Journal of Applied Economic Sciences
Volume XXI, Summer Issue, 3(93), 2026

Systemic Risk and Contagion in Global Equity Markets: An Applied Economic Analysis of Emerging Market Cascades

Ana Isabel CASTILLO PEREDA
https://orcid.org/0009-0002-7077-5971
Institute of Mathematics and Statistics
University of São Paulo, Brazil
anaicp@ime.usp.br anacp20@gmail.com

Article's History

Received 30th of March, 2026; *Revised* 4th of May, 2026; *Accepted* 10th of June, 2026; *Available online*: 30th of June, 2026. *Published* as research article in the Volume XXI, Summer, Issue 3(93), 2026.

Copyright© 2026 The Author(s). This article is distributed under the terms of the license CC-BY 4.0., which permits any further distribution in any medium, provided the original work is properly cited.

Suggested Citation

Castillo Pereda, A.I. (2026). Systemic Risk and Contagion in Global Equity Markets: An Applied Economic Analysis of Emerging Market Cascades. *Journal of Applied Economic Sciences*, Volume XXI, Summer, 3(93), 809 – 835. https://doi.org/10.57017/jaes.v21.3(93).07

Abstract

This study extends the Gai-Kapadia framework, originally developed for interbank contagion, to assess systemic risk and default cascades in global equity markets. We analyse a network of *30* assets comprising Brazilian and developed-market equities over the period *2015 – 2026,* constructing exposure-based financial networks from asset return co-movements. Threshold filtering ($\theta = 0.3$ and $\theta = 0.5$) is applied to identify significant interconnections.

Cascade dynamics are examined through a combination of deterministic propagation and stochastic Monte Carlo simulations ($n = 1{,}000$) under varying shock intensities. The results indicate a high degree of global resilience, with a negligible probability of large-scale failure, while preserving localised vulnerability within highly clustered subnetworks. Single shocks generate, on average, one failed asset, whereas simultaneous shocks lead to an average of two failed assets, suggesting limited contagion below a critical threshold.

Network analysis reveals a pronounced structural asymmetry between emerging and developed markets. Brazilian assets exhibit high clustering coefficients ($C_i \approx 0.8 - 1.0$) and dense connectivity, amplifying local shock propagation, whereas developed-market assets display lower clustering and weaker connectivity ($C_i \approx 0.2 - 0.5$), limiting the spread of contagion. Tail-risk analysis based on empirical CCDFs and Hill estimators confirms the presence of heavy-tailed loss distributions, particularly among emerging-market assets, indicating greater exposure to extreme events.

The findings demonstrate that systemic risk arises from the interaction between network topology and tail-risk behaviour rather than from isolated asset characteristics. The proposed framework provides a scalable and empirically grounded approach to systemic risk assessment and stress testing, offering practical insights for regulators, policymakers, and portfolio managers operating in increasingly interconnected financial markets.

Keywords: systemic risk, financial networks, default cascades, contagion, Monte Carlo simulation, global equity markets.

JEL Classification: G01; G15; C58; F36; G17; D85.

Introduction

Financial markets are not merely collections of individual assets; they are interconnected systems whose stability depends on the propagation of shocks through complex networks. Understanding how local disturbances evolve into systemic events has become a central challenge in financial economics, risk management, and regulatory policy.

Systemic risk and default cascades pose significant threats to financial stability, as interconnected assets can rapidly amplify shocks across global equity markets. Such cascades can generate substantial economic costs, including reduced credit supply, lower investment, higher unemployment, and long-term impacts on economic growth. These effects tend to be particularly severe in emerging economies, where financial systems are more volatile, credit markets are less developed, and firms depend heavily on equity financing (Bielecki et al., 2004).

This study extends the Gai-Kapadia framework (Gai & Kapadia, 2010), originally developed for interbank contagion, to the domain of global equity markets. We construct exposure networks based on price co-movements for a sample of 30 assets $(15\ Brazilian\ and\ 15\ developed - market\ equities)$ over the period $2015 - 2026$. Using correlation thresholds ($\theta = 0.3\ and\ \theta = 0.5$) and Monte Carlo simulations (n = 1,000) with shock intensities ranging from $10\%\ to\ 50\%$, we analyze the dynamics of default cascades in equity markets. Traditional risk measures such as $Value - at - Risk\ (VaR)$ and Conditional $Value - at - Risk\ (CVaR)$ provide important insights into individual asset risk but often fail to capture network-driven contagion effects (Mantegna & Stanley, 1999; Eisenberg & Noe, 2001).

This limitation has motivated the growing use of graph-theoretic approaches, which explicitly model interdependencies among financial assets (Newman, 2010; Strogatz, 2001; Li, & Zhang, 2024; Ellis et al., 2022). In this context, financial networks offer a powerful lens to understand shock propagation in complex systems. While the Gai-Kapadia framework provides a robust foundation for modelling systemic risk, its application to equity markets remains relatively underexplored (Glasserman & Young, 2016). Building upon the seminal contributions of Acemoglu et al. (2015) and Battiston et al. (2012), and extending systemic risk measures proposed by Billio et al. (2012) and Haldane & May (2011), this study integrates correlation-based exposure networks, tail-risk behaviour, and stochastic simulations into a unified framework. A central innovation of this paper is the incorporation of tail risk into the network approach.

Empirical evidence consistently shows that financial returns exhibit heavy-tailed distributions, implying a much higher probability of extreme events than predicted by Gaussian models (Cont, 2001; Mandelbrot, 1963). Highly connected assets combined with heavy-tailed losses can act as major amplifiers of contagion, especially in emerging markets where clustering coefficients tend to be higher. Recent geopolitical tensions, commodity price shocks, and macroeconomic instability have highlighted the vulnerability of globally interconnected equity markets.

In Brazil and other emerging economies, these shocks can spread rapidly through dense local networks, affecting firm-level capital allocation, market liquidity, and ultimately real economic activity. This dynamic illustrates the classic contagion-diversification trade-off: while dense connectivity may offer risk-sharing benefits during tranquil periods, it significantly increases systemic vulnerability during periods of stress. The main contributions of this study are as follows:

- Extension of the Gai-Kapadia framework to global equity markets using empirically grounded price-based exposure networks.
- Integration of network topology with tail risk (heavy-tailed distributions) in systemic risk analysis.
- Quantification of cascade dynamics through both deterministic and stochastic Monte Carlo simulations.
- Identification of structural asymmetries between emerging and developed equity markets.
- Empirical evidence of localised contagion driven by high clustering in emerging markets.

This paper builds upon our previous work (Castillo Pereda, 2025) by incorporating stochastic simulations, threshold sensitivity analysis, and explicit tail-risk modelling, thereby providing a more comprehensive and policy-relevant methodology. By combining network science, stochastic modelling, and applied economic analysis, this framework offers practical insights for regulators, supervisors, and portfolio managers. The results can support the design of better stress-testing methodologies, more effective macroprudential policies, and improved risk management strategies in increasingly interconnected financial systems, particularly in emerging economies.

1. Research Background

Financial networks and systemic risk have attracted increasing attention from researchers since the global financial crisis of 2008. Early theoretical contributions, such as those by Allen & Gale (2000) and Freixas et al. (2000), highlighted how interconnectedness in banking systems can amplify shocks and lead to contagion. Subsequent works by Gai & Kapadia (2010) and Eisenberg & Noe (2001) provided formal frameworks to model default cascades through interbank exposure networks, establishing the foundations of the network-based approach to systemic risk. A parallel strand of literature has focused on the empirical properties of financial markets.

Mantegna & Stanley (1999), Cont (2001), and Mandelbrot (1963) documented the heavy-tailed nature of asset returns and the limitations of traditional Gaussian-based risk models. These stylized facts motivated the integration of tail-risk measures into systemic risk analysis. Acemoglu et al. (2015), Battiston et al. (2012), and Glasserman & Young (2016) advanced the field by demonstrating that network topology, particularly degree distribution, clustering, and centrality, plays a central role in determining systemic stability or fragility. More recent studies have extended these ideas to broader financial markets.

Billio et al. (2012), Poledna et al. (2021), and Li & Zhang (2024) applied network methodologies to equity markets and overlapping portfolios, showing that indirect connections and common exposures can generate significant contagion channels even in the absence of direct interbank links. Haldane & May (2011) and Newman (2010) emphasized the importance of complex systems thinking when analysing financial stability. In the context of emerging markets, several authors have noted higher clustering coefficients and greater vulnerability to external shocks, although applications of the Gai-Kapadia framework specifically to equity markets remain relatively limited (Ellis et al., 2022; Das & Fasen-Hartmann, 2025).

Despite substantial progress, important gaps persist. Most existing models focus either on banking networks or stylized theoretical setups, with fewer empirical applications to global equity markets that combine price-based exposure networks, heavy-tailed distributions, and stochastic simulations. Furthermore, the structural differences between emerging and developed markets, particularly the contagion-diversification trade-off in highly clustered emerging economies such as Brazil - have not been sufficiently explored through the lens of the Gai-Kapadia model.

The present study addresses these gaps by extending the Gai-Kapadia framework to a sample of Brazilian and developed-market equities, integrating correlation-based networks, tail-risk behaviour, and Monte Carlo simulations. This approach contributes to the literature by providing a more applied economic perspective on how network structure and extreme events interact to generate systemic risk in real-world equity markets.

2. Research Methodology

2.1 Data and Risk Measures

The dataset consists of daily low prices for *30* equity assets spanning the period from $January\ 1, 2015, to\ April\ 2026,$ sourced from Yahoo Finance, a widely used and reliable public database for financial time series (Yahoo Finance, 2023). The sample includes a balanced selection of *15* Brazilian assets and *15* international assets from developed markets, chosen based on data availability, market capitalization, and sectoral diversity. This configuration ensures analytical tractability while preserving sufficient structural complexity for network analysis, as larger networks often result in excessively dense graphs that obscure topological insights (IMF, 2025).

The $30 - asset$ structure enables clear identification of nodes and edges, allowing for a meaningful comparison between emerging and developed market dynamics. Data pre-processing was conducted using Python, with the yfinance library for data acquisition, pandas and numpy for data manipulation, and matplotlib and seaborn for visualization. Missing observations were handled by excluding days with incomplete records, applying linear interpolation for minor gaps, and using forward and backward filling to ensure continuity of the time series.

