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Resilience in Complete Financial Networks: Key Characteristics

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Abstract

This paper asks: What network characteristics determine the resilience of fully connected financial networks? I use real-world data (BIS CBS) to simulate a collection of networks of financial institutions to study how failures cascade: how changes to a primitive asset (GDP shock) can start a cascade of failures and how discontinuity in the value of a financial institution (e.g., bankruptcy) can trigger further failures, and how this depends on the topology of the network. Focusing on fully connected networks (where each node is connected to every other node), I come up with both node-level and network-level metrics to classify the characteristics of a network that will be more resilient to a shock. Finally, I run a simulation across a parameter space to see how networks with different topologies handle different parameters (e.g., size of shock, number of nodes experiencing a shock).

Word Count: 4893

Contents

1 Introduction

The 2008 Global Financial Crisis fundamentally changed the study of financial risk. Since then, it has become common knowledge that network analysis is essential to capture how risk travels through the intricate web of financial relationships. Previous studies have demonstrated that network structure significantly influences risk contagion dynamics. For instance, while fully connected networks can absorb minor shocks by dispersing losses among many institutions, they face a heightened risk of systemic collapse when shocks are severe. In contrast, ring networks tend to resist large-scale failures, although they are less effective at mitigating even small shocks.

This paper focuses specifically on fully connected networks and investigates the characteristics that make some of these networks more resilient than others. Building on the framework introduced by Elliott, Golub, and Jackson (2014), this study extends the model by incorporating a bridge between the real and financial economies. In this extended model, shocks to primitive assets—represented by GDP declines—transmit through the financial system via banks' domestic and foreign claims. This paper addresses two main questions: What network characteristics determine the resilience of fully connected financial networks? And what defines a resilient node? The findings indicate that nodes heavily reliant on foreign claims tend to fail earlier when a shock originates in the foreign economy, while nodes primarily dependent on domestic claims exhibit greater resilience. Moreover, networks in which highly connected nodes are not predominantly interconnected tend to experience lower overall failure rates.

2 Literature Review

2.1 Theoretical Foundations

Allen and Gale (2000)'s foundational paper developed a model of an interbank market where banks are linked through lending and borrowing relationships. They show how the structure of these connections affects the risk of contagion. They find that structures that are more connected can absorb shocks better as the loss can be spread amongst a larger number of banks. Whilst sparser networks are more likely to trigger a chain reaction from a shock to a single bank, potentially leading to systemic collapse.

Elliott, Golub, and Jackson (2014) build on the work of Allen and Gale (2000) by allowing banks to have heterogeneous exposures. They provide a richer framework to analyze how shocks spread in a network. One of their contributions is the introduction of the concept of tipping points in the network. A small shock may be absorbed if banks remain within their thresholds, but once a threshold is breached, it can set off a chain reaction, leading to widespread failures. This model captures the non-linear nature of contagion, where even small initial shocks can lead to large-scale disruptions under specific conditions.

Acemoglu, Ozdaglar, and Tahbaz-Salehi (2015) then extended this by looking at the extent to which the structure of a network played a role in financial contagion. From their model, they found that under a certain threshold, a more diversified network (i.e., a complete network) was the best at absorbing shocks. On the other hand, a ring network (nodes connect sequentially in a closed loop) was the worst. These results match the claims by Allen and Gale (2000). However, they also found that above a certain threshold, a negative shock spread more easily in the more connected network, which affirms this idea of the "robust yet fragile" property of interconnected financial networks proposed by Haldane (2009).

2.2 Global Network Analysis

These works highlight the importance of understanding the structure of financial networks to better shape policy and regulation. Much of the work done has been on the interbank market within a country (see Iori, G. et al. (2008) and Bech, M.L. and Atalay, E. (2010)), but as globalization and global banking have increased, it is also critical to understand the landscape of the global banking network. Data from the Bank of International Settlements (BIS) shows that "Bank's global cross-border claims increased by $1.1 trillion during Q1 2024, driven by bank credit." Several works have explored the global banking network using data from the BIS, such as Avdjiev, S. et al. (2019) and Giudici, P. et al. (2016).

Avdjiev, S. et al. (2019) developed a method that combines an exposure-based approach, where you look at data on direct and indirect bilateral exposures between countries or banks to find paths for contagion, and a market-based approach, which looks at how the market perceives risk through credit default swap spreads and bond spreads. They develop a multi-layer network, where the layers are different sectors (banking, official, and non-banking private financial sector) and the nodes are countries. The edges represent how much country j owes country i normalized by how much all other countries owe country i. They use tensor decomposition to extract the relationship in the liabilities matrices and develop their own centrality measure tailored to the multi-layered structure. Overall, they demonstrate that a multi-layered, non-linear model provides a more robust framework for identifying potential contagion channels in the global banking network. Giudici, P. et al. (2016) used graphical network techniques to represent and assess the relationships between countries based on financial flows, aiming to identify which connections contribute most to potential financial instability.

Both these works make great contributions in assessing systemic risk on the global scale, but they don't look at the evolution of the structure of the global network. Silva, T.C. et al. (2016) studied the topology of the global finance network from 2005 to 2014. They found that leading up to 2008, the network was more fragile than after the crisis. They highlight the importance of looking at the evolution of networks for regulation. These results were similar to Camelia Minoiu and Javier A. Reyes (2013), who explored the global banking network (GBN) using cross-border bank lending data for 184 countries from 1978–2010. They analyzed the financial interconnectedness across these countries, focusing on how bank lending flows have evolved over the decades and their implications for systemic risk and financial stability. They found that network density co-moves with the global cycle of private capital flows, and country-level connectedness tends to increase before the onset of financial crises and to decrease afterward.

Although recent studies using BIS data have provided valuable insights into the evolution of global banking networks, they largely focus on macro-level changes over time. In contrast, this paper concentrates on the network-level determinants of resilience within fully connected networks. Using a novel simulation framework that explicitly links real economy shocks (via GDP) to financial contagion dynamics, this paper offers a novel perspective on how network topology influences the propagation of financial shocks. This focus on the relationship between domestic and foreign claims in triggering cascading failures provides both theoretical insights and practical implications for financial stability.

3 Data and Methodology

3.1 Data

The analysis in this paper relies on two primary data sources. First, I use the Bank for International Settlements' (BIS) Consolidated Banking Statistics (CBS). A key feature of the CBS is its adjustment for foreign branches and subsidiaries. For example, if a UK bank lends to a US company through its US subsidiary, the CBS records the transaction under the UK—the bank's home country—rather than the US, this is important as the risk is held by the home bank. In this study, I focus on the Total Claims metric, which aggregates the total amount banks in one country lend to those in another. Second, GDP data is sourced from the World Bank's National Accounts. The analysis spans seven years, from 2017 to 2023, and includes data for 17 countries, such as the United States, the United Kingdom, France, among others.

3.2 Network Construction and Model Framework

Following the methodology of Elliott, Golub, and Jackson (2014), I consider a set of n countries, denoted by

$$N = \{1, \dots, n\},$$

where each country is represented by banks headquartered within it. The banks' values are derived from primitive assets, which in our model are represented by GDP.

