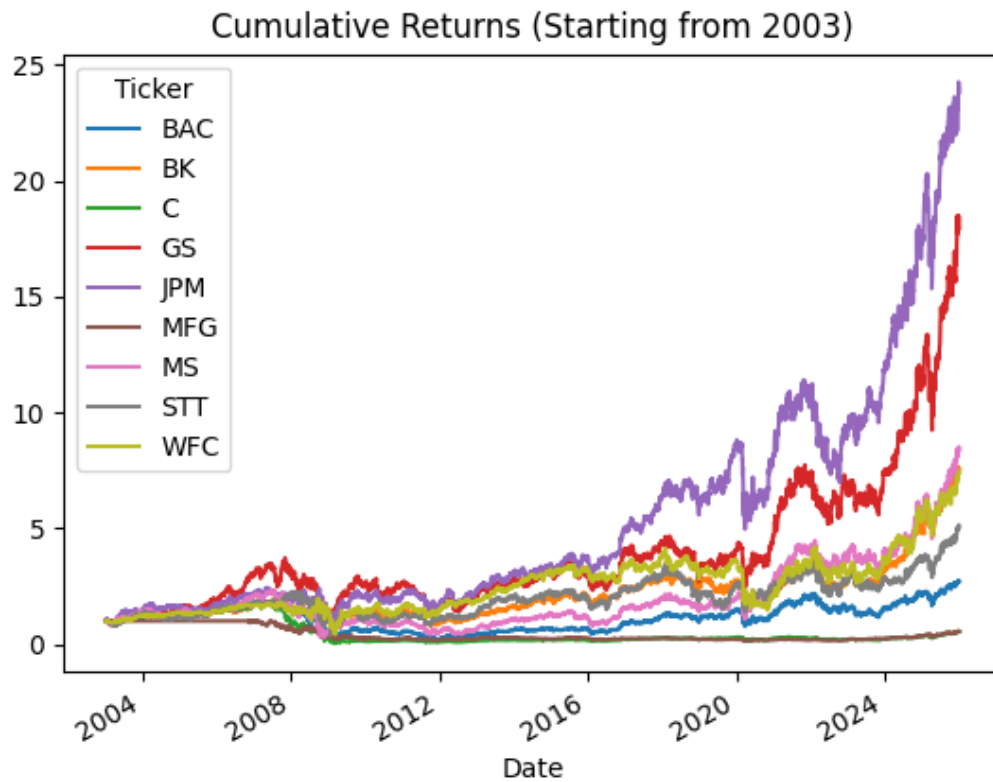


Figure 7: *Cumulative equity returns for a selection of major global banking institutions from 2003 to 2026. The plot illustrates the long-term performance and recovery trajectories of key players, highlighting the significant outperformance of JPMorgan Chase (JPM) and Goldman Sachs (GS) relative to peers such as Citigroup (C) and Mizuho Financial Group (MFG). See discussion in Section 6*