To mitigate the impact of extreme outliers while preserving tail behaviour, observations were filtered using the interquartile range (IQR) method, with bounds defined as $Q_1 - 1.5 \times IQR$ and $Q_3 + 1.5 \times IQR,$ where Q_1 and Q_3 denote the first and third quartiles, respectively (Páez & Boisjoly, 2022).The focus on daily low prices is intended to emphasize downside risk, aligning with the objective of capturing systemic vulnerability under adverse market conditions (Cont, 2001; Das & Fasen-Hartmann, 2025; Chen et al., 2021). Logarithmic returns were computed to standardize relative price variations across assets, according to the following equation:

$$r_{i,t} = ln\,(P_{i,t}\,/P_{i,t-1}) \tag{1}$$

where $P_{i,t}$ denotes the low price of asset i at time t. Individual risk exposure was quantified using $Value - at - Risk\ (VaR)$ and Conditional $Value - at - Risk\ (CVaR)$ at the *95%* confidence level. VaR is defined as:

$$VaR_{i,\alpha} = F_i^{-1}(1 - \alpha) \tag{2}$$

where F_i is the empirical cumulative distribution function of returns r_i, t, and $\alpha = 0.95$. $CVaR$, which captures the expected loss conditional on exceeding the VaR threshold, is computed as:

$$CVaR_{i,\alpha} = E[r_{i,t} \mid r_{i,t} \leq VaR_{i,\alpha}] \tag{3}$$

This formulation is consistent with coherent risk measure frameworks (Artzner et al., 1999). These tail risk measures play a central role in systemic risk analysis, as extreme losses in the lower tail of return distributions can act as triggers for cascading failures. By integrating VaR and $CVaR$ with network-based contagion modeling, this study captures both individual asset vulnerability and the propagation of extreme events through interconnected financial structures.

2.2 Network Construction

An exposure-based financial network is constructed using an adapted Gai-Kapadia framework. The correlation matrix ρ of log returns is first computed, where asset volatility σ_i is defined as the standard deviation of $r_{i,t}$.

Pairwise exposures between assets i and j are defined as:

$$E_{ij} = \rho_{ij} \cdot \sigma_i \cdot P_i, \tag{4}$$

where P_i represents a reference price level of asset i, used to scale exposures. This formulation induces a directed weighted network, where exposures are asymmetric and depend on the originating asset's volatility and scale. To extract the most relevant connections, exposures are filtered using thresholds $\theta \in \{0.3, 0.5\}$:

$$\underline{E_{ij}} = \{E_{ij} \ if \ E_{ij} \geq \theta, and\ 0\ otherwise. \tag{5}$$

The filtered matrix $\underline{E_{ij}}$ defines the adjacency structure of the network G, where nodes correspond to assets and edges represent significant exposure relationships. This proxy captures relative exposure intensity based on co-movement and volatility, rather than balance-sheet linkages. Local clustering coefficients are computed to quantify network connectivity:

$$C_i = \frac{2T_i}{K_i(K_i-1)} \tag{6}$$

where T_i denotes the number of triangles involving node i, and K_i is its degree. The network is visualized using a force-directed (spring) layout, with nodes colored according to their clustering coefficients C_i, enabling structural comparison across different threshold levels and shock scenarios.

The thresholds $\theta \in \{0.3, 0.5\}$ were selected to balance network density and sparsity, ensuring meaningful connectivity while avoiding overly dense graphs that obscure cascade dynamics, a standard approach in financial network analysis (Glasserman & Young, 2016). These statistical properties not only characterize individual asset risk but also directly shape the structure of the financial network, as volatility and correlations determine the intensity of inter-asset exposures.

2.3 Default Cascade Model

Default cascades are modelled using an adapted Gai-Kapadia framework, implemented through both stochastic and deterministic approaches. Stochastic Simulations. Each asset i is assigned an initial capital $K_i = 0.2 \cdot P_i$ and a failure threshold $K_{min,i} = 0.1 \cdot P_i$. A total of $n = 1{,}000$ Monte Carlo simulations are performed, where each iteration applies a random shock $s \sim Uniform(0.1, 0.5)$, drawn from a uniform distribution between 0.1 and 0.5, reducing the capital of affected assets. Losses propagate through the network according to:

$$L_{ij} = max\,(0, \underline{E_{ij}} - (K_i - D_i)) \tag{7}$$

where $D_i = \sum_j E_{ij}$represents the total incoming exposure to asset i. An asset j defaults if its capital falls below the threshold, i.e., $K_j < K_{min,j}$, triggering further contagion.

The process iterates until no additional defaults occur. Systemic failure is defined as the collapse of more than five assets. The simulations produce measures including the probability of systemic failure, the average number of failed assets, and patterns of network fragility. Deterministic Propagation. To analyze cascade dynamics, a deterministic version of the model is applied. An initial shock is introduced by setting a representative asset $(e.g., VIVT3.SA)$ to default, and propagation is simulated iteratively.

For each asset i, the influence from defaulted neighbors is given by:

$$I_i = \sum_j \rho_{ij} \cdot S_j\,, \tag{8}$$

where $S_j = 1$ if asset j is in default and 0 otherwise, and ρ_{ij} is filtered by the threshold θ. $Asset\ i$ enters default if:

$$I_i > T_i \tag{9}$$

where T_i is a fixed threshold (set to 0.5 in this study). The threshold $T_i = 0.5$ was chosen as a benchmark to represent a critical level of cumulative influence required to trigger default.

Default states are tracked across iterations to characterize cascade dynamics. Complementary evidence on the distribution of losses, including Pareto tail index estimates, is provided in Table 4, supporting the role of extreme events in shaping systemic vulnerability.

3. Results and Discussion

3.1 Evolution of Asset Prices and Descriptive Statistics

Evolution of Normalized Asset Prices Figure 1 illustrates the evolution of normalized asset prices for selected Brazilian and international equities over the period $2015 - 2026$. Financial markets are not merely collections of individual assets; they are interconnected systems whose dynamics reflect both local interactions and global economic conditions. The evolution of asset prices therefore provides an initial perspective on how shocks affect different segments of the financial network.

Normalized prices are computed as:

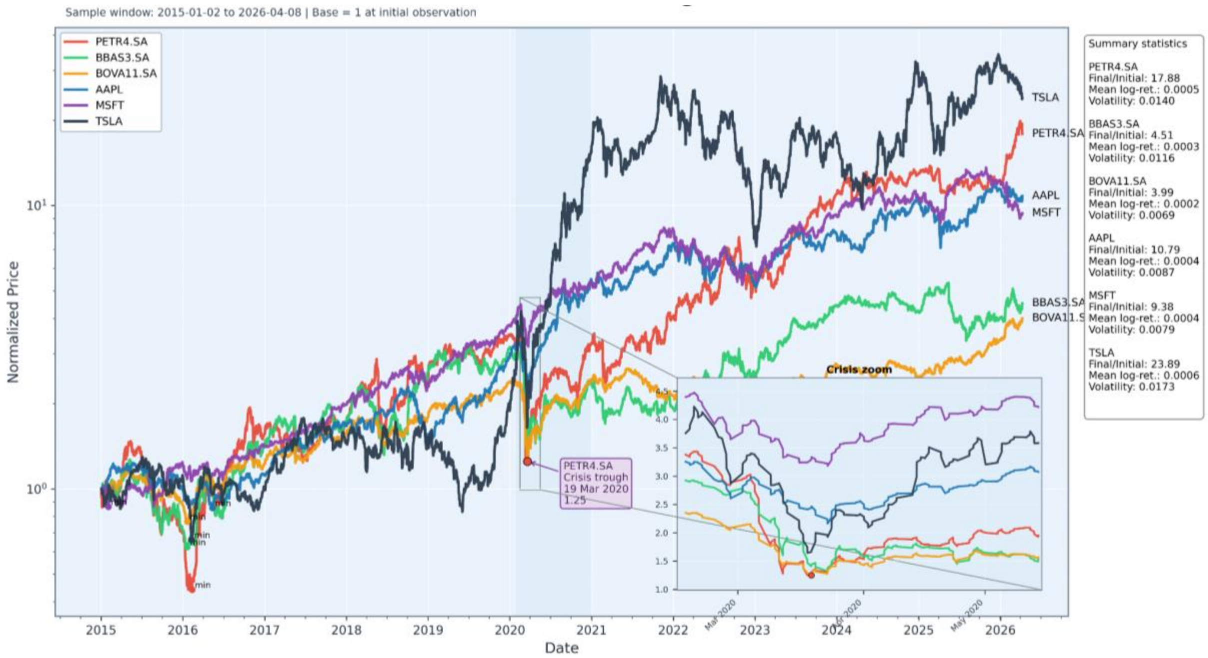
$$P_{norm,i,t} = \frac{P_{i,t}}{P_{i,0}}\,, \tag{10}$$

where $P_{i,t}$, denotes the price of asset i at time t and $P_{i,0}$ represents its initial price.

The use of a logarithmic scale facilitates the comparison of growth rates and volatility patterns across assets with different price levels.

Figure 1 reveals substantial heterogeneity between emerging and developed markets. Brazilian assets such as $PETR4.SA$ and $BBAS3.SA$ exhibit pronounced drawdowns during the 2020 market stress episode associated with the $COVID-19$ crisis, reflecting their greater sensitivity to external shocks and adverse market conditions. This behavior is consistent with the stronger intra-market connectivity observed in the Brazilian network and with the elevated clustering coefficients ($C_i \approx\ 0.7-1.0$) reported later in the analysis. By contrast, developed-market assets such as $AAPL$ and $AMZN$ display smoother trajectories, lower volatility, and more stable recovery patterns. These characteristics are consistent with the lower clustering levels and weaker local interdependencies identified in the network analysis, suggesting greater resilience to systemic disturbances (see Table 1).

Figure 1: Normalized Asset Price Dynamics (2015–2026)



Note: Normalized asset prices for selected Brazilian and developed-market assets (2015–2026, log scale). The shaded area indicates the 2020 market shock. Brazilian assets display stronger drawdowns and wider dispersion than developed-market assets.

Source: Author's own elaboration using data obtained from Yahoo Finance

The contrast between emerging and developed markets highlights an important feature of systemic risk. By contrast, lower connectivity in developed-market assets $(C_i \approx 0.2-0.4)$ is associated with greater resilience, may support information transmission and market integration during normal periods, it can also amplify the effects of adverse shocks during periods of stress. Consequently, the stronger drawdowns observed among Brazilian assets provide an initial indication of the contagion mechanisms explored in the subsequent network and cascade analyses.

Overall, these dynamics illustrate the heterogeneous impact of systemic shocks across markets, providing visual support for the contagion mechanisms analysed in Sections 3.3 and 3.4, where emerging-market assets exhibit higher susceptibility to cascade effects. These findings reinforce the interpretation of financial markets as clustered networks, where densely connected regions amplify local shocks, leading to asymmetric propagation patterns.

Table 1 reports the descriptive statistics of log returns for the full set of assets. A clear distinction emerges between emerging and developed markets in terms of volatility and extreme returns. Brazilian assets such as $PETR4.SA$ ($Std.Dev. = 0.0140$) and $MGLU3.SA$ ($Std.Dev. = 0.0190$) exhibit substantially higher volatility than developed-market assets such as $AAPL$ ($Std.Dev. = 0.0087$) and MSFT ($Std.Dev. = 0.0079$), indicating greater sensitivity to market shocks.