3.2.1 Definitions

- **GDP Vector P:** Let P_k denote the present value of asset k (GDP). This vector is normalized by setting one of the entries to 1; in my application, I set $P_7 = 1$.
- **Asset Ownership Matrix D:** Let $D_{ik} > 0$ be the share of asset k held by organization i. I assume that each country exclusively owns its own GDP, which is used to pay debt; therefore, the asset ownership matrix is given by:

$$D = I.$$

- **Cross-Holdings Matrix C:** For any two countries i and j, let $C_{ij} \geq 0$ denote the fraction of bank j's (or country j's) GDP owned by bank i. In other words, it represents the proportion of country j's borrowed funds that come from bank i. To ensure that C is invertible, I set:

$$C_{ii} = 0 \quad \text{for all } i.$$

- **Residual Ownership Matrix $\hat{C}$:** This matrix captures the fraction of each country's GDP that is not held by any other bank in the network. Since it reflects banks that only operate domestically, $\hat{C}$ is a diagonal matrix, defined as:

$$\hat{C} = I - C.$$

- **Dependency Matrix A:** The dependency matrix A accounts for all the claims that banks have on each other. This matrix is column stochastic, emphasizing that the primitive asset is fully leveraged among the banks in the network. It is defined as:

$$A = \hat{C}(I - C)^{-1}.$$

- **Market Value V:** Each bank has a market value based on its claims on the primitive asset, given by:

$$V = \hat{C}(I - C)^{-1}DP = ADP.$$

A key contribution of this paper is the decomposition of the dependency matrix into two distinct stages:

$$V = WADP,$$

where:

  - A captures the banks' claims on GDP, reflecting their lending to various sectors of the economy in other countries. To calculate A, the BIS CBS total claims to all sectors were used.
  - W captures the claims among banks within the interbank market. To calculate W, the BIS CBS total claims to banks were used.

This two-stage framework allows us to simulate scenarios where a bank is exposed exclusively to the financial network, yet it still experiences the impact of shocks to the real economy through its interconnected claims.

- **Bankruptcy Vector β:** To incorporate the cost of bankruptcy, the original framework introduces a discontinuity in asset values via a vector $\beta(V, P)$. Specifically, the market value is redefined as:

$$V = WA[DP - \beta(V, P)],$$

where $\beta_i > 0$ only when bank i fails. This term can be interpreted as the cost of bankruptcy, which reduces GDP due to the expense of bailing out institutions.

3.2.2 Propagation Algorithm

The resulting framework assigns each node a market value, allowing me to simulate shock propagation through the network. The algorithm for shock propagation is as follows:

1. **Initialization:** Set $Z_0 = \emptyset$ (the set of failed nodes at time $t = 0$).

2. **Time Update:** For each time step $t = t + 1$, update the bankruptcy cost vector $\beta^{(t-1)}$ as follows:

$$\beta_i^{(t-1)} = \begin{cases} 0, & \text{if country } i \notin Z_{t-1}, \\ \text{cost} \times V_i, & \text{if country } i \in Z_{t-1}. \end{cases}$$

3. **Failure Determination:** Define the set Z_t as all nodes k for which:

$$\left[WA(\hat{P} - \beta^{(t-1)})\right]_k < \theta \, [WAP]_k \,,$$

where $\theta \in [0, 1]$ is a threshold parameter. Here, $(1 - \theta)$ can be interpreted as the capital requirement; if losses exceed this fraction of a bank's value, the bank fails.

4. **Termination Check:** The algorithm terminates if $Z_t = Z_{t-1}$; otherwise, return to Step 2.

- **Assumptions:** I assume that shocks occur independently, focusing the analysis on the resilience of unpredictable events rather than on deliberate economic decisions. Additionally, I assume that the cost of bankruptcy is uniform across nodes. Although these assumptions simplify the model, they allow us to isolate the effect of network topology on shock propagation.

3.3 Empirical Strategy

3.3.1 Expected Number of Failures

From the shock propagation algorithm, a large amount of data was collected. The first and most important metric was the expected number of failures for a given network. Since multiple shocks could be applied to a network in each round of simulation, the total cost of a shock is defined as the sum of the GDP value removed from the network:

$$\text{Total cost} = \sum_{i=1}^{n} \gamma P_i$$

Each round of the simulation generates its own total cost, which depends on the shock size parameter γ and the randomly selected n nodes. To categorize shocks, I define:

- **Low-cost shock:** Total cost ≤ 0.6
- **High-cost shock:** Total cost > 0.6

(The threshold 0.6 was chosen based on Figure 3 since there was two clear groups of total cost)

The expected number of failures, conditional γ and θ, is computed as:

$$\begin{aligned} E[\text{num of failures} \mid \gamma, \theta] = {} & \frac{\text{num of low-cost shocks}}{\text{num of simulations}} E[\text{failures} \mid \text{low-cost shock}, \gamma, \theta] \\ & + \frac{\text{num of high-cost shocks}}{\text{num of simulations}} E[\text{failures} \mid \text{high-cost shock}, \gamma, \theta] \end{aligned} \tag{1}$$

This metric provides an objective measure of network resilience under a wide range of shock scenarios and origins.

3.3.2 Weighted Out-Degree

To explain the variations in the expected number of failures across different networks, I first define the **weighted out-degree** of a node as the sum of the weights of its outgoing connections. Mathematically, this is expressed as

$$\text{Weighted out-degree} = \sum_{i=1}^{n} w_{ji},$$

where w_{ji} represents the weight of the connection from node j to node i. This metric reflects the total claims a bank has on other nodes, including domestic claims, and is computed as the row sum of the A (or W) matrix. For example, if a bank has outgoing connections with weights 0.3, 0.5, and 0.2, its weighted out-degree would be $0.3 + 0.5 + 0.2 = 1.0$. This basic measure lays the foundation for more advanced metrics, such as the **Connectedness Score** and the **Connectedness Score Squared (CSS)**.

3.3.3 Connectedness

Connectedness is a binary attribute assigned to each node:

- A node is assigned connectedness = 1 if its total weighted out-degree is greater than the mean weighted out-degree in the network.
- Otherwise, it is assigned connectedness = 0.

This classification identifies nodes that are at higher risk of being affected by shocks. For example, consider a node with a weighted out-degree of 0.8, while the network average is 0.5; this node would be classified as highly connected (connectedness = 1) and would have more avenues for the shock to reach it.

Using this attribute, I define a measure to determine whether a network's connections are primarily between highly connected nodes or between highly connected and weakly connected nodes. Each node receives a connectedness score, computed as:

$$\textbf{Connectedness score}_j = \sum_{\substack{i=1 \\ \text{connectedness}(i)=0}}^{n} w_{ji} - \sum_{\substack{i=1 \\ \text{connectedness}(i)=1}}^{n} w_{ji}.$$

- A negative score indicates that the node is primarily connected to highly connected nodes.
- A positive score indicates that the node is primarily connected to weakly connected nodes.

Averaging all nodes' connectedness scores provides a measure of how the network is structured in terms of connectivity.

Using the connectedness score, I define a second measure to capture not just whether a node is connected to weakly or highly connected nodes, but also whether those neighboring nodes themselves tend to be connected to nodes with similar (low or high) connectivity. In other words, if a node is connected mostly to weakly connected nodes, and those weakly connected nodes are also primarily connected to other weakly connected nodes, then shocks may spread more slowly through that portion of the network. Conversely, if a node is connected to highly connected nodes, and those nodes are in turn connected to many other highly connected nodes, the shock is likely to propagate rapidly.

The second measure, which I call the **Connectedness Score Squared** (CSS), is defined as:

$$\textbf{CSS}_j = \sum_{\substack{i=1 \\ \text{connectedness score}(i)>0}}^{n} w_{ji} - \sum_{\substack{i=1 \\ \text{connectedness score}(i)<0}}^{n} w_{ji}.$$

The network in Figure 1 helps conceptualize the idea behind our second connectedness measure. In the diagram, blue nodes have connectedness scores greater than 0, meaning they are primarily connected to lowly connected nodes. In contrast, red nodes have connectedness scores less than 0, indicating that they are predominantly linked to other highly connected nodes. The thickness of the lines represents the strength of the connections between nodes, while the size of each node is scaled according to its absolute value of *Connectedness Score Squared* (CSS).