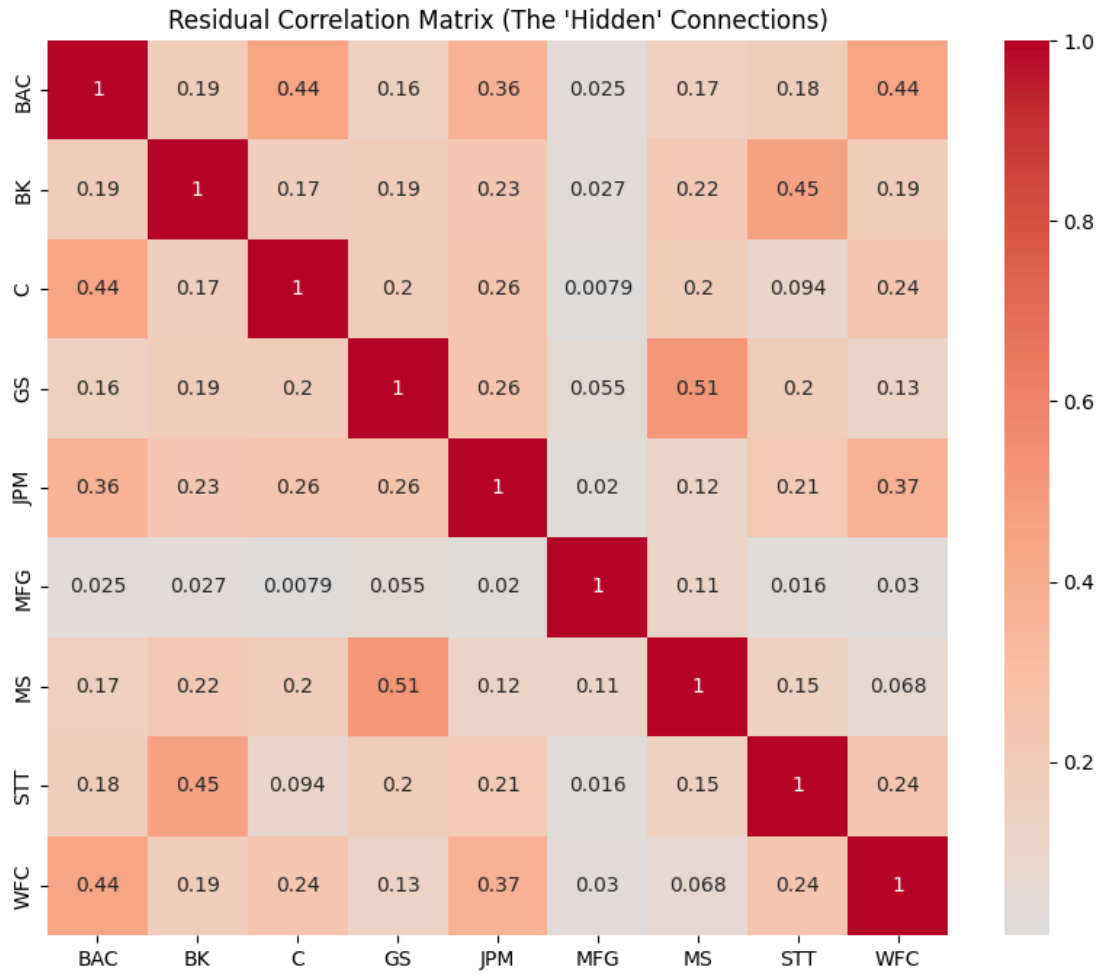


Figure 8: This matrix displays the pairwise correlations of residuals for the biggest financial institutions. By removing common factor variance, the visualization isolates unique institutional linkages. The color scale indicates the strength of the relationship, with values closer to 1.0 representing significant idiosyncratic co-movement between specific banking pairs. For instance, the dark orange square at the intersection of GS and MS displays a correlation of 0.51, indicating that Goldman Sachs and Morgan Stanley share substantial firm-specific shocks that are not explained by the common Fama-French factors. See discussion in Section 6

Residual Shock Transmission Network: Full Sample (2003–2025)