Table 1: Descriptive statistics of log returns (2015–2026)

Asset	Mean	Std. Dev.	Min	Max
VIVT3.SA	0,0003	0,0072	-0,0569	0,0361
PETR4.SA	0,0005	0,0140	-0,2084	0,1292
ABEV3.SA	0,0001	0,0075	-0,0642	0,0654
AMER3.SA	-0,0010	0,0308	-1,0553	0,4155
BBAS3.SA	0,0003	0,0116	-0,1507	0,0925
BBDC4.SA	0,0002	0,0099	-0,1021	0,0615
BOVA11.SA	0,0002	0,0069	-0,0804	0,0492
RAIL3.SA	0,0000	0,0149	-0,2371	0,2202
CSNA3.SA	0,0001	0,0165	-0,1710	0,0980
ITUB4.SA	0,0003	0,0086	-0,1110	0,0528
MGLU3.SA	0,0003	0,0190	-0,1420	0,1438
VALE3.SA	0,0004	0,0119	-0,0984	0,1071
WEGE3.SA	0,0004	0,0093	-0,0787	0,0887
SUZB3.SA	0,0002	0,0092	-0,0864	0,1168
LREN3.SA	0,0001	0,0121	-0,1666	0,0667
AAPL	0,0004	0,0087	-0,0716	0,0606
JPM	0,0003	0,0085	-0,1265	0,0921
AMZN	0,0005	0,0101	-0,0740	0,0669
MSFT	0,0004	0,0079	-0,0824	0,1001
GOOGL	0,0004	0,0085	-0,0497	0,0738
TSLA	0,0006	0,0173	-0,1114	0,1125
V	0,0003	0,0075	-0,0874	0,0535
SAP	0,0002	0,0084	-0,1396	0,0519
NSRGY	0,0001	0,0058	-0,0434	0,0470
SAN	0,0001	0,0108	-0,1220	0,0706
HSBC	0,0002	0,0078	-0,0733	0,0571
BABA	0,0000	0,0129	-0,1786	0,0902
TM	0,0001	0,0072	-0,0519	0,0612
SONY	0,0003	0,0093	-0,0672	0,0649
HMC	0,0000	0,0080	-0,0753	0,0603

Note: Mean, standard deviation, minimum, and maximum daily log returns for 30 assets across Brazilian and developed markets during 2015–2026.

Source: Author's own elaboration using data obtained from Yahoo Finance.

In addition, some emerging-market assets display pronounced downside risk. For example, $AMER3.SA$ exhibits extremely negative returns $(Min = -1.0553)$, suggesting exposure to idiosyncratic shocks and structural fragility. In contrast, developed-market assets tend to present more concentrated return distributions and less severe extremes, reflecting higher levels of market stability and liquidity (Fu et al. 2025; Mantegna & Stanley, 1999).

These differences in volatility and extreme behaviour are consistent with well-documented stylized facts in financial markets, where emerging economies typically exhibit heavier tails and higher kurtosis than developed markets (Cont, 2001; Mandelbrot, 1963). This asymmetry is particularly relevant for systemic risk analysis because assets characterized by higher volatility and more extreme losses contribute disproportionately to tail risk, as further evidenced by the VaR and $CVaR$ measures reported in Table 2.

Importantly, these statistical properties directly influence the construction of the exposure-based network analysed in Section 3.2. In particular, asset volatility (σ_{i}) enters the exposure metric $E_{\mathrm{ij}} = \rho_{\mathrm{ij}} \cdot \sigma_{\mathrm{i}} \cdot P_{\mathrm{i}}$, amplifying connections associated with more volatile assets and increasing their potential to propagate shocks throughout the network.

Overall, the descriptive statistics reveal a heterogeneous risk structure across assets and markets, providing a quantitative foundation for the network-based systemic analysis developed in the subsequent sections. The results suggest that emerging-market assets play a disproportionately important role in amplifying contagion dynamics under stress conditions. More broadly, the evidence supports the interpretation of financial markets as interconnected and clustered systems, in which volatility, correlation, and extreme losses jointly determine the pathways through which systemic risk propagates.

3.2 Network Structure and Clustering Analysis

Correlation Matrix Figure 2 presents the Pearson correlation matrix of asset log returns. The Pearson correlation coefficient is defined as:

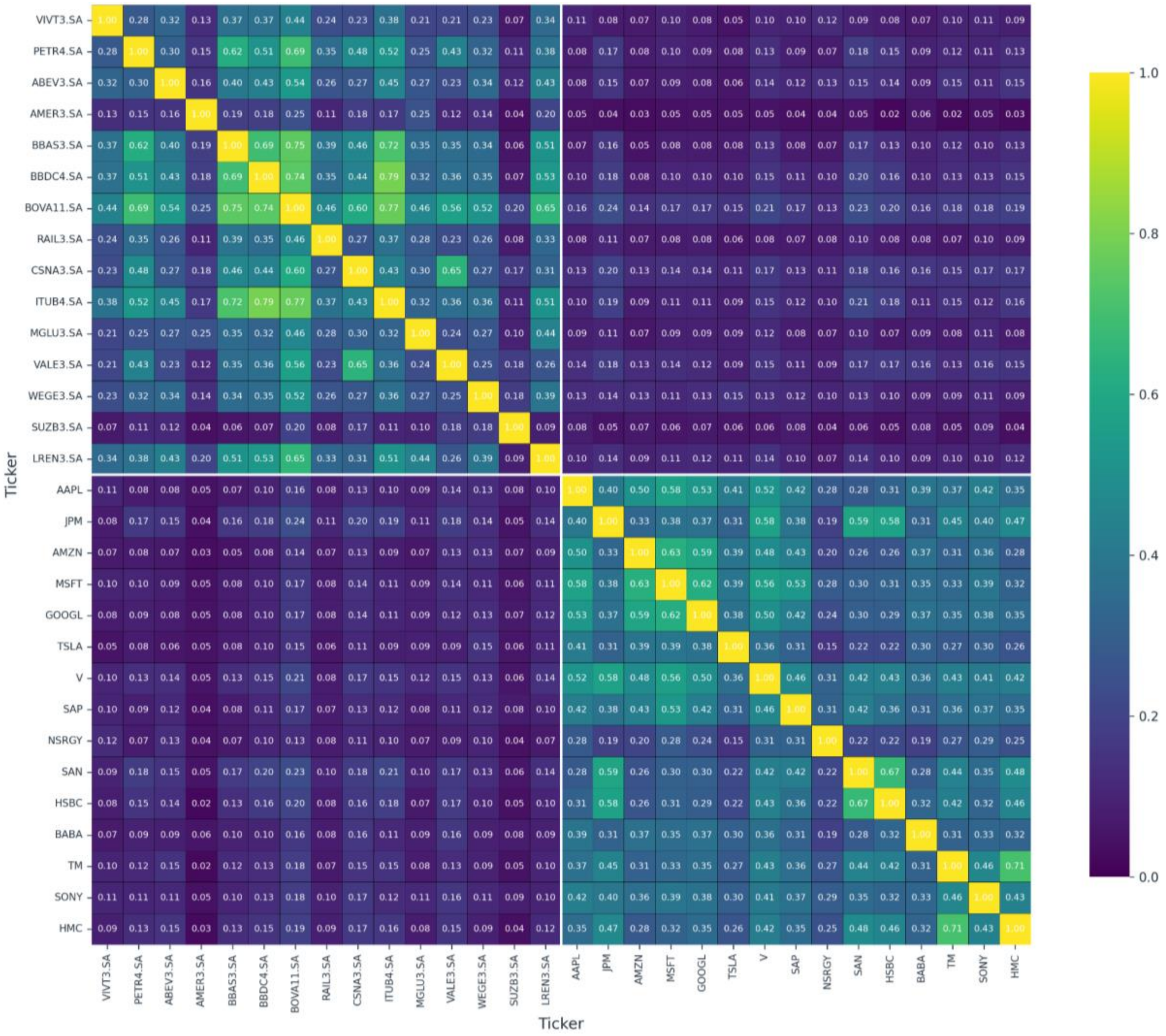
$$\boldsymbol{\rho_{ij}} = \frac{\boldsymbol{Cov(R_i, R_j)}}{\boldsymbol{\sigma R_i \sigma R_j}}, \tag{11}$$

where: $Cov(R_i, R_j)$ denotes the covariance between asset returns, and $\sigma R_i, \sigma R_j$ represent their respective standard deviations.

The correlation matrix reveals a clear block structure, characterized by strong intra-market correlations among Brazilian assets and more moderate correlations among developed-market assets. Several Brazilian financial institutions, including $BBAS3.SA,$ $ITUB4.SA,$ and $BBDC4.SA,$ exhibit consistently high pairwise correlations, often exceeding 0.6, indicating synchronized movements within the domestic market. In contrast, $cross - market$ correlations between Brazilian and $developed - market\ assets$, such as $AAPL$ and $MSFT$, remain substantially lower, typically ranging between 0.1 and 0.3. This pattern suggests partial decoupling between markets and highlights potential diversification benefits.

This correlation structure directly informs the construction of the exposure-based network in Section 3.2, where ρ_{ij} enters the exposure metric $E_{ij} = \rho_{ij} \cdot \sigma_i \cdot P_i$. As a result, densely connected clusters particularly within the Brazilian market generate stronger effective links, increasing the likelihood of localised shock amplification.

Figure 2: Correlation Structure of Brazilian and Developed-Market Assets (2015–2026)



Note: Pearson correlation matrix of daily log returns for 30 Brazilian and developed-market assets (2015–2026), highlighting stronger local correlations and weaker cross-market linkages.

Source: Author's own elaboration using data obtained from Yahoo Finance.

These findings are consistent with the cascade dynamics analysed in Section 3.3. Shocks tend to propagate more rapidly within highly correlated subnetworks, particularly among Brazilian assets, while transmission to less connected developed-market assets remain comparatively limited. As a result, the correlation matrix provides empirical evidence of a clustered network topology in which tightly connected regions act as primary channels of contagion, whereas weaker cross-market links contribute to overall systemic resilience.

More broadly, this empirical structure is consistent with network-based theories of systemic risk, which emphasize the role of clustering, connectivity, and heterogeneity in determining contagion pathways and financial stability (Halaj et al., 2024; Acemoglu et al., 2015; Newman, 2010; Strogatz, 2001).

3.3 Deterministic Shock Analysis

Figure 3 compares the network structure before and after a deterministic negative shock of *30%* applied to $VIVT3.SA$. The results indicate that the clustering coefficients of Brazilian assets undergo noticeable adjustments following the shock, reflecting a reconfiguration of local connectivity patterns within the domestic market cluster.