For example, large red nodes—such as node 6—are more at risk because they are highly connected, and most of their connections are to other highly connected nodes. In

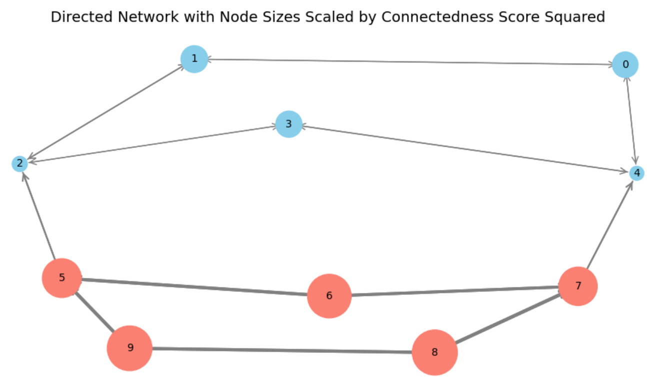

Figure 1: CSS

this area of the network, shocks are likely to propagate more rapidly. However, these nodes can also distribute the impact among themselves, reducing reliance on any single node. Conversely, nodes like 2 and 4 exhibit low CSS values because the weights of their connections to lowly connected (blue) nodes tend to offset those to highly connected (red) nodes, thereby reducing their overall risk of rapid shock transmission.

3.3.4 Internal

Similarly, I define another binary attribute, *internal*, to classify nodes based on their reliance on domestic claims:

- $Internal = 1$ if over 50% of a node's total weighted out-degree comes from domestic claims.
- $Internal = 0$ otherwise.

Nodes with $internal = 0$ are more exposed to shocks originating in foreign economies. To capture the structure of these relationships, I define an **internal score** similar to the connectedness score:

$$\textbf{Internal score}_j = \sum_{\substack{i=1 \\ \text{internal}(i)=1}}^{n} w_{ji} - \sum_{\substack{i=1 \\ \text{internal}(i)=0}}^{n} w_{ji}.$$

- A negative score indicates that the node is primarily connected to others that depend on foreign claims.
- A positive score indicates that the node is primarily connected to others that depend on domestic claims.

Averaging all nodes' internal scores provides a network-wide measure of exposure to foreign versus domestic risk.

Similarly, using the **internal score**, I define a second measure to capture not only whether a node is connected to domestically dependent or foreignly dependent nodes but also whether those neighbouring nodes tend to be connected to nodes with similar dependencies. In other words, if a node is connected mostly to domestically dependent nodes—and those nodes are in turn primarily connected to other domestically dependent nodes—then shocks may spread more slowly through that portion of the network.

The second measure, which I call the **Internal Score Squared (ISS)**, is defined as:

$$\mathbf{ISS}_j = \sum_{\substack{i=1 \\ \text{internal score}(i)>0}}^{n} w_{ji} - \sum_{\substack{i=1 \\ \text{internal score}(i)<0}}^{n} w_{ji}.$$

This measure captures the extent to which a node's network is clustered by domestic versus foreign dependencies. A positive ISS indicates that a node is predominantly connected to nodes that are mainly domestically dependent, which could act as a buffer against foreign shocks. Conversely, a negative ISS suggests that the node is more exposed to foreign dependencies, potentially making it more vulnerable to shocks originating outside the domestic economy.

4 Results

4.1 Preliminary Results:

One of the benefits of using real-world data instead of generating random networks is that the network can capture extreme values more accurately. This is illustrated in Figure 2, which shows the cumulative distribution of the out-degrees from the A matrix. The complete homogeneous network serves as a benchmark; the further the cumulative distribution deviates from the vertical line representing the complete homogeneous network, the more extreme the out-degrees in the network. In other words, a large deviation indicates that some nodes hold very large claims while others hold very little. In contrast, the Random 1 and Random 2 networks demonstrate that even when data is generated randomly, these extreme disparities are not reproduced. This suggests that real-world network structures inherently exhibit a higher degree of inequality in node connectivity.

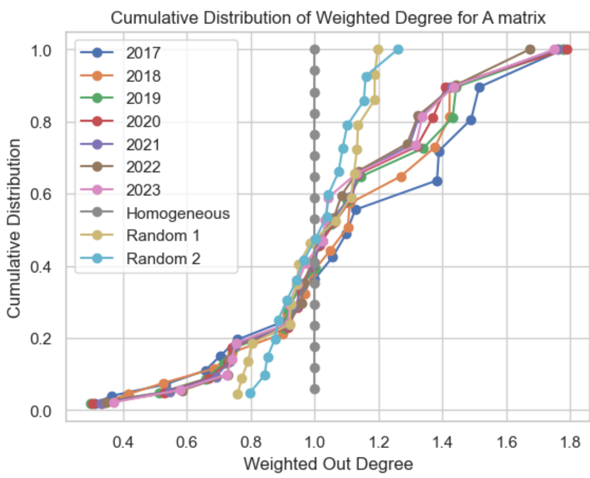

Figure 2: CDF A

Furthermore, when the A matrix is multiplied by the W matrix, the distributions become even more skewed, as shown in Figure 8. A complete set of preliminary results is provided in the appendix, including graphs illustrating how the six attributes—CSS, ISS, Internal Score, Connectedness Score, Connectedness, and Internal—relate to each other.

In summary, there is a positive relationship among CSS, ISS, Internal Score, and Connectedness Score. Nodes with high Internal Scores also tend to have high Connectedness Scores. That is, nodes that are more connected to weakly connected nodes are also more connected to internal nodes (Figure 8), suggesting that internal nodes are less connected overall. Additionally, if a node's neighbors are mostly connected to weakly connected nodes, those neighbors are also likely to be internal nodes. This pattern suggests the formation of clusters composed of weakly connected, internal nodes.

This is further supported by the observation that internal nodes tend to have higher Internal Scores, while nodes with connectedness = 1 typically have lower (often negative) Internal Scores (Figures 11 and 12).

4.2 Simulation Results

In my initial simulation, I randomly selected 3 nodes (n) and shocked them by applying a 12.5% (γ) decrease in GDP. The capital reserve level (θ) was set to 0.925, and the simulation was run 500 times.

Figure 3 plots the total cost of the shock on the x-axis against the number of node failures on the y-axis. I would like to draw particular attention to the last two graphs, which show the behaviour of the ring network and the complete homogeneous network. These serve as robustness checks, demonstrating that the simulation produces behaviour consistent with theoretical expectations.

4.2.1 Key Observations

Ring vs. Complete Homogeneous Network:

- The ring network exhibits a larger number of failures at low shock levels. This result highlights the non-linearity of shock propagation; the same magnitude of shock can lead to different outcomes depending on which nodes are shocked.
- Proportionally, the ring network tends to have fewer total failures when at least one node fails compared to the complete homogeneous network, where failure of one node triggers the failure of every node. This is consistent with findings from Acemoglu et al. (2015) and confirms that the model behaves as expected.

Temporal Variation in Network Behaviour (2017–2023):

- Networks from 2017 to 2023 tend to approximate the behaviour of the complete homogeneous network, with the 2023 network showing very similar failure patterns.
- However, a key difference is observed at low shock levels: the 2023 network still experiences a few failures, whereas the complete homogeneous network does not fail at all under low shock levels and can handle a significant number of high shock levels without any failures.
- In earlier years, even low-level shocks can lead to complete network failure with the given set of parameters. This demonstrates that networks are not identical—some are inherently more resilient than others.