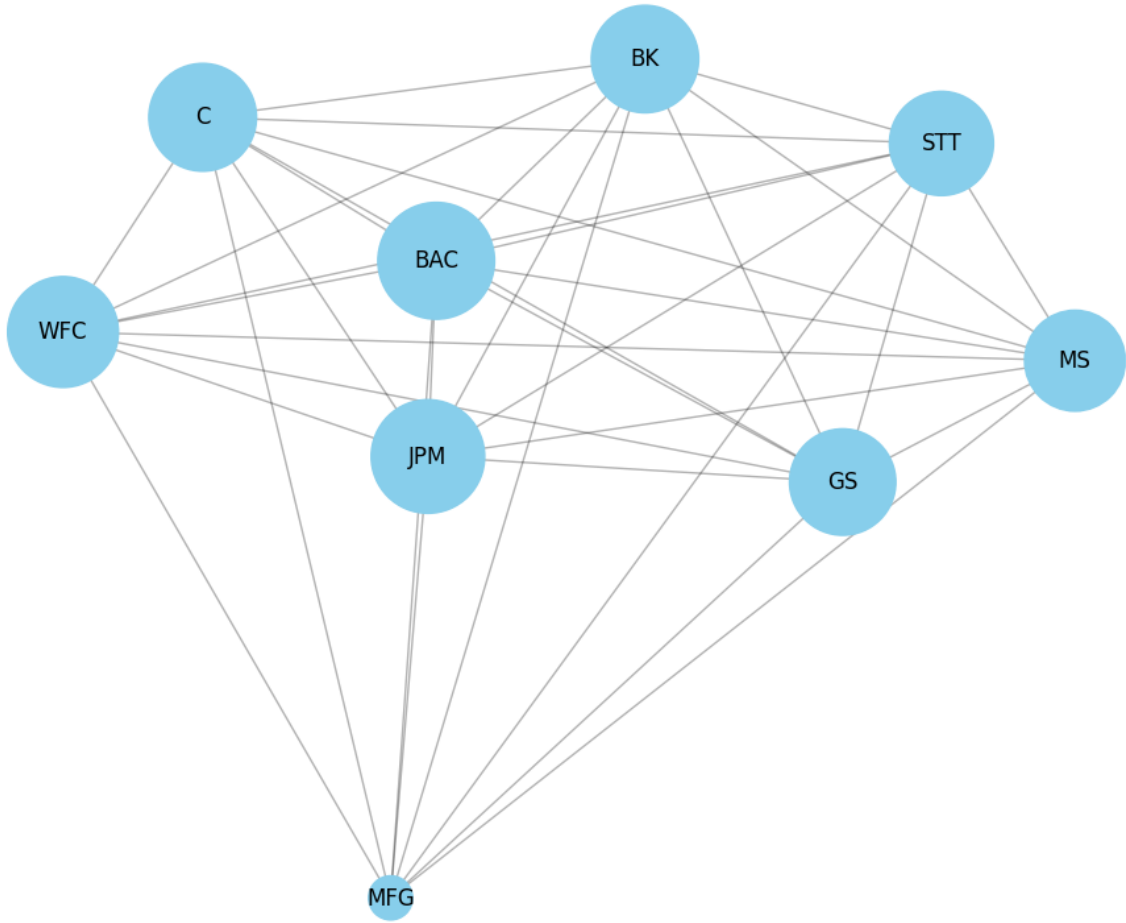


Figure 9: *This graph visualizes the structural dependencies between financial institutions using Fama–French residuals. Nodes represent individual firms, while edge thickness indicates the strength of the correlation after controlling for systemic factors. The central cluster (BAC, JPM, GS) suggests a high degree of mutual dependency, whereas MFG appears as a peripheral outlier, indicating lower idiosyncratic alignment with the domestic US banking core. See discussion in Section 6*