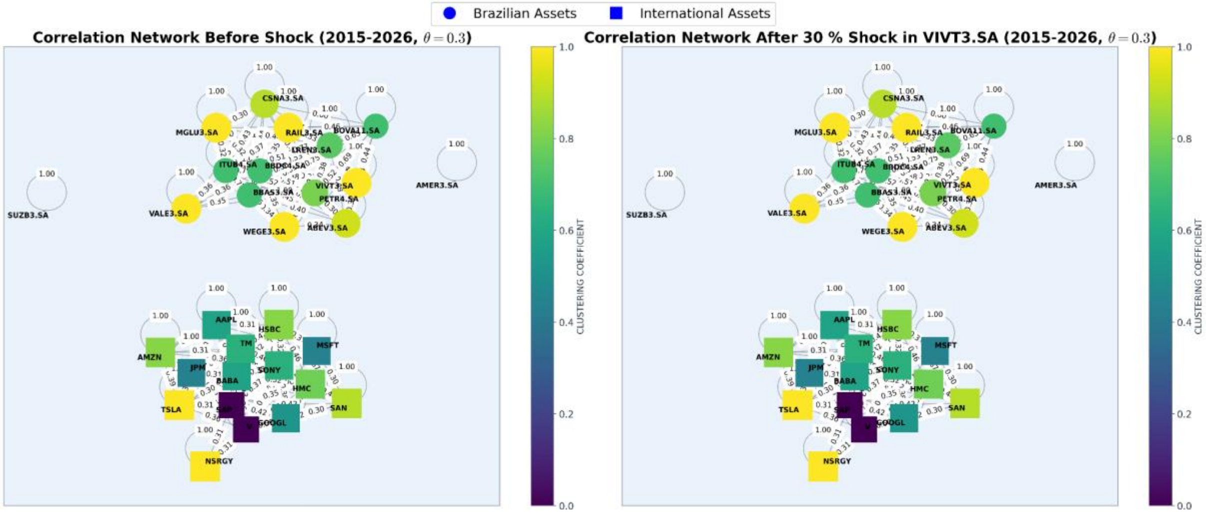
Highly connected assets such as $PETR4.SA, BBAS3.SA,$ and $ITUB4.SA$ remain central to the network structure. However, changes in connection strengths and clustering patterns suggest a redistribution of dependencies after the shock. These adjustments reveal how disturbances affecting a single asset can alter the local architecture of the network and modify potential contagion pathways.

In contrast, developed-market assets exhibit only minor changes in their clustering coefficients, remaining largely insulated from the localised disturbance. This finding suggests that weaker cross-market connectivity limits shock transmission between the Brazilian and developed-market subnetworks.

From a systemic risk perspective, the results indicate that deterministic shocks primarily affect densely connected regions of the network, where higher clustering facilitates local contagion. Conversely, lower connectivity within the developed-market subnetwork contributes to greater structural resilience and reduces the likelihood of widespread cascade effects.

These findings highlight the importance of network topology in determining the propagation of financial shocks. While localised disturbances may not generate global system failures, they can significantly alter the structure of highly interconnected clusters, increasing vulnerability to subsequent shocks and amplifying systemic risk within specific market segments.

Figure 3. Network Topology Before and After a Deterministic Shock



Note: Correlation network under a 30% shock to VIVT3.SA. Node colours represent clustering coefficients. The shock mainly affects the Brazilian subnetwork, while developed-market assets remain relatively stable.

Source: Author's own elaboration based on computational simulations using data obtained from Yahoo Finance.

This result reinforces the interpretation that clustering plays a central role in shaping shock propagation, acting as a local amplification mechanism within financial networks.

Threshold Sensitivity and Cascade Effects

Figures 4–7 extend the network analysis by examining the effects of alternative correlation thresholds and exposure-based interactions on shock propagation and systemic vulnerability.

When a higher correlation threshold ($\theta = 0.5$) is applied, the correlation network becomes substantially sparser, retaining only the strongest relationships among assets. Under this specification, the Brazilian subnetwork remains relatively cohesive, whereas developed-market assets appear more fragmented. Following the shock applied to $VIVT3.SA$, only minor structural adjustments are observed, suggesting that stronger correlations are more stable and less sensitive to localised disturbances.

In contrast, the exposure-based networks reveal a richer and more dynamic structure. Even before the cascade event, the network exhibits heterogeneous connectivity patterns, with certain assets emerging as hubs due to the combined effects of correlation and volatility. After the cascade, the network undergoes a visible reconfiguration characterized by increased edge density and stronger connections surrounding key nodes.

A notable result is the persistence of a tightly connected Brazilian core across both threshold levels. Developed-market assets, by comparison, remain more peripherally connected and less exposed to localised disturbances. This pattern reinforces the role of clustered structures in facilitating local contagion and concentrating systemic vulnerability within specific regions of the network.

From a systemic risk perspective, these findings demonstrate that shock propagation is highly sensitive to both network construction and threshold selection. Higher thresholds isolate the most stable connections and tend to reduce the apparent scope of contagion. Exposure-based networks, however, capture amplification mechanisms more effectively by incorporating both correlation and volatility, thereby providing a more realistic representation of systemic risk transmission.

These results further suggest that network topology plays a critical role in determining the resilience of financial systems. The interaction between connectivity, clustering, and volatility creates channels through which localised disturbances may evolve into broader systemic events. Consequently, models that jointly account for these factors offer a more comprehensive framework for stress testing, contagion analysis, and financial stability assessment.

3.4 Default Cascades and Stochastic Simulations

Figure 8 illustrates the exposure-based network before and after a default cascade simulation. In this experiment, a random shock ranging from *10%* to *50%* is applied to $VIVT3.SA$, triggering loss propagation through the network according to the Gai-Kapadia contagion mechanism.

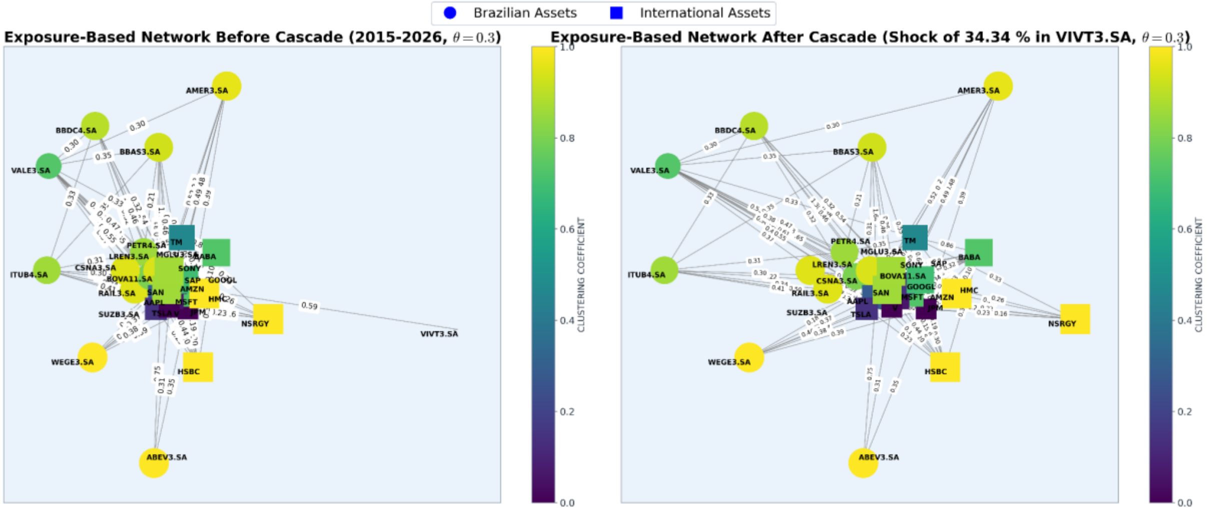
The results indicate that the simulated shock produces only limited cascade effects, with minimal node removal and no evidence of large-scale systemic collapse. Nevertheless, observable adjustments in local clustering patterns emerge following the shock, particularly around the initially affected node. For example, the clustering coefficient of $VIVT3.SA$ decreases by approximately $\Delta C \approx -0.05$, indicating a localised reconfiguration of network connectivity.

Although the immediate impact remains contained, the simulation highlights the importance of network structure in determining the transmission of financial distress. Even relatively small topological adjustments may alter contagion pathways and influence the system's vulnerability to subsequent shocks.

The stochastic framework provides a more realistic representation of financial markets than purely deterministic approaches, as it incorporates uncertainty in both shock magnitude and propagation dynamics. This allows the analysis to capture a broader range of potential outcomes and assess the resilience of the network under varying stress conditions.

Overall, the results suggest that the equity network exhibits substantial resilience to isolated shocks. However, localised contagion effects remain present within highly interconnected clusters, reinforcing the importance of monitoring network topology when assessing systemic risk and financial stability.

Figure 4. Exposure-Based Network Before and After a Default Cascade Simulation



Note: Exposure-based network before and after a default cascade simulation (θ = 0.3). A shock to VIVT3.SA alters local connectivity and clustering, illustrating how localised disturbances reshape contagion pathways without triggering systemic failure.

Source: Author's own elaboration based on computational simulations using data obtained from Yahoo Finance.

Network Structure Before and After Shock

Figures 3 and 4 illustrate the network structure before and after a *30%* negative shock applied to $VIVT3.SA$. The results reveal a clear structural distinction between Brazilian and developed-market assets.

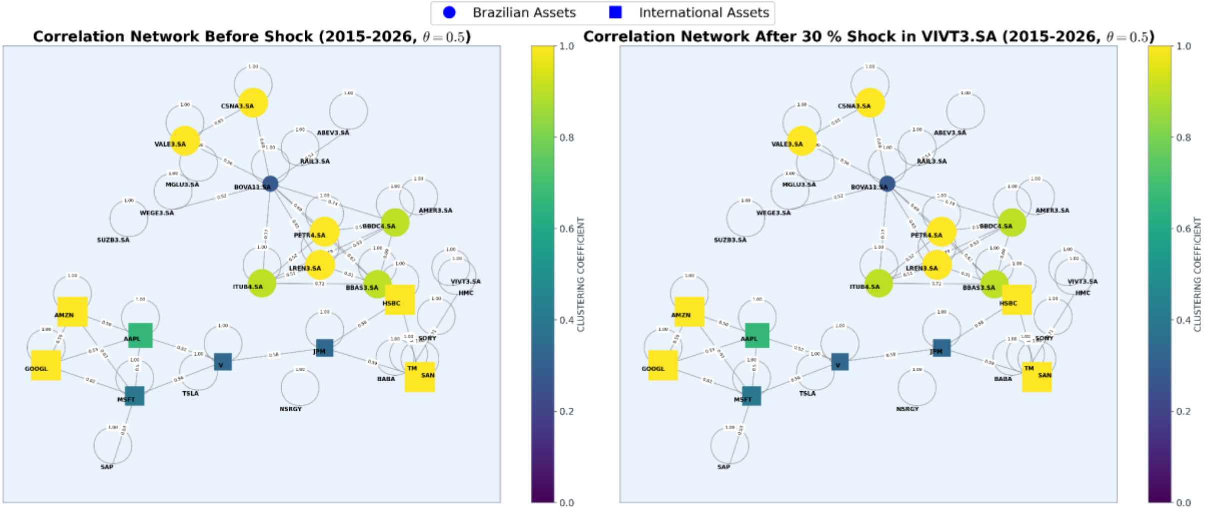
Brazilian assets, including $BBAS3.SA$ and $BOVA11.SA$, form a densely connected core characterized by high clustering coefficients ($C_i \approx 0.8 - 1.0$). This dense connectivity reflects strong local interdependencies and creates potential channels for localised contagion. In contrast, developed-market assets such as $AAPL$ and $AMZN$ exhibit lower clustering coefficients ($C_i \approx 0.0 - 0.4$), indicating weaker local connectivity and a more dispersed network structure.