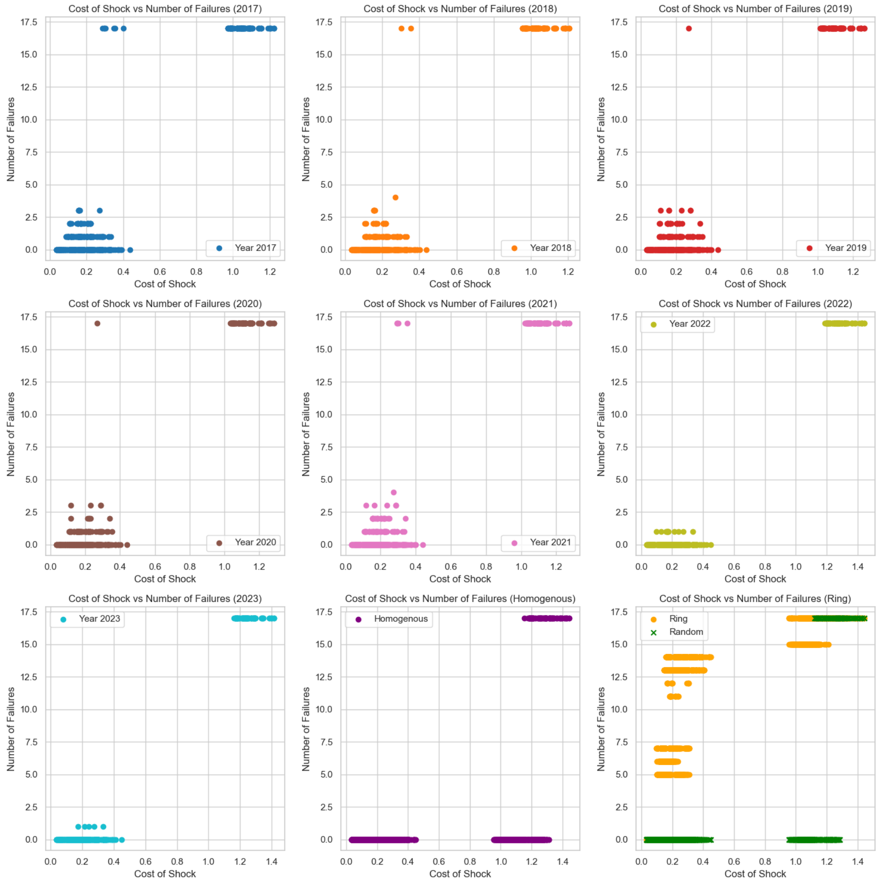

Figure 3: Cost of shock VS number of failures

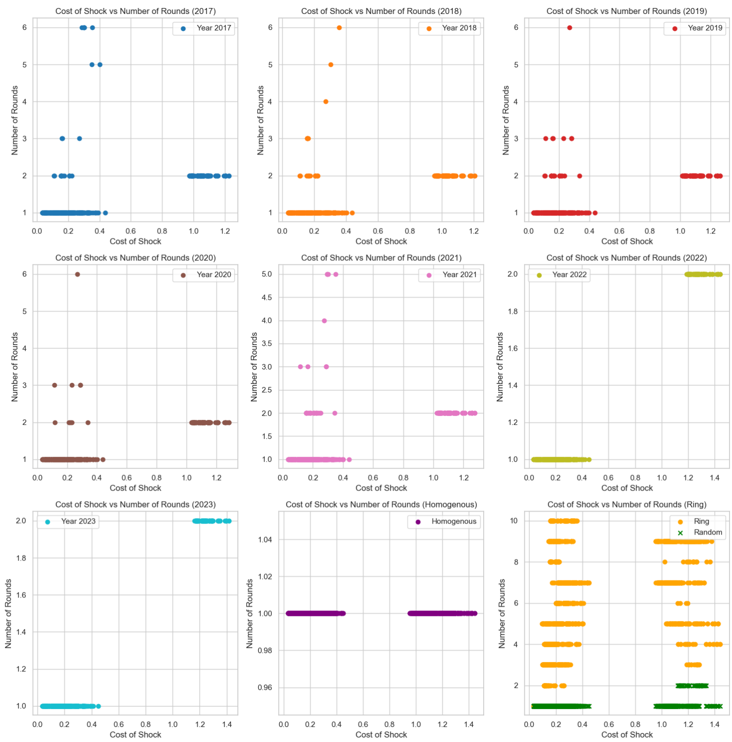

Figure 4: Cost of shock VS number of rounds

4.2.2 Shock Propagation

- Figure 4 illustrates how long the shock takes to dissipate through the network. The ring and complete homogeneous networks behave as predicted by theory: the ring network requires several rounds for the shock to circulate, whereas the homogeneous network experiences a rapid, all-at-once failure.

- From a policy perspective, a slower dissipation of shocks is preferable because it provides regulators with additional time to intervene. For example, although early-year networks (e.g., 2017, 2018) may fail completely at low shock levels, the fact that these failures occur over at least four rounds offers a window for regulatory intervention, which might be better than a sudden collapse as seen in the 2023 network.

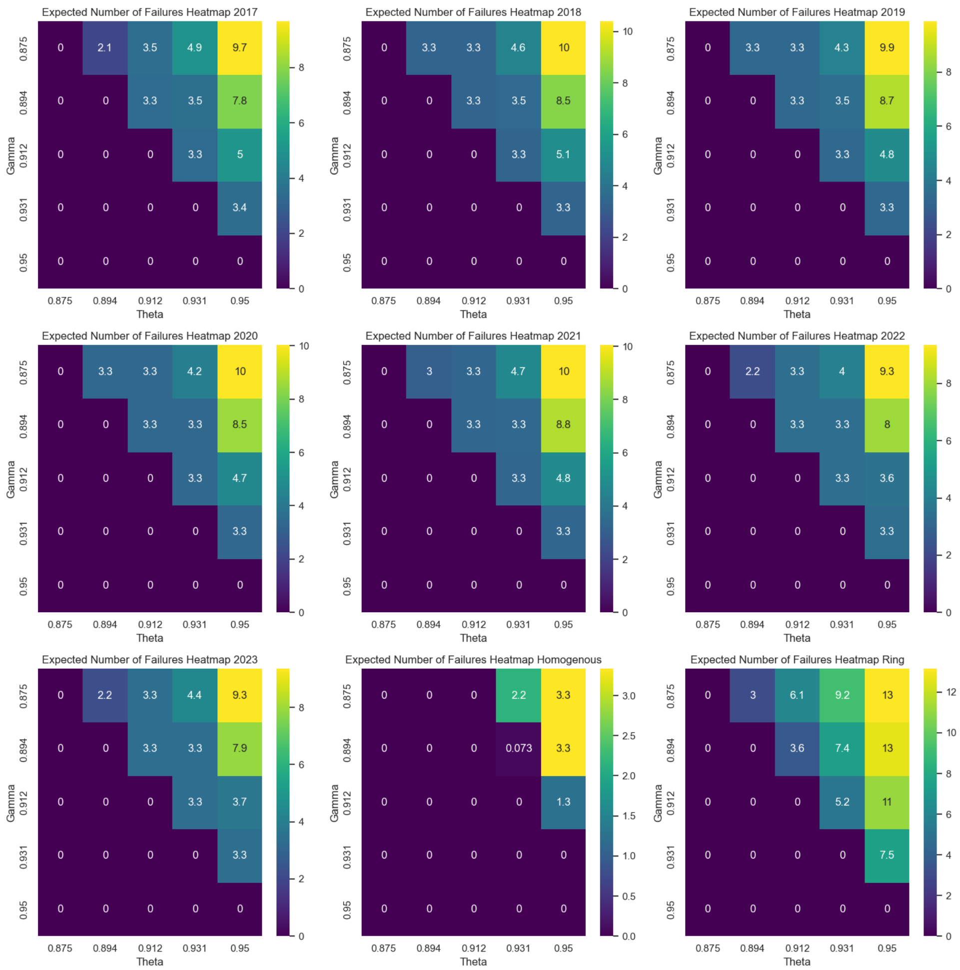

Figure 5: Parameter space

4.2.3 Robustness Across Parameters

- I also ran the simulation across a broader set of parameters: $\gamma, \theta \in [0.875, 0.95]$, as shown in Figure 5. Once again, the ring and complete homogeneous networks support the theory that the homogeneous network is more resilient than the ring, as evidenced by a lower expected number of failures.

- Although there is some variation in the number of expected failures, this variation is less pronounced when considering a range of parameters. Overall, the networks tend to be quite resilient—most parameter combinations yield an expected number of failures equal to 0. Yet, the observed variation suggests that differences in network characteristics play an important role in determining resilience.