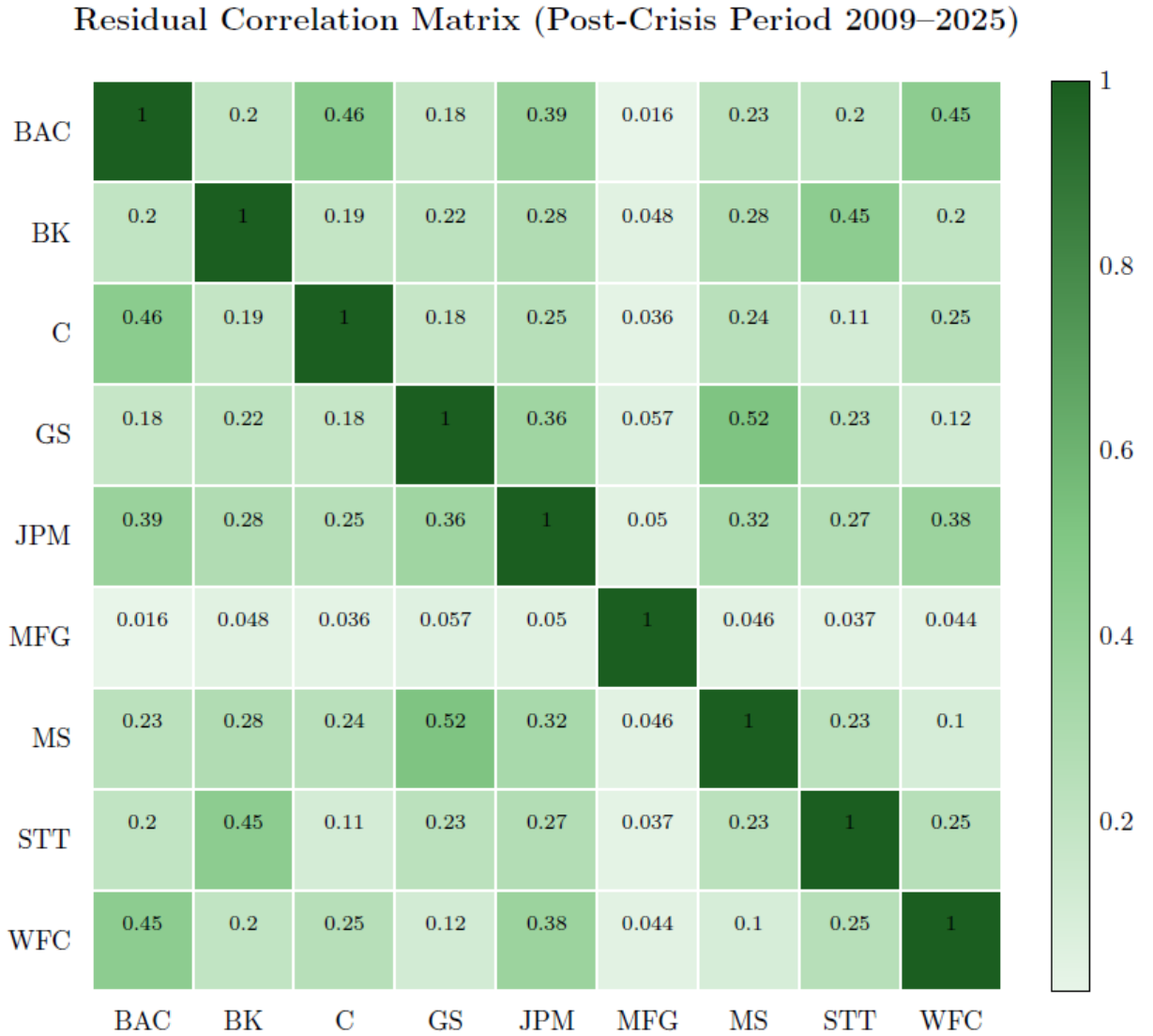


Figure 10: *This figure presents the residual correlation matrix for the post-crisis period (2009–2025), constructed after filtering out systemic variance using the Fama–French three-factor model. By isolating the idiosyncratic component of returns, the heatmap uncovers ‘hidden’ structural dependencies that persist independently of broad market movements. Darker green cells signify intense co-movement clusters, most notably between Goldman Sachs (GS) and Morgan Stanley (MS) at 0.52, and the custodial leaders Bank of New York Mellon (BK) and State Street (STT) at 0.45. The strong linkages among BAC, JPM, and WFC further illustrate a cohesive commercial banking core. Conversely, the near-zero correlations observed for MFG (ranging from 0.016 to 0.057) confirm its status as a peripheral actor with minimal idiosyncratic exposure to the US domestic banking network, suggesting that its risk profile is driven by fundamentally different underlying factors. See discussion in Section 6*

Residual Shock Transmission Network: Post-Crisis Period (2009–2025)

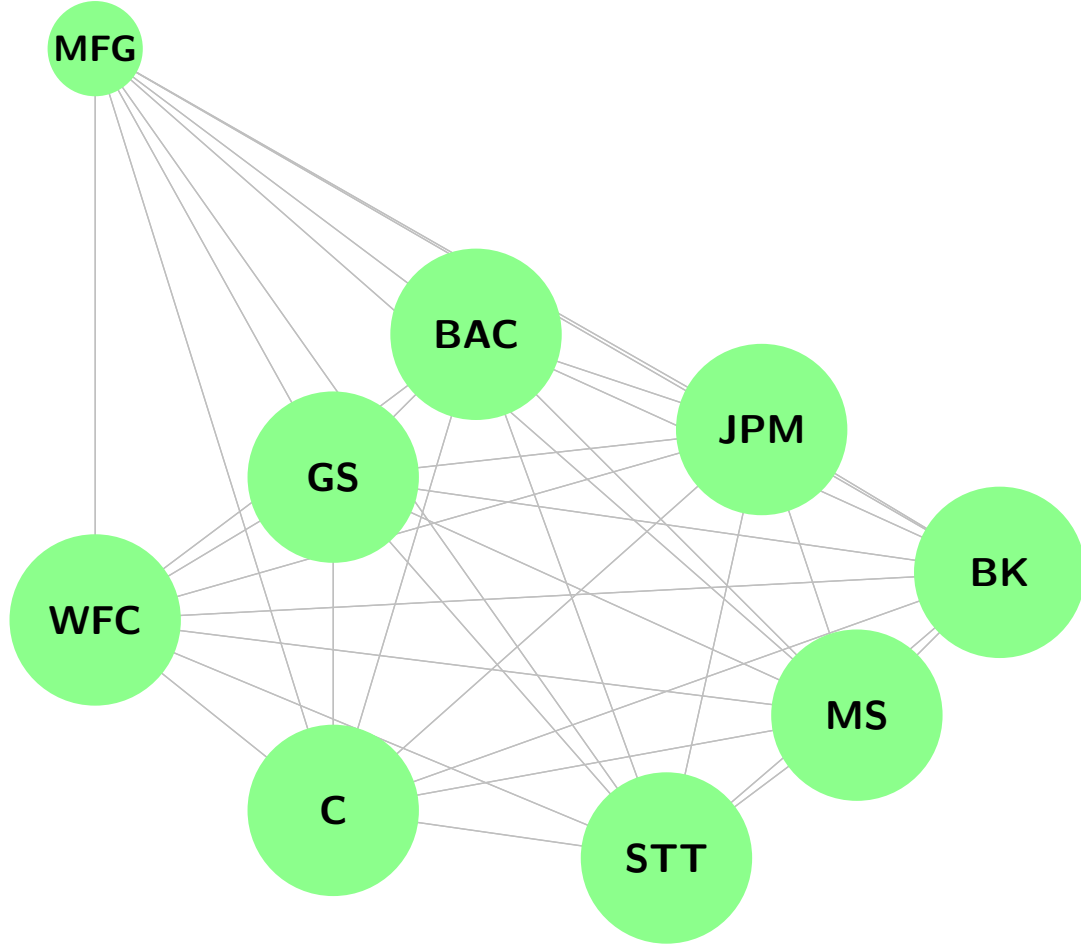


Figure 11: *This figure visualizes the idiosyncratic banking network during the post-crisis era (2009–2025), with the node size and positioning reflecting the Eigenvector Centrality rankings. JPMorgan Chase (JPM) occupies the primary structural nexus of the system, acting as the most influential node in the propagation of residual shocks. The dense web of thin edges illustrates a highly integrated core among US domestic majors, where firm-specific risks are closely coupled. Consistent with the centrality scores, Mizuho Financial Group (MFG) is represented by a reduced node size and a more isolated coordinate, signifying its limited integration into the idiosyncratic risk profile of the US banking center. See discussion in Section 6*