Following the shock, the overall topology remains largely unchanged. The persistence of the network structure suggests a significant degree of resilience to localised disturbances, with no evidence of large-scale structural disruption. Although minor adjustments in connectivity patterns are observed, the core-periphery organization of the network remains intact.

These findings indicate that the financial system is capable of absorbing isolated shocks without generating widespread topological changes. At the same time, the concentration of connectivity within the Brazilian subnetwork highlights the existence of localised regions of vulnerability, where future shocks may propagate more efficiently through clustered structures.

Overall, the results provide additional evidence that network resilience and systemic vulnerability coexist within the same financial system. While the global structure remains stable, highly connected clusters continue to represent potential channels for contagion under more severe stress scenarios.

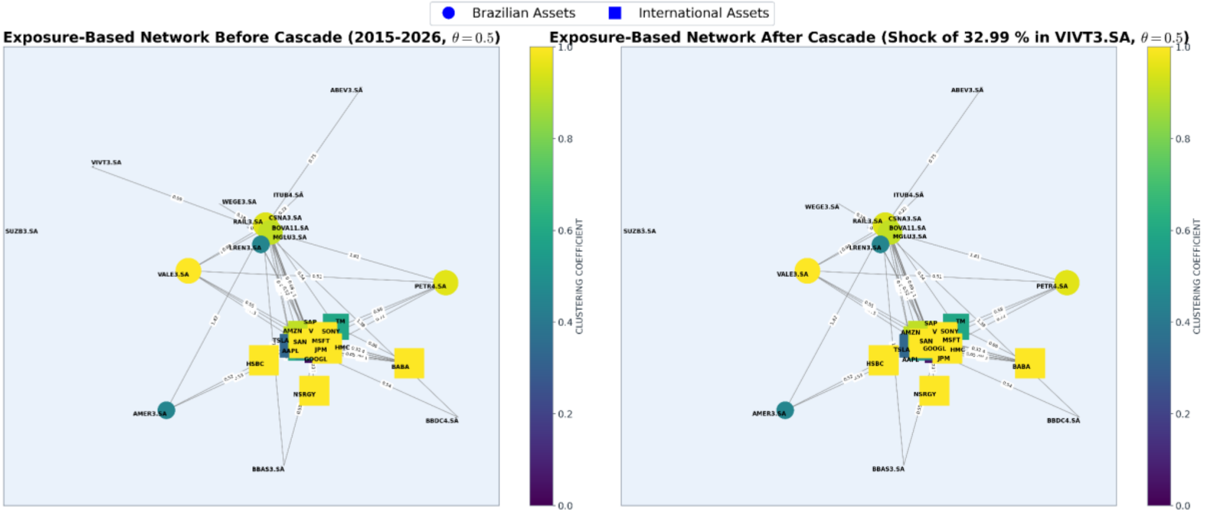
Figure 5. Correlation Network Structure Before Shock (θ = 0.5)



Note: Correlation-based network (θ = 0.5) for 2015–2026. Node colours reflect clustering coefficients. Retaining only strong correlations produces a sparse structure, revealing a dense Brazilian core and a more fragmented developed-market subnetwork.

Source: Author's own elaboration using data obtained from Yahoo Finance.

Figure 6. Correlation Network Structure After a 30% Shock in VIVT3.SA (θ = 0.5)



Note: Correlation-based network after a 30% shock to VIVT3.SA (2015–2026, θ = 0.5). Node colours indicate clustering coefficients. The network remains largely stable, with only minor clustering changes, mainly within the Brazilian subnetwork.

Source: Author's own elaboration using data obtained from Yahoo Finance.

Relevance of Network Visualizations

Figures 3–6 collectively illustrate the structural dynamics of correlation and exposure-based networks under alternative shock scenarios and correlation thresholds ($\theta = 0.3 \text{ and } \theta = 0.5$).

These visualizations provide important insights into systemic risk propagation by revealing how network topology influences cascade dynamics. Brazilian assets consistently exhibit high clustering coefficients ($C_i \approx 0.8 - 1.0$) and substantially higher average degrees than developed-market assets, forming a dense and highly interconnected subnetwork. This structure facilitates rapid local shock transmission, as evidenced by the pronounced structural adjustments observed following shocks to $VIVT3.SA$, including changes in clustering patterns and local connectivity.

By contrast, developed-market assets exhibit lower clustering coefficients ($C_i \approx 0.0-0.4$) and sparser connectivity structures. As a result, these assets experience fewer topological adjustments following shocks, indicating greater resilience to localised disturbances. The weaker connectivity of this subnetwork acts as a natural buffer against contagion, limiting the transmission of shocks across regions.

The exposure-based networks further emphasize these mechanisms by incorporating both correlation and volatility into the construction of financial linkages. Following cascade simulations, localised reductions in connectivity and changes in edge intensity emerge around highly connected nodes, reflecting the sensitivity of systemic outcomes to exposure thresholds within the Gai-Kapadia framework.

Taken together, the analysis of clustering coefficients, average degree, and edge dynamics provides a robust framework for identifying systemic vulnerabilities and contagion channels. Consistent with the financial network literature (Gai & Kapadia, 2010; Glasserman & Young, 2016), the results highlight the critical role of clustered connectivity in amplifying contagion while simultaneously shaping the resilience of financial systems. These findings are particularly relevant for identifying systemically important assets and for supporting diversification, stress testing, and financial stability assessment.

Clustering Coefficients and Tail Risk

Table 2 reports clustering coefficients for $\theta = 0.3$ and $\theta = 0.5$ together with tail-risk measures. The results confirm that Brazilian assets exhibit consistently higher clustering levels than developed-market assets. For example, $PETR4.SA$ presents clustering coefficients of $0.855\,(\theta = 0.3)$ and $0.700\,(\theta = 0.5)$, while $BBAS3.SA$ reaches $0.929\ at\ \theta = 0.3$. In comparison, developed-market assets such as $JPM\ (C_i = 0.473)$ and $MSFT\ (C_i = 0.505)$ display more moderate clustering values, although a few highly connected exceptions remain, including $NSRGY\ (C_i = 1.000)$.

These differences reveal a more densely interconnected Brazilian subnetwork, where high clustering coefficients reflect tightly connected local structures capable of facilitating rapid intra-cluster shock transmission. Consistent with the deterministic shock analysis, disturbances affecting $VIVT3.SA$ generate visible reconfigurations within this cluster, producing changes in both connectivity and clustering patterns.

The relationship between clustering and tail risk is particularly noteworthy. Assets characterized by high clustering frequently exhibit elevated downside risk measures. For example, $AMER3.SA$ combines a clustering coefficient of $0.964\ (\theta = 0.3)$ with a $CVaR$ of −0.0633, indicating both strong local interconnectedness and heightened vulnerability to extreme losses.

These findings suggest that clustering plays a central role in shaping contagion dynamics within financial networks. Highly clustered assets not only facilitate the local transmission of shocks but may also act as amplifiers of systemic risk when combined with substantial tail-risk exposure. Consequently, the joint analysis of network topology and downside risk provides a more comprehensive assessment of systemic vulnerability than either approach considered in isolation.

Table 2: Clustering Coefficients and Tail-Risk Measures of Assets (2015–2026)

Asset	θ = 0.3	θ = 0.5	VaR (95%)	CVaR (95%)
VIVT3.SA	0,000	0,000	-0,0110	-0,0169
PETR4.SA	0,855	0,700	-0,0191	-0,0336
ABEV3.SA	1,000	0,000	-0,0108	-0,0179
AMER3.SA	0,964	0,333	-0,0302	-0,0633
BBAS3.SA	0,929	0,000	-0,0164	-0,0267
BBDC4.SA	0,893	0,000	-0,0143	-0,0232
BOVA11.SA	0,407	0,026	-0,0098	-0,0156
RAIL3.SA	0,952	0,000	-0,0189	-0,0361
CSNA3.SA	0,802	0,694	-0,0249	-0,0367
ITUB4.SA	0,857	0,000	-0,0120	-0,0193
MGLU3.SA	0,944	0,667	-0,0282	-0,0446
VALE3.SA	0,733	0,733	-0,0178	-0,0269
WEGE3.SA	1,000	0,000	-0,0132	-0,0213
SUZB3.SA	0,000	0,000	-0,0133	-0,0211
LREN3.SA	0,952	0,333	-0,0173	-0,0276
AAPL	0,626	0,769	-0,0135	-0,0210
JPM	0,473	0,468	-0,0124	-0,0204
AMZN	0,857	0,945	-0,0150	-0,0243
MSFT	0,505	0,437	-0,0121	-0,0191
GOOGL	0,547	0,705	-0,0132	-0,0205
TSLA	0,547	0,625	-0,0263	-0,0422
V	0,473	0,480	-0,0115	-0,0193
SAP	0,838	0,945	-0,0122	-0,0202
NSRGY	1,000	1,000	-0,0084	-0,0135
SAN	0,924	1,000	-0,0162	-0,0258
HSBC	1,000	1,000	-0,0121	-0,0195
BABA	0,857	1,000	-0,0193	-0,0301
TM	0,719	0,769	-0,0112	-0,0168
SONY	0,927	1,000	-0,0136	-0,0218
HMC	1,000	1,000	-0,0127	-0,0185

Note: Clustering coefficients are reported for correlation thresholds θ = 0.3 and θ = 0.5, while VaR (95%) and CVaR (95%) are estimated from daily log returns (2015–2026). Lower thresholds produce denser networks, whereas higher thresholds retain only stronger connections, providing insights into connectivity and tail risk.

Source: Author's own calculations based on data obtained from Yahoo Finance.

In contrast, the lower clustering of developed market assets reflects a more fragmented network structure, contributing to their resilience against contagion, as evidenced by the absence of failures beyond Brazilian assets in stochastic simulations (Section 3.4).

3.5 Risk Measures

Table 2 reports VaR and $CVaR$ at the *95%* confidence level together with clustering coefficients. The results reveal substantially higher tail-risk exposure among several emerging-market assets. For example, $AMER3.SA$ exhibits a $CVaR$ of -0.0633, while $MGLU3.SA$ reaches -0.0446. In contrast, developed-market assets such as $AAPL$ ($CVaR = -0.0210$) and $MSFT$ ($CVaR = -0.0191$) display considerably lower downside risk.

These findings highlight a heterogeneous distribution of extreme-loss exposure across markets. From a systemic risk perspective, this distinction becomes particularly important when combined with the elevated clustering coefficients observed among Brazilian assets ($C_i \approx 0.8 - 1.0$). In highly interconnected subnetworks, extreme losses are more likely to propagate locally, amplifying the impact of adverse shocks and increasing systemic vulnerability.