4.2.4 First and last Failures

Table 1 shows that for 2017 and 2018, the Avg. ISS (Internal Score Squared) is identical to the Avg. CSS (Connectedness Score Squared). This suggests that the nodes with an internal score of 0 (i.e., those that are not predominantly domestic) are also the ones with a connectedness score of 1 (i.e., primarily connected to highly connected nodes). Figure 6 further illustrates that the nodes which fail first—when the shock does not directly hit them—tend to be those that depend mainly on foreign claims. In contrast, connectedness appears to have a less pronounced effect on the timing of failures, as evidenced by an approximately even (50/50) split between nodes with connectedness = 1 and those with connectedness = 0.

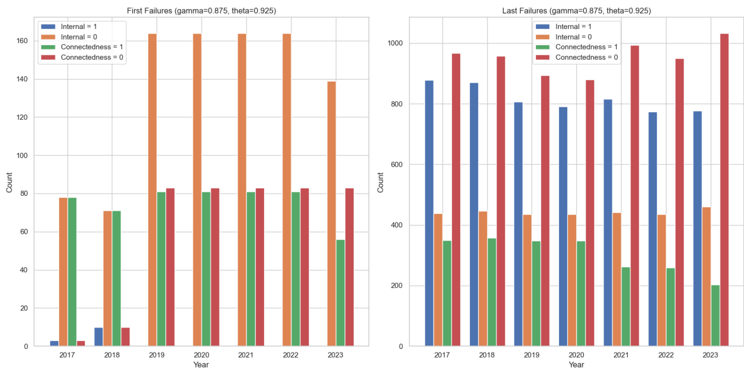

Figure 6: First failures and Last failures $gamma = 0.875, \theta = 0.925$

Figure 6 demonstrates that the nodes which fail last in the shock propagation process are those with an internal score of 1 and/or a connectedness score of 0. This outcome is intuitive: these nodes are less exposed to external shocks because they depend primarily on domestic claims and maintain lower connectivity with other nodes. Consequently, when the shock originates elsewhere, they are better insulated from its impact. The full set of results for first and last failures are in the appendix along with first and last failures for the connectedness and internal score.

4.3 Discussion and Interpretation

The networks with the lowest expected number of failures were those from 2022 and 2023. These networks appear to have fewer nodes classified as highly connected. This suggests that, while the highly connected nodes in these years are extremely well-connected (raising the overall mean), only a few nodes exceed this mean in terms of weighted out-degree. In contrast, the number of nodes that are more domestically focused remains relatively similar across years.

In 2022 and 2023, the highly connected nodes are primarily linked to weakly connected nodes, with average connectedness scores of 0.497 (3 s.f.) and 0.914 (3 s.f.), respectively.

Table 1: Network metrics. For full metric definitions, see Appendix 2

Metric	2017	2018	2019	2020	2021	2022	2023
E[number of failures]	1.862	1.953	1.916	1.897	1.92	1.75	1.768
Num Connected nodes	6.00	6.00	6.00	6.00	5.00	5.00	4.00
Num Internal nodes	10.00	10.00	9.00	9.00	9.00	9.00	9.00
Connectedness Score (high).	0.224	0.176	0.177	0.161	0.414	0.497	0.914
Connectedness Score (low).	0.333	0.359	0.358	0.367	0.411	0.376	0.411
Connectedness Score	0.294	0.294	0.294	0.294	0.412	0.412	0.529
CSS (high type)	0.086	0.052	0.075	0.078	0.365	0.610	0.409
CSS (low type)	0.767	0.775	0.770	0.769	0.915	0.899	0.912
CSS	0.647	0.647	0.647	0.647	0.882	0.882	0.882
Internal Score (int).	0.325	0.347	0.319	0.341	0.362	0.313	0.292
Internal Score (non-int)	-0.036	-0.067	-0.234	-0.258	-0.282	-0.227	-0.204
Internal Score	0.176	0.176	0.059	0.059	0.059	0.059	0.059
ISS (int)	0.086	0.052	-0.121	-0.258	-0.282	-0.123	-0.111
ISS (non-int)	0.767	0.775	0.385	0.341	0.362	0.522	0.515
ISS	0.647	0.647	0.176	0.059	0.059	0.294	0.294

In other years, lower scores indicate that highly connected nodes are more frequently connected to other highly connected nodes. When examining the average connection to high-type nodes, the networks seem to form three groups: 2017–2020, 2021–2022, and 2023. Within each group, the networks share similar averages, but there are notable differences in how highly and lowly connected nodes interact.

In general, the greater the weight of connections from highly connected nodes to weakly connected nodes, the lower the network's expected number of failures. One possible explanation is that while highly connected nodes are more at risk of failing, their connection to weakly connected nodes—who have a smaller chance of failing first since they also tend to be internal nodes—reduces the overall risk of failure for these highly connected nodes.

The Connectedness Score Squared (CSS) further supports this observation. The CSS reveals two distinct groups: one for 2017–2020 and another for 2021–2023. The latter exhibits a higher CSS, indicating that neighbouring nodes are also predominantly connected to weakly connected nodes. However, within the 2021–2023 group, 2021 stands out with a higher expected number of failures and a notably lower CSS for highly connected nodes, even though the overall average remains the same. This suggests that in 2021, the neighbours of highly connected nodes are more frequently themselves highly connected, compared to 2022 and 2023.

Furthermore, connections to internal nodes also shed light on network resilience. A more balanced network—where connections between internal and non-internal nodes are more evenly distributed—tends to be more resilient. For example, networks from 2017–2018 have a higher average internal score (0.176, 3 s.f.), indicating that a larger proportion of connections are to internal nodes. In contrast, the other networks have an average internal score of 0.059 (3 s.f.), suggesting a more balanced mix of connections. This balance helps spread risk, ensuring that nodes more dependent on foreign claims are not bearing the risk alone.

Finally, the Internal Score Squared (ISS) suggests that there might be an optimal cluster size for internal nodes. If internal node clusters are too large, nodes outside these clusters might fail, potentially triggering the cluster to failure. For instance, the ISS values show that 2017/2018 have an ISS of 0.647, 2020/2021 have an ISS of 0.059, and 2022/2023 have an ISS of 0.294. These differences imply that networks with moderate clustering of internal nodes may be more resilient than those with either too little or too much clustering.

5 Conclusion

In conclusion, using data from the BIS CBS, I constructed several networks representing the global banking system. Although these networks include only 17 countries and are not designed to replicate every real-world connection, they provide valuable insights into the optimal structure for global banking resilience. My findings indicate that networks are less vulnerable when highly connected nodes distribute their connections more evenly across less-connected nodes. Furthermore, a balanced mix of connections between internal and external nodes enhances overall network resilience. Clustering effects, as measured by the Internal Score Squared (ISS), reveal that moderate clustering of internal nodes contributes to stability, while excessive clustering may create vulnerabilities outside those clusters. For policymakers, these results suggest that promoting network characteristics similar to those observed in 2022 and 2023 could reduce systemic risk. However, regulators must also balance the ability to intervene promptly in a failing network with the frequency of network failures. The key takeaway is that having highly connected nodes is not inherently detrimental; rather, it is crucial to ensure that these nodes do not become pathways for rapid shock propagation. This study is subject to certain limitations. The analysis is based on data covering a limited number of years and only 17 countries, which may not fully represent the global banking system. Moreover, the simulation assumes that shocks are independent and that the cost of bankruptcy is uniform, simplifying the complex realities of financial contagion. Future research could address these limitations by incorporating a broader dataset and more nuanced assumptions regarding shock dependencies and bankruptcy costs.