JPMorgan Chase Dominance in the Interconnectedness Network Comparison vs. Peer Group (2010-2025)

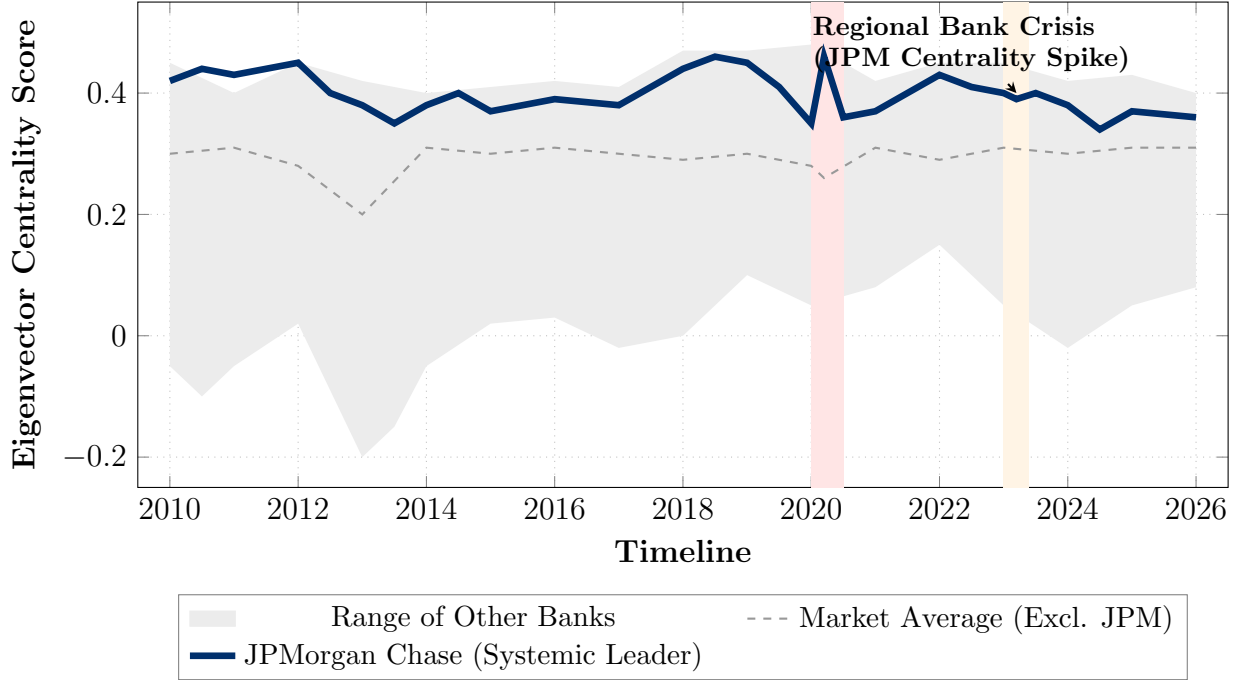


Figure 12: *This figure illustrates the intertemporal evolution of Eigenvector Centrality scores from 2010 to 2025, highlighting the persistent systemic dominance of JPMorgan Chase (JPM) within the idiosyncratic banking network. The thick blue line tracks JPM's centrality, consistently remaining at the upper bound of the peer group range (represented by the light gray shaded area) and significantly above the market average (dashed line). Vertical highlighted columns denote periods of heightened market stress—specifically the 2020 pandemic onset and the 2023 regional banking crisis—where JPM's centrality often exhibits counter-cyclical spikes. These spikes, particularly during the 2023 liquidity crunch, suggest that JPM serves as a structural 'safe haven' or anchor; as peripheral banks decouple or experience distress, JPM's idiosyncratic connections to the remaining healthy core intensify, further solidifying its role as the primary nexus of the US financial architecture. See discussion in Section 6*

JPM Net Volatility Spillover (2004-2024)