The deterministic shock analysis provides further evidence of this mechanism. Disturbances affecting $VIVT3.SA$ generate localised reconfigurations within the Brazilian cluster, whereas the lower $tail - risk$ exposure and weaker connectivity of developed-market assets contribute to greater resilience and more limited contagion effects.

Overall, the joint evidence from downside risk measures and network topology suggests that systemic risk emerges from the interaction between extreme-loss potential and clustered connectivity rather than from isolated asset characteristics alone. This finding reinforces the importance of integrating financial network analysis with traditional $tail - risk$ measures when assessing systemic vulnerability.

3.6 Stochastic and Deterministic Cascade Analysis

Stochastic Simulations

Table 3 summarizes the results of the Monte Carlo simulations ($n = 1000$). Across all scenarios and correlation thresholds ($\theta = 0.3 \text{ and } \theta = 0.5$), the probability of systemic failure, defined as more than five assets failing simultaneously, remains equal to zero. This result indicates the absence of large-scale collapse under the simulated conditions.

Regardless of the shock specification, whether involving a single asset ($e.g., ITUB4.SA$) or simultaneous shocks affecting multiple assets ($e.g., ITUB4.SA \text{ and } VALE3.SA$), the average number of failed assets remains remarkably stable. Isolated shocks generate, on average, one failed asset, whereas simultaneous shocks produce approximately two failed assets. This consistency suggests that disturbances remain largely confined to local regions of the network.

The findings indicate that the system exhibits localised vulnerability without reaching the critical threshold required for widespread cascade failures. Although shocks propagate through the network, their effects remain concentrated within highly connected clusters and do not trigger systemic breakdowns. Importantly, this behaviour remains robust across both correlation thresholds considered in the analysis.

From a financial stability perspective, these results suggest that the network possesses substantial resilience to moderate shocks. Nevertheless, localised contagion effects persist within densely connected subnetworks, highlighting the importance of monitoring clustered structures and systemically important assets.

Overall, the Monte Carlo simulations support the interpretation that systemic risk in global equity markets is characterized by contained and localised failures rather than large-scale collapse, consistent with the predictions of the Gai-Kapadia framework. The coexistence of global resilience and local fragility emerges as one of the central findings of this study.

Table 3. Monte Carlo Results by Shock Scenario (n = 1,000) and Correlation Threshold

Scenario / Metric	θ	Failure Probability (>5 Assets)	Average Failed Assets
General Simulation	0.3	0.000	1.000
General Simulation	0.5	0.000	1.000
Single Shock (VIVT3.SA)	0.3	0.000	1.000
Single Shock (VIVT3.SA)	0.5	0.000	1.000
Simultaneous Shock (VIVT3.SA + AAPL)	0.3	0.000	2.000
Simultaneous Shock (VIVT3.SA + AAPL)	0.5	0.000	2.000

Note: Based on 1,000 Monte Carlo simulations under alternative shock scenarios and correlation thresholds (θ = 0.3, 0.5). No systemic failures (>5 assets) were observed; average failures remained limited to one asset under isolated shocks and two under simultaneous shocks.

Source: Author's own calculations based on Monte Carlo simulations using data obtained from Yahoo Finance.

Default Propagation Dynamics

To further investigate the temporal evolution of contagion, we analyse the propagation of defaults across successive iterations within the Gai-Kapadia framework. Rather than focusing solely on the final number of failed assets, this approach allows us to examine how financial distress spreads through the network over time and how contagion pathways evolve during the cascade process.

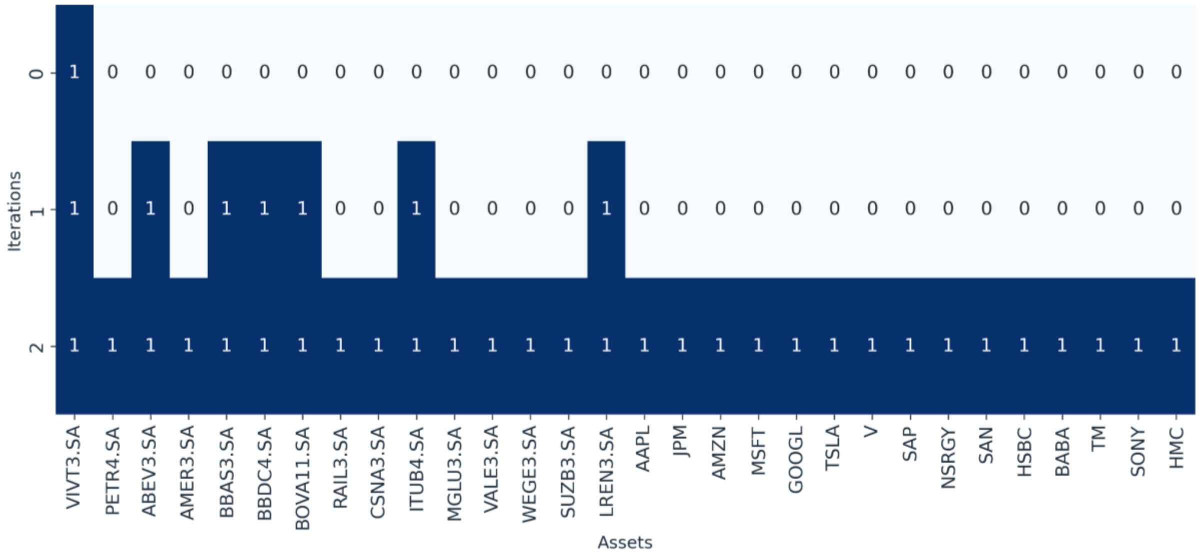
Figure 7 presents a heatmap representation of default states, where each row corresponds to an iteration step and each column represents an individual asset. Defaulted assets are highlighted according to their state at each stage of the simulation, providing a visual representation of the timing and extent of contagion.

The heatmap reveals that default propagation remains largely localised throughout the simulation horizon. Most failures occur during the initial iterations and remain concentrated within a limited subset of highly connected assets. As the cascade evolves, the number of newly affected assets rapidly stabilizes, indicating that contagion dissipates before reaching a system-wide scale.

These results are consistent with the Monte Carlo simulations and deterministic shock analysis, both of which indicate that the network operates below the critical threshold required for widespread systemic collapse. While localised contagion effects are clearly present, the propagation process remains contained, reflecting the overall resilience of the financial system.

From a systemic risk perspective, the temporal analysis highlights the importance of network topology in shaping the speed and extent of contagion. Highly clustered regions facilitate the initial transmission of shocks, whereas weaker inter-cluster connections act as barriers that limit further propagation. Consequently, the dynamics of default propagation provide additional evidence of the coexistence of local fragility and global resilience within the network.

Figure 7. Default Propagation Dynamics Under the Gai-Kapadia Framework (θ = 0.3)



Note: Heatmap of default propagation following a shock to VIVT3.SA under the Gai-Kapadia framework (θ = 0.3). Contagion remains concentrated within the Brazilian subnetwork and dissipates before reaching systemic scale.

Source: Author's own elaboration based on computational simulations using data obtained from Yahoo Finance.

Default Propagation Dynamics

The heatmap reveals a rapid transition from an initial localised shock to a stable configuration in which failures remain confined to a limited subset of assets. Notably, the propagation process stabilizes after only a few iterations, indicating that the system reaches a steady state without triggering a large-scale cascade. Formally, the default dynamics follow the recursive condition given by

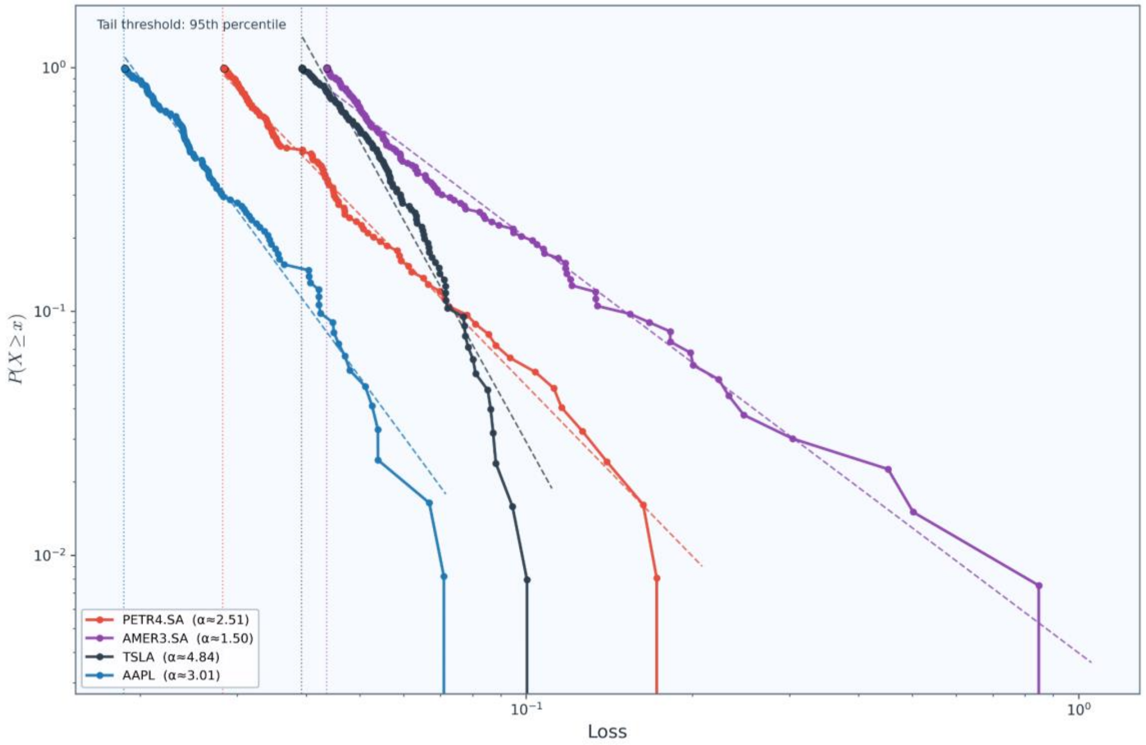
$$Di^{(t+1)} = I\ (\textstyle\sum_j E_{ij}\, Di^{(t)} > \tau_i), \qquad (12)$$

where $Di^{(t)}$denotes the default state of asset i at iteration t, E_{ij} represents the exposure matrix, and τ_i is the default threshold associated with asset i.

The results indicate that contagion is primarily governed by local network structure and exposure intensity rather than by global interdependence. Failures remain concentrated within highly connected clusters, while weaker inter-cluster connections limit the transmission of distress to the broader system.

These findings are consistent with the Monte Carlo simulations and deterministic shock analyses presented earlier, reinforcing the conclusion that the financial network operates below the critical threshold required for widespread systemic collapse. Although localised contagion effects are clearly present, they remain contained within specific regions of the network.

Figure 8. Empirical Tail-Risk Profiles of Selected Assets



Note: Empirical CCDFs of losses with power-law fits above the 95th percentile. Brazilian equities exhibit heavier tails than developed-market assets, indicating greater exposure to extreme losses and tail risk.