6 Appendix

6.1 Tables

Table 2: Definitions of Network Metrics

Metric	**Definition**
E[number of failures]	The expected number of nodes that fail in response to an initial shock in the financial network.
Num Connected Nodes	Nodes with total weighted out-degree above the network mean.
Num Internal Nodes	Nodes with over 50% of claims from the domestic asset.
Connectedness Score (high)	Average connectedness score for high types.
Connectedness Score (low)	Average connectedness score for low types.
Connectedness score	Average score across the network.
CSS (high type)	Average CSS for highly connected nodes.
CSS (low type)	Average CSS for weakly connected nodes.
CSS	Average CSS for all nodes.
Internal score (int)	Internal score for nodes with internal = 1.
Internal score (non-int)	Internal score for nodes with internal = 0.
Internal score	Average across all nodes.
ISS (int)	ISS for internal = 1 nodes.
ISS (non-int)	ISS for internal = 0 nodes.
ISS	Network-wide average ISS.

6.2 Graphs

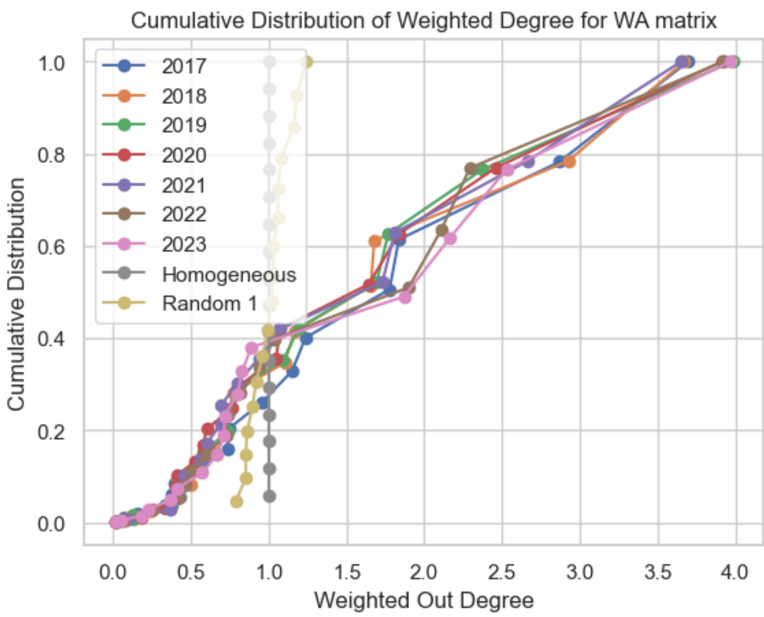

Figure 7: CDF WA

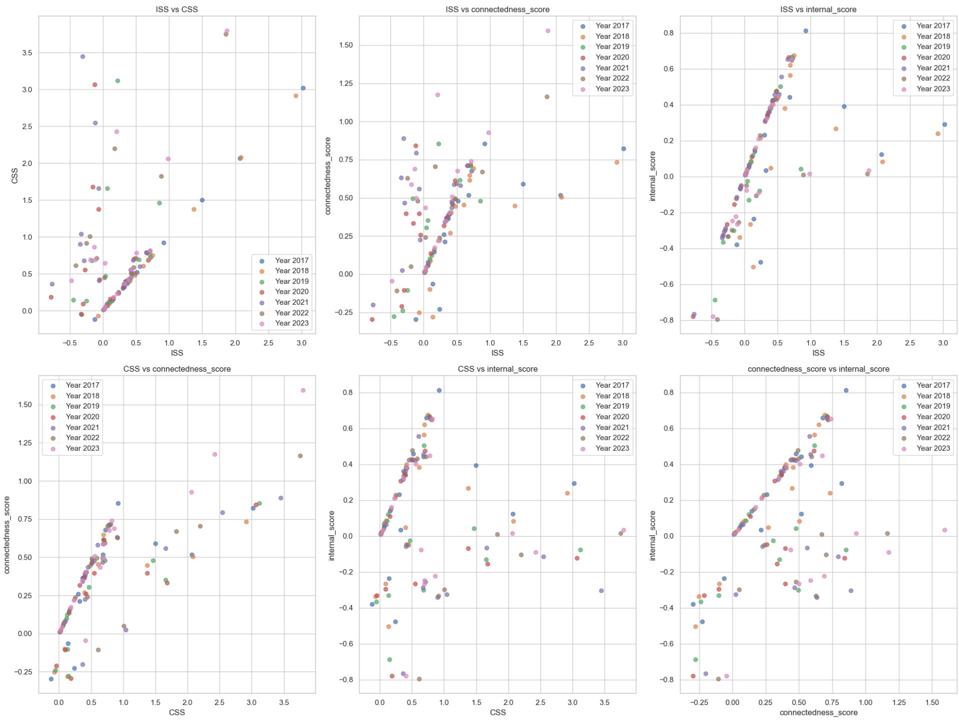

Figure 8: Attribute plot

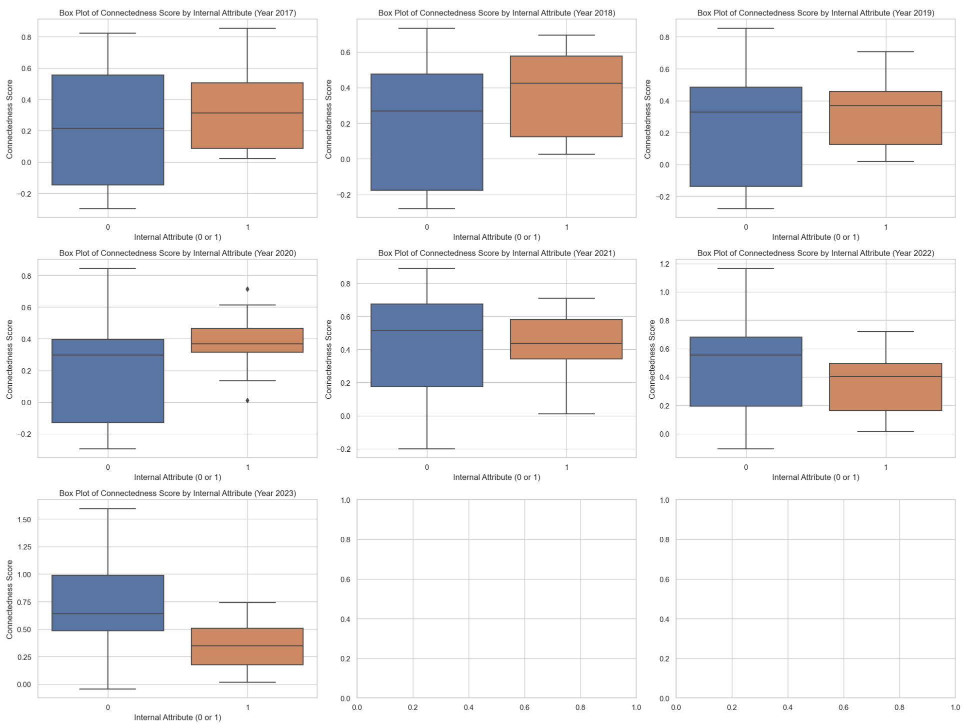

Figure 9: Connectedness score vs Internal

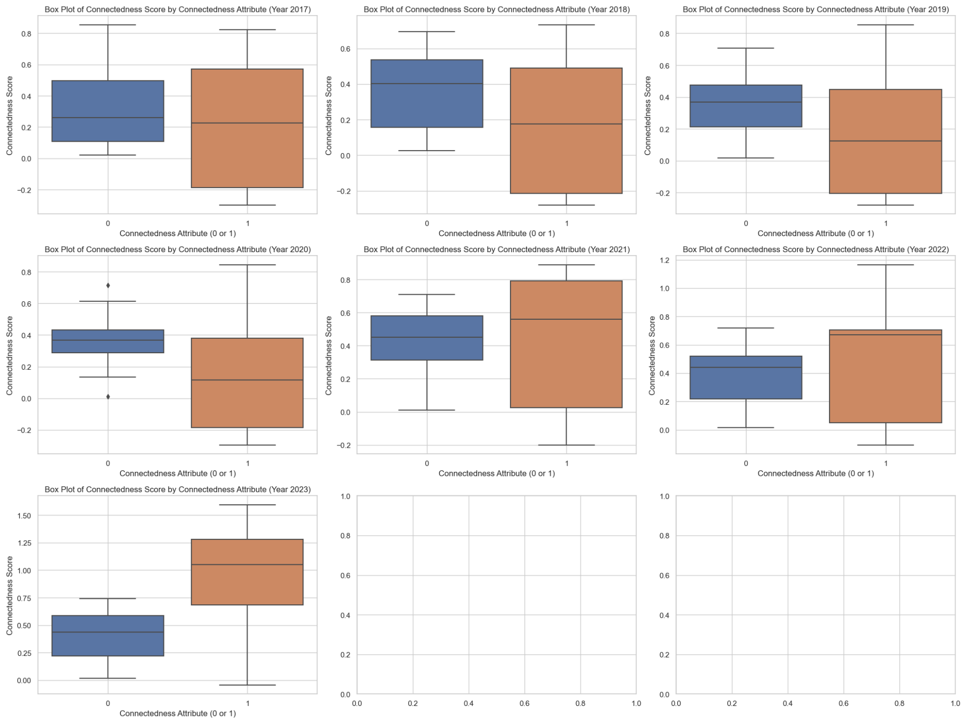

Figure 10: Connectedness score vs connectedness

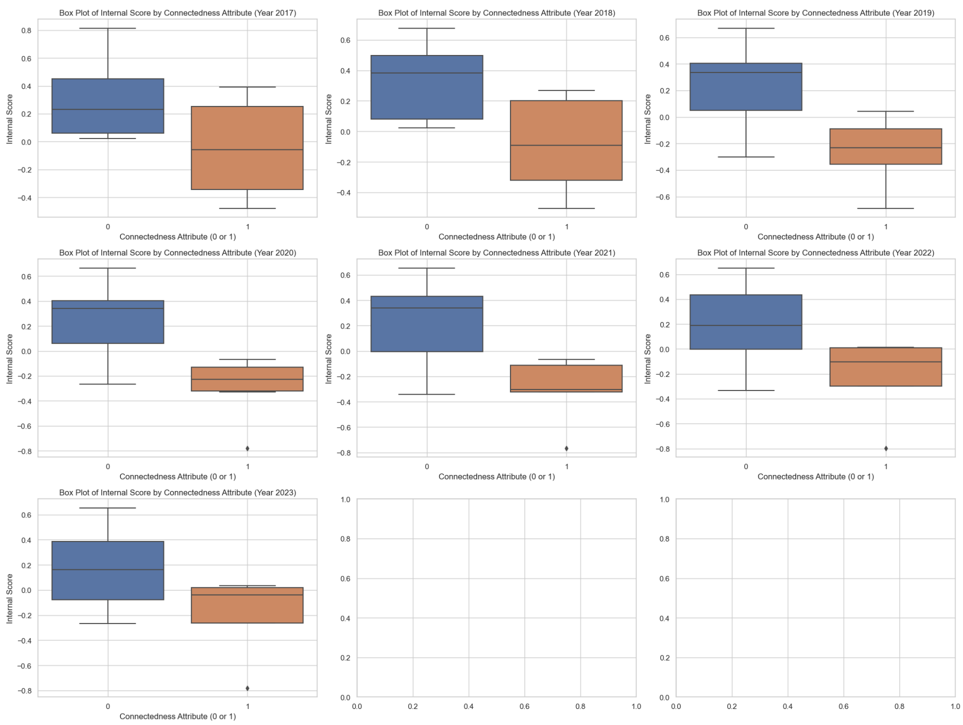

Figure 11: Internal score vs Connectedness

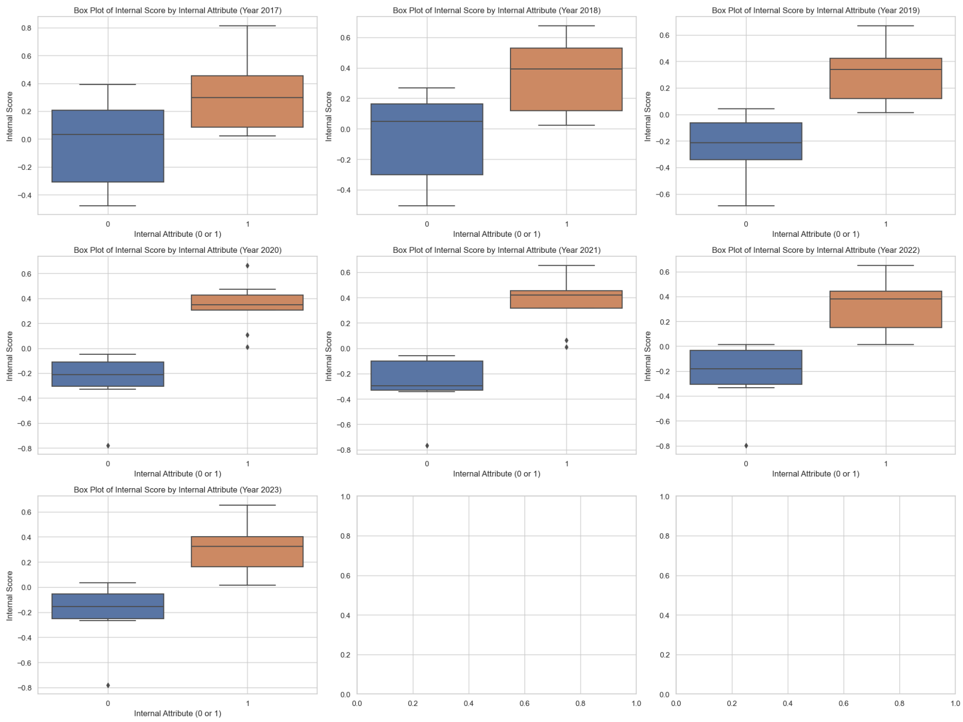

Figure 12: Internal score vs Internal

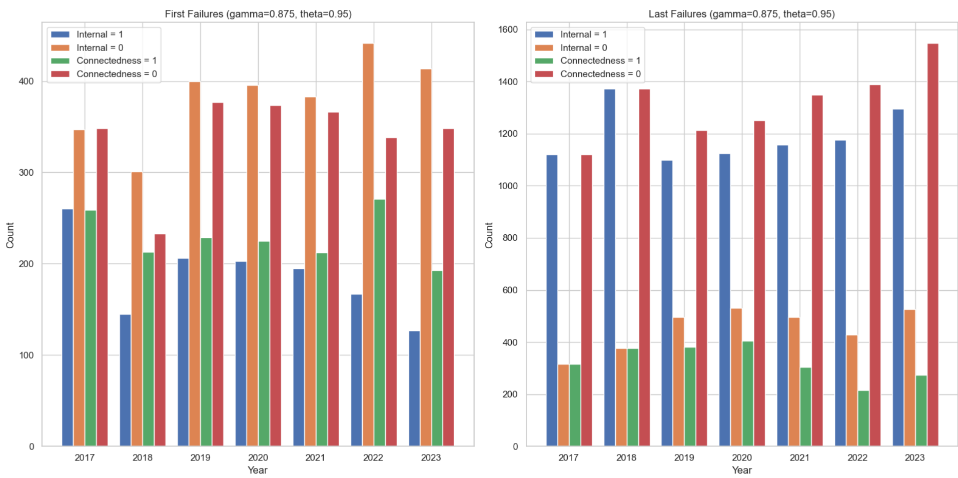