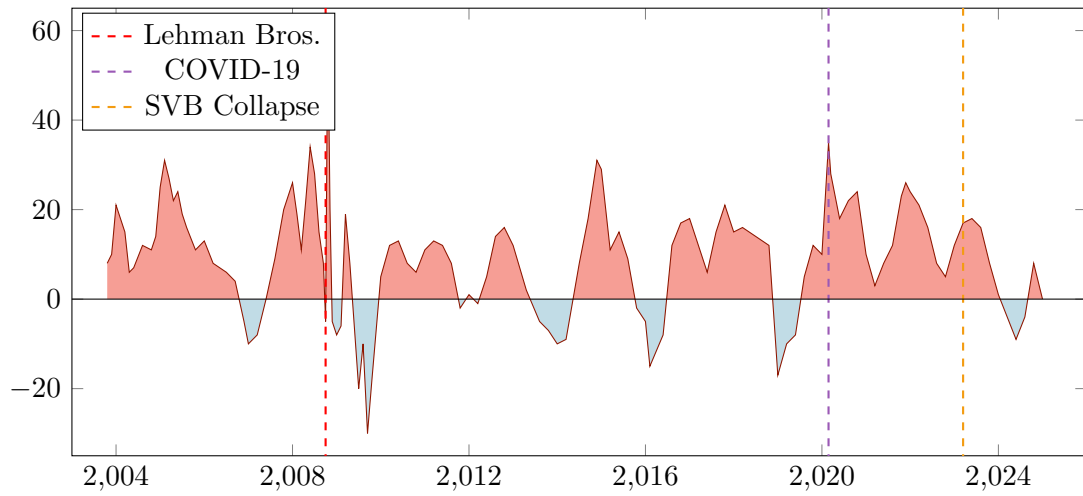


Figure 13: *Dynamic evolution of JPM’s net directional volatility connectedness from 2004 through 2024. The time-series plot illustrates the institution’s shifting role within the financial network, where positive (shaded) regions denote periods where JPM acted as a net transmitter of systemic shocks, and negative regions indicate periods of net volatility absorption. Vertical dashed lines identify structural breaks corresponding to major exogenous shocks—the 2008 Global Financial Crisis, the 2020 COVID-19 pandemic, and the 2023 regional banking turmoil—revealing the persistent sensitivity of the bank’s spillover profile to periods of heightened market stress. See discussion in Section 7*

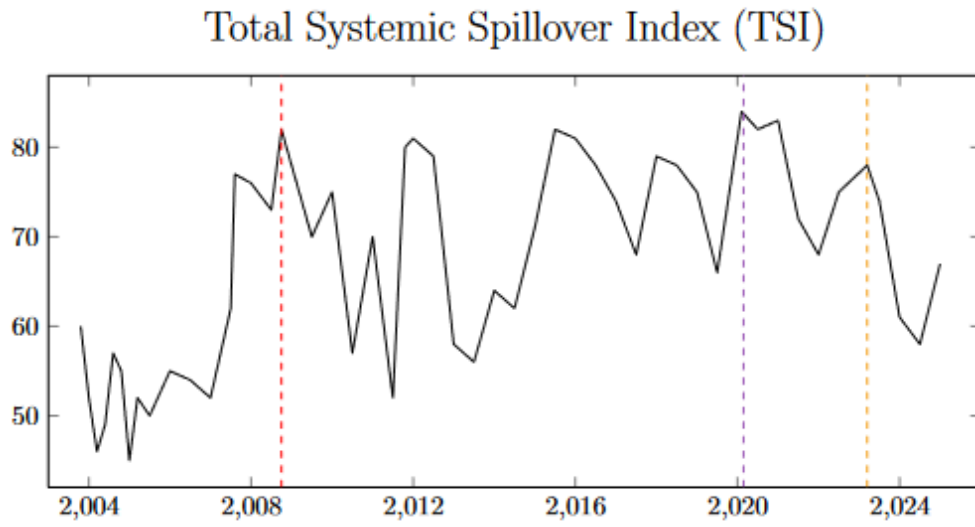


Figure 14: *Temporal dynamics of the Total Systemic Spillover Index (TSI) for the banking network (2004–2024). The index quantifies the aggregate intensity of volatility connect- edness, representing the share of forecast error variance generated by cross-institution spillovers. Pronounced escalations in the TSI coincide with periods of extreme market stress, specifically Lehman Brothers collapse (red), COVID-19 outbreak (purple), and the SVB collapse (orange) reflecting a high degree of systemic interdependence and synchro- nized risk propagation during contractionary regimes. See discussion in Section 7*