Source: Author's own calculations based on daily return data obtained from Yahoo Finance.

Tail Behaviour and Power-Law Scaling

The empirical CCDF exhibits an approximately linear pattern on a log-log scale, suggesting that the tail behaviour can be described by a power-law distribution of the form given in:

$$P(X \geq x) \sim x^{-\alpha} \tag{13}$$

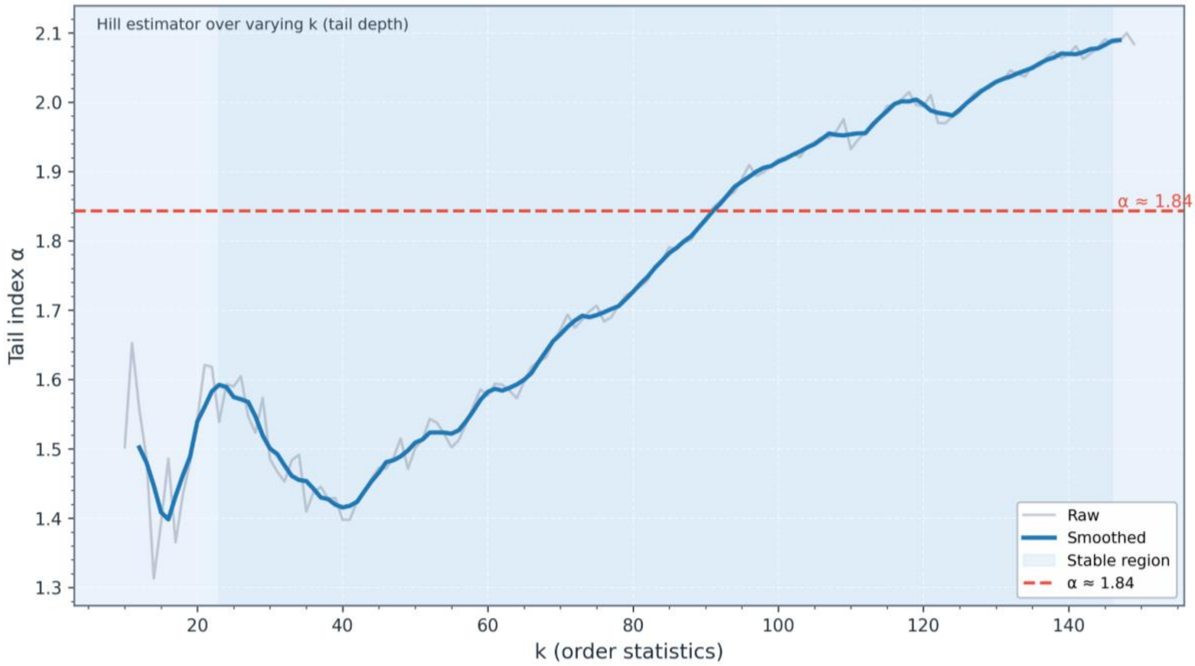
where α denotes the Pareto tail index.

The estimated tail behaviour reveals substantial heterogeneity across assets. In particular, assets such as $AMER3.SA$ exhibit relatively heavy tails ($\alpha \approx$ *1.5*), indicating a significantly higher probability of extreme losses. By contrast, developed-market assets generally display larger tail exponents and steeper decay rates, reflecting greater stability and lower exposure to rare but severe adverse events.

From a systemic risk perspective, these findings are particularly relevant because $heavy - tailed$ losses increase the likelihood of large shocks entering the financial network. When combined with highly clustered network structures, such shocks may be amplified through local contagion mechanisms, increasing overall systemic vulnerability.

The results therefore provide empirical support for integrating $tail - risk$ analysis with network-based contagion models. While network topology determines how shocks propagate, tail behavior influences the magnitude and frequency of the shocks entering the system. Together, these mechanisms shape the emergence and transmission of systemic risk in financial markets.

Figure 9. Hill Estimator for the Pareto Tail Index of AMER3.SA



Note: Hill plot for AMER3.SA showing the Pareto tail index (α). The stable region yields α ≈ 1.84, indicating a heavy-tailed distribution and elevated exposure to extreme losses.

Source: Author's own calculations based on daily return data obtained from Yahoo Finance.

Tail Index Estimation

To assess the robustness of the observed tail behaviour, we estimate the Pareto tail index using the Hill estimator, a widely used method in extreme-value theory for quantifying tail heaviness.

The Hill plot presented in Figure 9 exhibits a relatively stable region around $\alpha \approx 1.84$, suggesting that the tail behavior of $AMER3.SA$ is consistent with a heavy-tailed distribution. Such values indicate a substantially higher probability of extreme losses than would be predicted under Gaussian assumptions.

From a financial stability perspective, this result is particularly relevant because heavy-tailed assets are more likely to generate large shocks capable of triggering contagion mechanisms within interconnected financial networks. When combined with high clustering coefficients and strong local connectivity, $heavy-tailed$ assets may act as amplifiers of systemic vulnerability.

The estimated tail index therefore complements the VaR and $CVaR$ measures reported previously by providing a direct characterization of the statistical structure of extreme losses. Together, these results reinforce the importance of integrating network topology and tail-risk analysis when assessing systemic risk in global equity markets.

Tail Index Estimation and Contagion Dynamics

The Hill estimator is defined by:

$$\hat{\alpha}^{-1}(k) = (1/k)\, \Sigma_{i=1}{}^{k} \left[log\, X_{(i)} - log\, X_{(k+1)}\right] \tag{14}$$

where $X_{(i)}$ denotes the ordered sample observations and k represents the number of upper-order statistics used in the estimation.

The Hill plot reveals a relatively stable region for intermediate values of k, providing evidence of robust power-law behaviour in the tail of the loss distribution. The estimated tail exponent ($\alpha \approx 1.84$) confirms the presence of $heavy-tailed$ dynamics and indicates that extreme losses are substantially more likely than under Gaussian assumptions.

This result is consistent with the CCDF analysis and reinforces the importance of tail risk as a fundamental component of systemic vulnerability. Assets characterized by $heavy-tailed$ loss distributions are more likely to generate large shocks capable of triggering contagion mechanisms within interconnected financial networks.

The temporal evolution of defaults provides additional insight into how such shocks propagate through the system. Starting from an initial disturbance affecting $VIVT3.SA,$ failures spread rapidly to a subset of Brazilian assets during the first iteration, reflecting strong local interdependence driven by elevated correlations and exposure levels. By the second iteration, the cascade reaches a stable configuration in which defaults remain confined to a localised cluster, with no evidence of further propagation throughout the broader network. This finding indicates that contagion is present but remains limited by the underlying network structure, preventing the emergence of large-scale systemic cascades.

A notable asymmetry emerges between markets. Developed-market assets, including AAPL, remain unaffected throughout the propagation process, reflecting lower connectivity and weaker exposure to contagion channels. In contrast, Brazilian assets exhibit stronger local transmission mechanisms associated with higher clustering coefficients and denser connectivity patterns.

Table 4: Pareto Tail Index Estimates and Loss Statistics for All Assets (2015–2026) - selected assets

Asset	Pareto α	N_{losses}	Tail Type
AMER3.SA	1.501	2643	Heavy tail
BBAS3.SA	1.862	2555	Heavy tail
BOVA11.SA	2.067	2576	Heavy tail
RAIL3.SA	2.195	2547	Heavy tail
. . .	. . .	. . .	. . .
VALE3.SA	3.358	2653	Moderate tail
SONY	3.796	2652	Moderate tail
GOOGL	3.816	2490	Moderate tail
TSLA	4.844	2512	Moderate tail

Note: Pareto tail indices (α) were estimated using the Hill estimator. Assets with α < 3 are classified as heavy-tailed, indicating greater exposure to extreme losses.

Source: Author's own calculations based on daily return data obtained from Yahoo Finance.

These results demonstrate that systemic vulnerability depends not only on magnitude of extreme losses but also on the structure through which those losses propagate. Heavy-tailed shocks increase the likelihood of severe disturbances, while network topology determines whether those disturbances remain localised or evolve into broader contagion events.

4. Discussion

This study integrates deterministic cascade modelling and stochastic simulations within an extended Gai-Kapadia framework to investigate systemic risk in a global equity network composed of 30 assets over the period 2015 – 2016. The results consistently indicate that systemic risk emerges from the interaction between network topology and tail-risk characteristics rather than from either mechanism in isolation.

The network analysis reveals a pronounced structural asymmetry between emerging and developed markets. Brazilian assets exhibit high clustering coefficients $(C_i \approx\ 0.8 - 1.0)$ and dense connectivity, forming tightly interconnected subnetworks that facilitate local shock transmission. In contrast, developed-market assets display lower clustering levels and more dispersed connectivity patterns, which contribute to greater resilience against contagion.

The deterministic cascade analysis shows that shocks propagate rapidly within the Brazilian subnetwork but stabilize after only a few iterations without triggering widespread failures. This finding is reinforced by Monte Carlo simulations (n = 1,000) which produce a zero probability of large-scale collapse across all scenarios considered. Although localised failures occur, the system remains below the critical threshold required for self-sustaining contagion.

These findings contribute to an important debate in the systemic risk literature. Highly interconnected systems are often associated with greater risk-sharing and diversification benefits during normal market conditions. However, the same structures may become channels of contagion during periods of stress. The results suggest that this trade-off is particularly relevant in emerging markets, where dense local connectivity increases vulnerability to localised disturbances while simultaneously supporting market integration.

$Tail - risk$ analysis provides an additional perspective on systemic vulnerability. The CCDF analysis and Hill estimator reveal heavy-tailed behavior, particularly among emerging-market assets, with estimated Pareto exponents in the range of approximately $1.5 - 2.0$. Such values imply a significantly higher probability of extreme events than predicted by Gaussian models. Importantly, the results indicate that tail risk and network topology reinforce one another. Large shocks generated by heavy-tailed assets become especially relevant when transmitted through highly clustered structures.

From an economic perspective, these findings suggest that systemic vulnerability cannot be adequately assessed through traditional risk measures alone. Metrics such as VaR and $CVaR$ provide valuable information regarding downside exposure but do not capture how losses propagate through interconnected systems. Likewise, network measures alone do not quantify the magnitude of the shocks entering the system. The joint consideration of network topology and $tail - risk$ behavior therefore provides a more comprehensive framework for understanding financial fragility.

The results also carry implications for financial regulation and risk management. The identification of highly connected assets with elevated tail risk may help regulators and portfolio managers identify potential sources of systemic vulnerability before periods of market stress. In this sense, network-based stress testing can complement traditional approaches by explicitly accounting for contagion channels and structural interdependencies.

Despite these contributions, several limitations remain. The analysis abstracts from liquidity effects, funding constraints, and fire-sale mechanisms that often amplify losses during financial crises. In addition, the use of static correlation thresholds $(\theta = 0.3\ and\ \theta = 0.5)$ simplifies the dynamic evolution of financial networks over time. These assumptions may lead to an underestimation of systemic risk under severe market conditions.