Figure 13: First and last failures $\gamma = 0.875, \theta = 0.95$

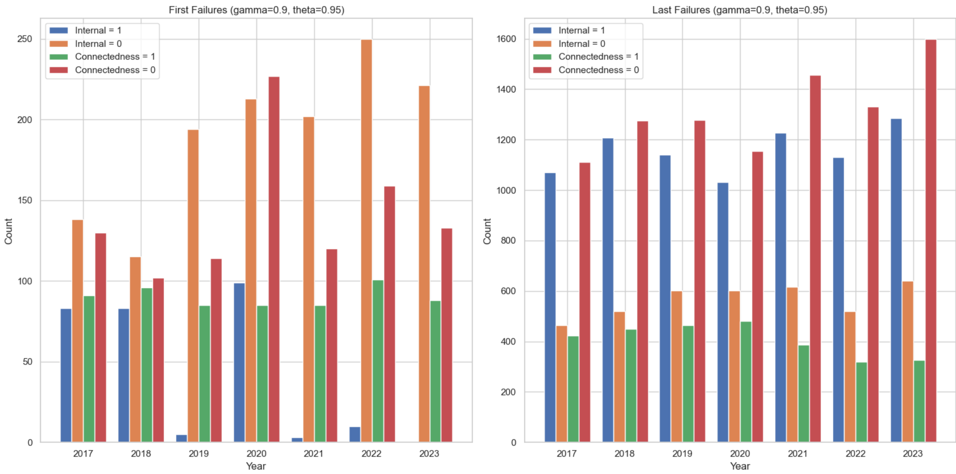

Figure 14: First and last failures $\gamma = 0.9, \theta = 0.95$

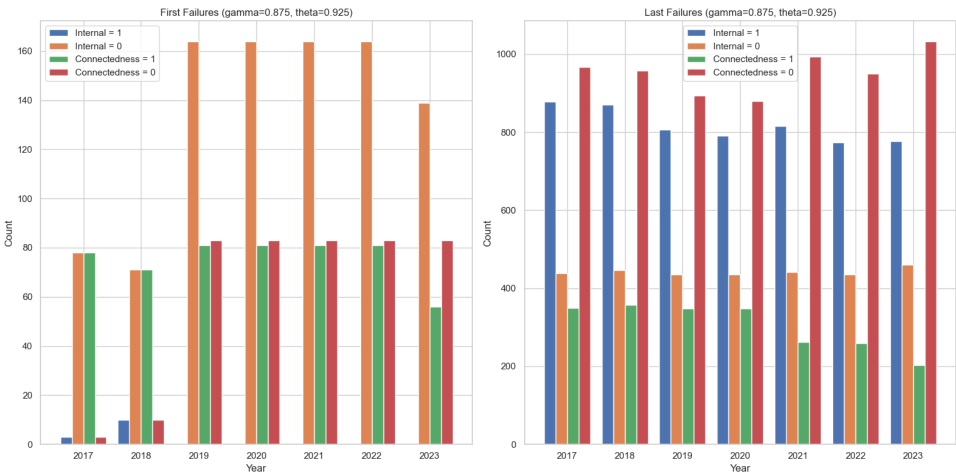

Figure 15: First and last failures $\gamma = 0.875, \theta = 0.925$

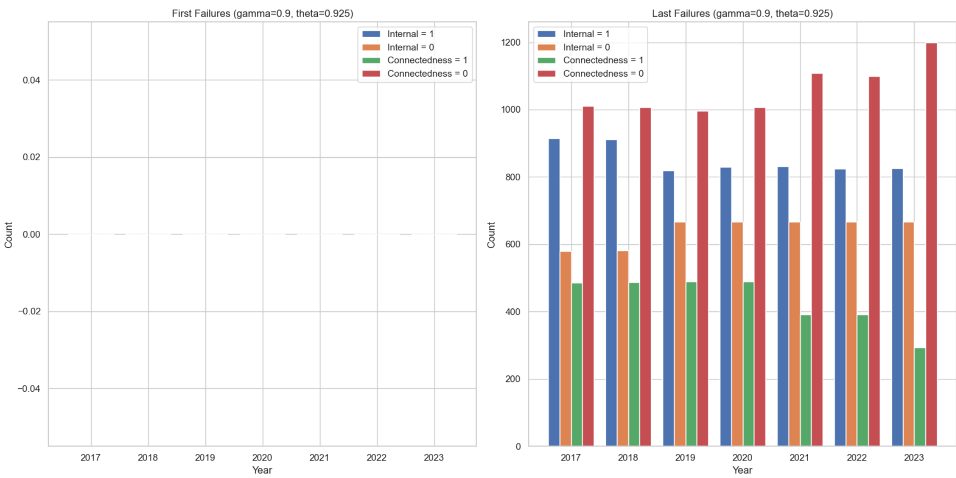

Figure 16: First and last failures $\gamma = 0.9, \theta = 0.925$

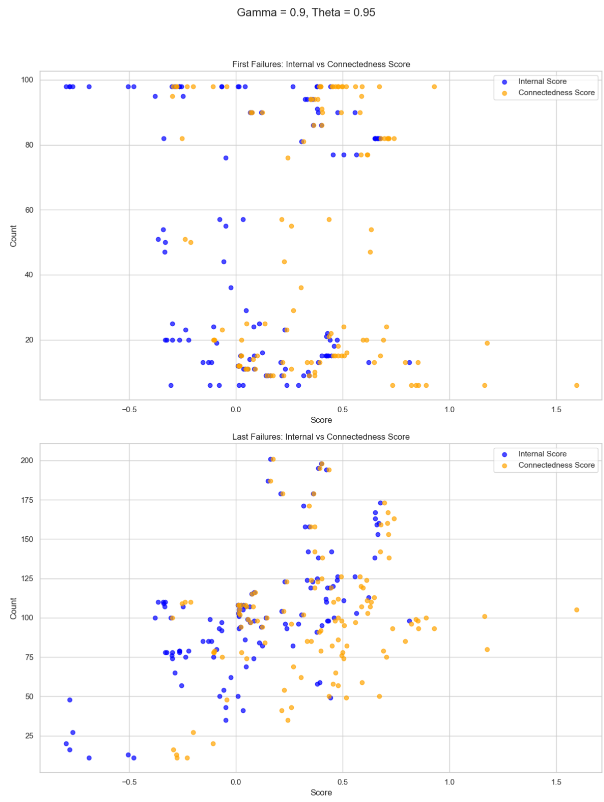

Figure 17: First and last failures $\gamma = 0.9, \theta = 0.95$

Figure 18: First and last failures $\gamma = 0.9, \theta = 0.925$

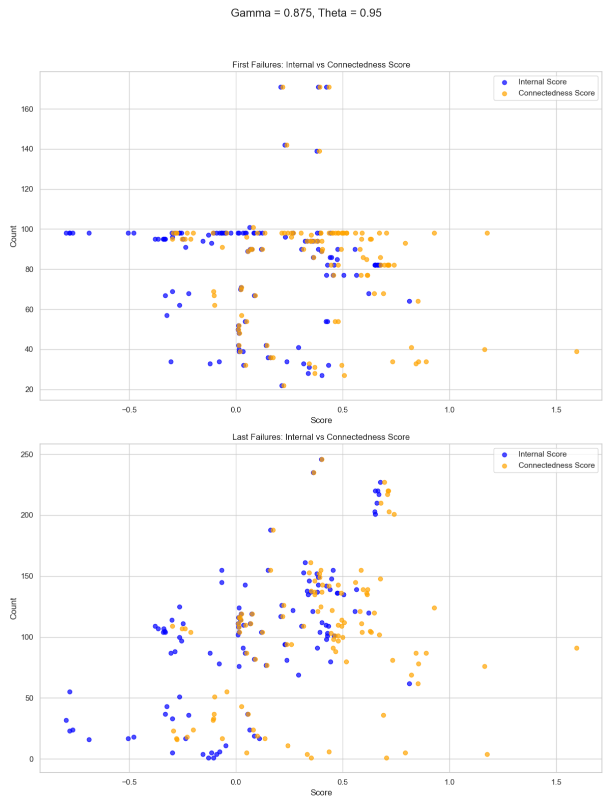

Figure 19: First and last failures $\gamma = 0.875, \theta = 0.95$

Figure 20: First and last failures $\gamma = 0.875, \theta = 0.925$

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