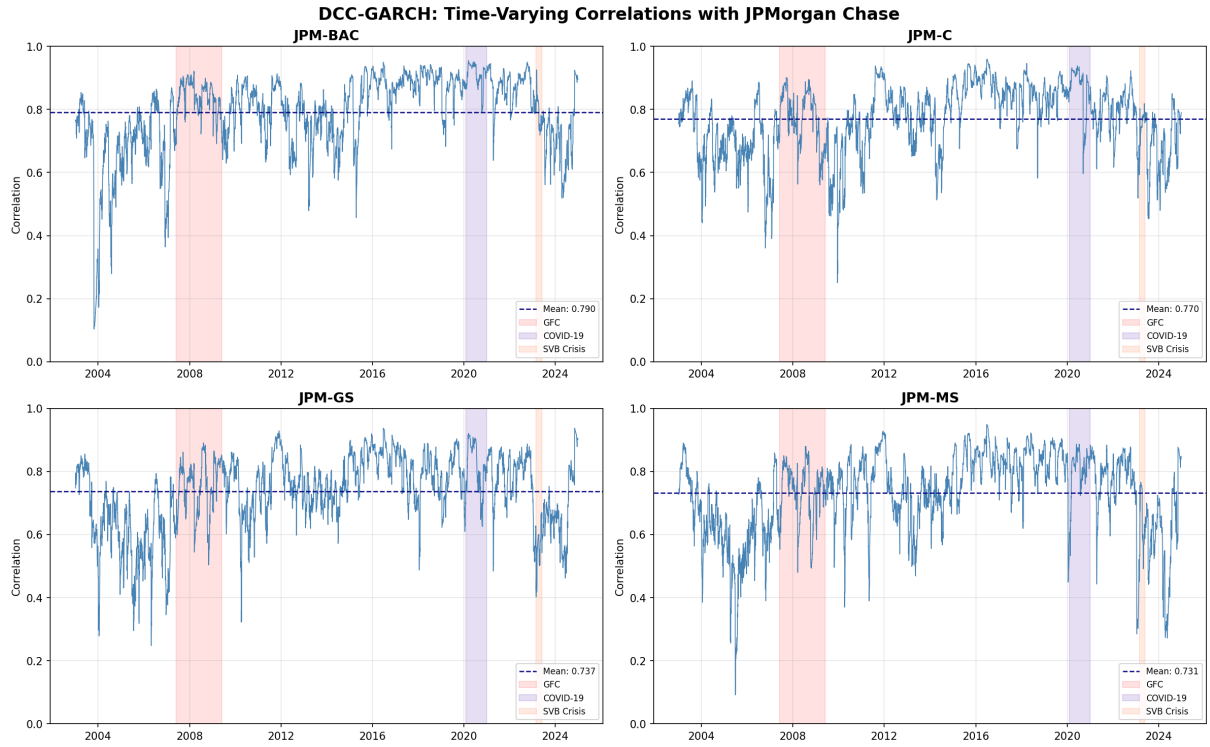


Figure 15: *Dynamic Conditional Correlations for JPMorgan Chase (JPM) against Selected Peer Institutions (2003–2024).* This figure illustrates the evolution of time-varying pairwise correlations between JPM and four major U.S. financial counterparts, estimated via a DCC-GARCH framework. Horizontal dashed lines represent the long-run unconditional correlation means for each pair. Shaded regions highlight critical periods of systemic distress: the 2008 Global Financial Crisis (red), the 2020 COVID-19 pandemic shock (purple), and the 2023 Silicon Valley Bank (SVB) liquidity crisis (orange). The observed spikes during these intervals underscore the presence of volatility spillovers and heightened sectoral contagion during exogenous shocks. See discussion in Section 8