Future research may extend this framework by incorporating adaptive networks, liquidity feedback effects, multilayer financial structures, and larger asset universes. Such extensions would allow for a more realistic representation of financial contagion and provide further insights into the mechanisms underlying systemic instability.

Overall, the empirical evidence points to a financial system characterized by global resilience but local fragility. While the network remains robust to moderate shocks at the aggregate level, densely connected clusters continue to serve as potential amplification channels for extreme events. This coexistence of resilience and vulnerability emerges as a central feature of systemic risk in modern equity markets.

5. Case Study and Computational Experiments

This study develops and evaluates a computational framework for systemic risk analysis in global equity markets based on an extended Gai-Kapadia contagion model. The framework combines financial network analysis, deterministic shock propagation, stochastic Monte Carlo simulations, and tail-risk estimation within a unified methodology.

The empirical application was conducted using a network composed of 30 equities, including 15 Brazilian assets and 15 developed-market assets, covering the period from 2015 to 2026. Financial networks were constructed from asset return correlations and transformed into exposure-based structures under alternative correlation thresholds $(\theta = 0.3\ and\ \theta = 0.5)$.

A series of computational experiments was performed to evaluate the propagation of shocks across the network. These experiments included deterministic shocks, default cascade simulations, Monte Carlo $stress - testing$ procedures $(n = 1000)$, clustering analysis, and $tail - risk$ estimation using both CCDF analysis and the Hill estimator.

The results demonstrate that network topology plays a central role in shaping systemic risk. Highly clustered Brazilian assets exhibit stronger local contagion effects, while developed-market assets remain comparatively resilient due to lower connectivity levels. Furthermore, the integration of $tail - risk$ measures reveal that assets characterized by $heavy - tailed$ loss distributions may act as potential amplifiers of systemic disturbances.

The main innovation of the proposed framework lies in the joint analysis of network connectivity and extreme-loss behaviour. By combining contagion dynamics with tail-risk estimation, the methodology provides a more comprehensive assessment of systemic vulnerability than approaches based solely on traditional risk measures or network analysis.

The framework is fully scalable and may be extended to larger financial systems, alternative asset classes, adaptive networks, and more complex contagion mechanisms, making it a useful tool for both academic research and financial stability assessment.

Conclusion

This study develops a comprehensive framework for analysing systemic risk and default cascades in global equity markets through an extended Gai-Kapadia approach. By integrating network topology, stochastic simulations, and $tail - risk$ analysis, the proposed framework provides a unified perspective on how systemic risk emerges, propagates, and affects financial stability.

The results indicate that the global equity network exhibits substantial resilience under a wide range of shock scenarios, with a negligible probability of large-scale collapse. Nevertheless, important pockets of vulnerability remain concentrated within highly clustered subnetworks, particularly among emerging-market assets. This finding suggests that systemic risk is not uniformly distributed across financial systems but is instead shaped by the underlying network structure and the concentration of interconnected exposures.

The incorporation of tail-risk measures further highlights the importance of extreme events in determining systemic outcomes. Assets characterized by heavy-tailed loss distributions and strong network connectivity emerge as potential amplifiers of contagion, emphasizing the need to jointly consider statistical risk characteristics and network topology when assessing financial stability.

These findings extend the applicability of the Gai-Kapadia framework beyond its original interbank setting and demonstrate its effectiveness in capturing price-driven contagion mechanisms in equity markets. The results also provide empirical evidence that network structure plays a critical role in determining the resilience of financial systems and the transmission of shocks across markets.

From a policy perspective, the identification of highly connected and vulnerable nodes may support more targeted macroprudential supervision, stress-testing exercises, and systemic risk monitoring. For investors and portfolio managers, the findings reinforce the importance of diversification across structurally distinct regions of the network rather than relying solely on traditional risk measures.

Future research may further enhance this framework through the incorporation of dynamic network structures, liquidity channels, feedback effects, and alternative shock-generation mechanisms. Such extensions would contribute to narrowing the gap between theoretical contagion models and the complexity of real-world financial systems.

Overall, this study contributes to the growing literature on financial networks, systemic risk, and financial stability by providing a scalable and empirically grounded methodology for analysing contagion in global equity markets. As financial systems become increasingly interconnected, understanding how shocks propagate through complex networks remains essential for both economic resilience and effective risk management.

Credit Authorship Contribution Statement

Ana Isabel Castillo Pereda conceived the study, developed the methodology, collected and analysed the data, performed the simulations, interpreted the results, and wrote, reviewed, and revised the manuscript. The author has read and approved the final version of the manuscript.

Acknowledgments/Funding

The author would like to thank colleagues and researchers whose discussions and insights contributed to the development of this work. No specific funding was received for this research.

Conflict of Interest Statement

The author declares that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Data Availability Statement

The data that support the findings of this study were obtained from Yahoo Finance and are publicly available at https://finance.yahoo.com.

Ethical Approval Statement

This study is theoretical and computational in nature and did not involve human participants, personal data, or animal subjects. Therefore, ethical approval was not required.

References

Acemoglu, D., Ozdaglar, A., & Tahbaz-Salehi, A. (2015). Systemic risk and stability in financial networks. *American Economic Review*, *105*, 564–608. https://doi.org.10.1257/aer.20130456

Allen, F., & Gale, D. (2000). Financial contagion. *Journal of Political Economy*, *108*(1), 1–33. https://doi.org/10.1086/262109

Artzner, P., Delbaen, F., Eber, J. M., & Heath, D. (1999). Coherent Measures of Risk. *Mathematical Finance*, *9*, 203-228. https://doi.org/10.1111/1467-9965.00068

Barabási, A.-L., & Albert, R. (1999). Emergence of scaling in random networks. *Science*, *286*, 509–512. https://doi.org/10.1126/science.286.5439.509

Battiston, S., Delli Gatti, D., Gallegati, M., Greenwald, B. C., & Stiglitz, J. E. (2012). Liaisons dangereuses: Increasing connectivity, risk sharing, and systemic risk. *Journal of Economic Dynamics and Control, 36*(8), 1121–1141. https://doi.org/10.1016/j.jedc.2012.04.001

Bielecki, T., Duffie, D., & Singleton, K. J. (2004). Credit Risk: Pricing, Measurement and Management. *Journal of Economics, 81*, 84–87. https://doi.org/10.1007/s00712-003-0038-6

Billio, M., Getmansky, M., Lo, A. W., & Pelizzon, L. (2012). Econometric measures of connectedness and systemic risk in the finance and insurance sectors. *Journal of Financial Economics*, *104*(3), 535–559. https://doi.org/10.1016/j.jfineco.2011.12.010

Castillo Pereda, A. I. (2025). Systemic risk and default cascades in global equity markets: Extending the Gai-Kapadia framework with stochastic simulations and network analysis. arXiv. https://arxiv.org/abs/2504.01969

Chen, H., Wang, T., & Yao, D. D. (2021). Financial Network and Systemic Risk - A Dynamic Model. *Production and Operations Management*, *30*(8), 2441-2466. https://doi.org/10.1111/poms.13384

Cont, R. (2001). Empirical properties of asset returns: Stylized facts and statistical issues. *Quantitative Finance*, *1*(2), 223–236.https://doi.org/10.1080/713665670

Das, B., & Fasen-Hartmann, V. (2025): Measuring risk contagion in financial networks with CoVaR, *Finance and Stochastics*, *29*(3), 707-755, https://doi.org/10.1007/s00780-025-00564-6

Eisenberg, L., & Noe, T. H. (2001). Systemic risk in financial systems. *Management Science*, *47*(2), 236–249. https://doi.org/10.1287/mnsc.47.2.236.9835

Ellis, S., Sharma, S., & Brzeszczyński, J. (2022). Systemic risk measures and regulatory challenges. *Journal of Financial Stability*, 61, Article 100960. https://doi.org/10.1016/j.jfs.2021.100960

Freixas, X., Parigi, B. M., & Rochet, J.-C. (2000). Systemic risk, interbank relations, and liquidity provision by the central bank. *Journal of Money, Credit and Banking*, *32*(3), 611–638. https://doi.org/10.2307/2601198

Gai, P., & Kapadia, S. (2010). Contagion in financial networks. *Proceedings of the Royal Society A*, 466, 2401–2423. https://www.bankofengland.co.uk/-/media/boe/files/working-paper/2010/contagion-in-financial-networks.pdf

Glasserman, P., & Young, H. P. (2016). Contagion in financial networks. *Journal of Economic Literature*, *54*, 779–831.https://doi.org. 10.1257/jel.20151228

Hałaj, G., Martinez-Jaramillo, S., & Battiston, S. (2024). Financial stability through the lens of complex systems. *Journal of Financial Stability,* Volume *71*, 101228. https://doi.org/10.1016/j.jfs.2024.101228

Haldane, A. G., & May, R. M. (2011). Systemic risk in banking ecosystems. *Nature*, *469*, 351–355. https://doi.org/10.1038/nature09659

International Monetary Fund. (2025). Regional Economic Outlook: Western Hemisphere, April 2025. International Monetary Fund Publications. https://www.imf.org/en/publications/reo/wh/issues/2025/04/25/regional-economic-outlook-western-hemisphere-april-2025

Fu, M. C., Li, B., Li, F., & Wu, R. (2025). Contagion network, portfolio credit risk, and financial crisis, *European Journal of Operational Research*, Volume 321, Issue 3, 942-957. https://doi.org/10.1016/j.ejor.2024.09.026

Mantegna, R. N., & Stanley, H. E. (1999). Introduction to econophysics: Correlations and complexity in finance. Cambridge University Press. https://aip.brightspotcdn.com/PTO.v53.i12.70_1.online.pdf

Newman, M. E. J. (2010). Networks: An introduction. Oxford University Press. 772 pages. ISBN-978-0-19-920665-0. *Artificial Life*, 2012; 18(2), 241–242. https://doi.org/10.1162/ARTL_r_00062

Poledna, S., Martínez-Jaramillo, S., Caccioli, F., & Thurner, S. (2021). Quantification of systemic risk from overlapping portfolios in the financial system. *Journal of Financial Stability*, *52*, Article 100808. https://doi.org/10.1016/j.jfs.2020.100808

Li, B., & Zhang, X. (2024). Systemic risk and financial networks. The Quarterly Review of Economics and Finance, Volume 94, 25-36. https://doi.org/10.1016/j.qref.2023.12.012

Strogatz, S. H. (2001). Exploring complex networks. *Nature*, *410*, 268–276. https://doi.org/10.1038/35065725

Páez, A., & Boisjoly, G. (2022). Exploratory Data Analysis. In: Discrete Choice Analysis with R. Use R! Springer, Cham. https://doi.org/10.1007/978-3-031-20719-8_2

World Bank. (2025). Global Economic Prospects, January 2025. World Bank Group Publications. © World Bank. http://hdl.handle.net/10986/42452 License: CC BY 3.0 IGO. https://doi.org/10.1596/978-1-4648-2147-9

Yahoo Finance. (2023). Historical financial data. https://finance.yahoo.com