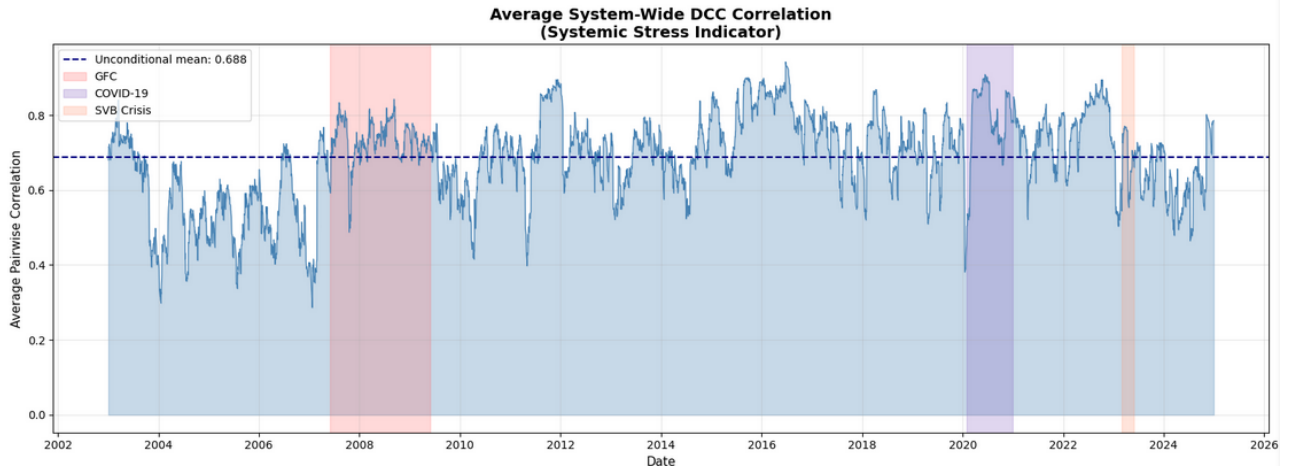


Figure 16: *Average System-Wide Dynamic Conditional Correlations as a Measure of Systemic Stress (2003–2024)*. This figure displays the time-varying cross-sectional average of all pairwise correlations within the eight-bank system, estimated via the DCC-GARCH model. The horizontal dashed line identifies the long-run unconditional mean (0.688), which serves as a benchmark for normal market integration. Pronounced spikes in the average correlation during the Global Financial Crisis (red), the COVID-19 pandemic shock (purple), and the 2023 regional banking turmoil (orange) provide empirical evidence of the “diversification meltdown” phenomenon, where idiosyncratic risks are subsumed by systemic shocks, leading to heightened financial contagion across the sector. See discussion in Section 8

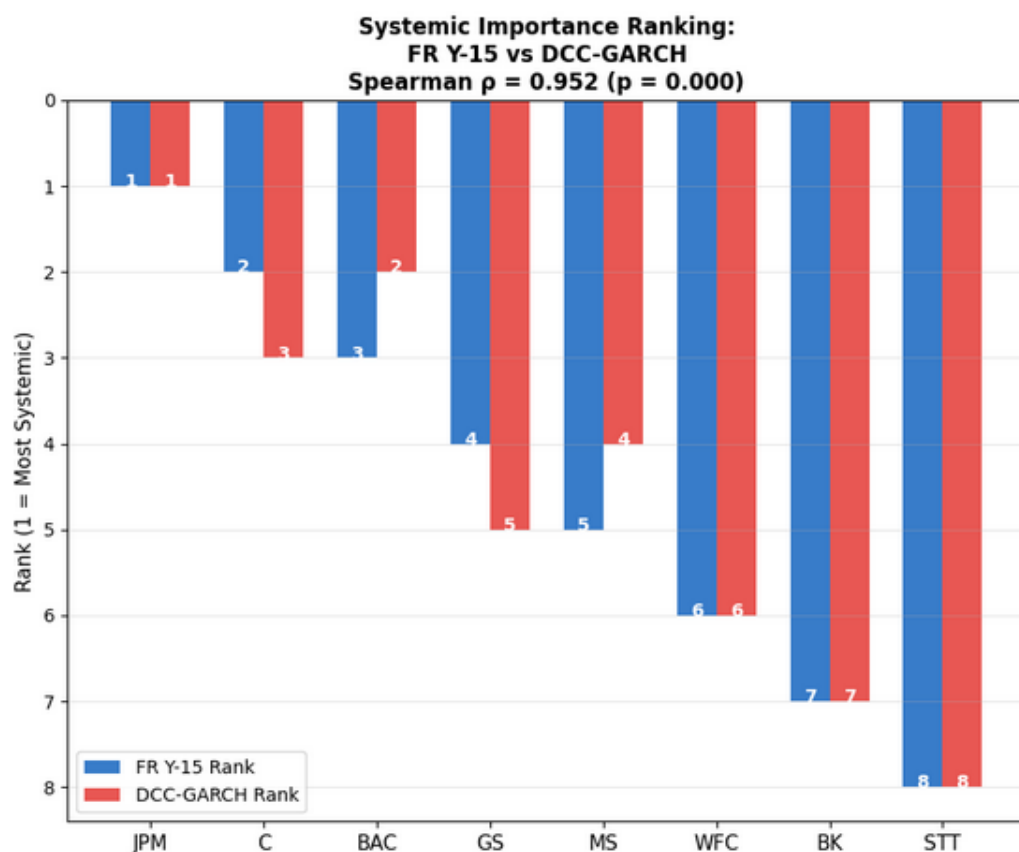


Figure 17: *Systemic importance ranking comparison between the FR Y-15 Interconnectedness Index and the DCC-GARCH market-implied ranking. Blue bars denote FR Y-15 ranks and red bars denote DCC-GARCH ranks, with rank 1 indicating the most systemically important institution. The near-perfect overlap across all institutions confirms the consistency of the two methodologies. Spearman rank correlation: $\rho = 0.952$ ($p < 0.001$). See discussion in Section 8*