Dependency and systemic risk in dynamic financial networks

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Abstract

This study introduces an innovative methodology for predicting systemic risk by leveraging multi-layer network characteristics. We select the daily closing price of financial companies listed in the $S\&P500$ index as our dataset and analyze various dimensions of risk channels, incorporating Correlation, Euclidean, ARIMA model distances, and variance decomposition layers. We focus on introducing Influence as a novel network centrality measure. Unlike traditional centrality measures, Influence incorporates time-varying probabilities for connections, offering flexibility across diverse scenarios. The results show a robust positive relation between centrality measures and systemic risk, with the Influence measure demonstrating a more pronounced effect on future systemic risk. Recognizing the need for practical tools for regulators and investors, this work proposes an effective method for systemic risk monitoring. We introduce a new version of the Influence Maximization model that identifies influential companies with the largest possible loss, aiding targeted risk-based monitoring of the network. This comprehensive approach advances our understanding of systemic risk and equips stakeholders with actionable insights for informed decision-making and risk management.

Keywords: Systemic Risk, Network analysis, Influence Maximization, Value at Risk, Conditional Value at Risk, Shock propagation, Centrality Network analysis

1. Introduction

Systemic risk is a commonly used concept, but its definition is often ambiguous. Identifying such risks is complex and tied to various triggers rather than a clear-cut definition. According to Minsky (1977) and Adrian and Brunnermeier (2016), systemic risk refers to the possibility of many market participants experiencing significant losses simultaneously, posing a threat to the entire financial system. Recent research has increasingly focused on the connections among firms in the market due to the profound consequences of global systemic crises (Acemoglu et al., 2015; He, 2020; Gong et al., 2022). However, there is an ongoing debate about the accurate understanding of the complexity of these relationships and the role of firms in

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the network. This debate stems from limitations in single-layer approaches that may not capture sufficient connections in real financial networks Cao (2021) and the shortcomings of current tools in explaining the role of firms in systemic risk. Classical centrality measures are inadequate in showing the comprehensive impact of firms in transmitting and absorbing risk, and they cannot identify the most probable path of a crisis.

Some crises develop gradually, while others emerge suddenly. When a crisis occurs gradually, the impact can spread through interconnections (Langfield et al., 2014; Baumöhl et al., 2022). Researchers have introduced various definitions for interconnections to establish a network between firms see Bostanci (2020); Cheng et al. (2022); He (2022); Gong (2019); Keilbar and Wang (2022). For instance, Tafakori et al. (2022) show that defaults in contracts among financial institutions increase the likelihood of transmitting negative shocks to others through liability linkages. Yu et al. (2024) show the connection between industries as the volume of purchase and sales transactions within every pair of industries. Additionally, Huang et al. (2013) develop the cascading failure model to illustrate the process of domino effects. This study introduces risk measures to quantify systemic risk and assesses the effectiveness of dynamic centrality in predicting systemic risk.

Modelling a financial system as a network (the stocks as nodes and their relations as connections) offers a clearer understanding of systemic risk. However, a single-layer network may not be sufficient as stakeholders such as regulators and investors often lack comprehensive information, leading to a biased understanding of the market structure. Various types of interactions among firms, including return correlations Hale (2019); Nguyen et al. (2019); Cheng et al. (2022), obligations Cao (2021); Tafakori et al. (2022); Le (2022), shareholdings Barberis and Shleifer (2003); Qian et al. (2010); Anton and Polk (2014); Faias and Ferreira (2017), and causality in returns Wang (2018); Gong (2019); Zareei (2019); Bostanci (2020) and the interrelations among these layers, emphasizing the need for a multilayer network structure. In a multilayer network, different layers connect the same set of firms. Through these layers, shock in one layer can propagate to other layers, highlighting the inadequacy of viewing risks from a single-layer network with only one type of relationship between firms.

Multi-layer networks analysis has appeared recently to consider different aspects of relations between firms, Xie (2022) and Gong et al. (2023) study connections in daily/even hourly returns and idiosyncratic risk in the equity market. They both study 3-layer networks, where Xie (2022) considers linear, non-linear, and tail dependency, and Gong et al. (2023) proposes implied volatility, realized volatility, and variance risk premium as the layers. Cao (2021) consider two layers that one layer represents liability relation between banks and another layer for cross-holding of shares. Gong et al. (2022) propose a 2-layer network which contains stock volatility and investor sentiment. They also use the Tail-Event driven Network risk (TENET) approach to include more information about shock propagation. These studies offer a comprehensive overview of the multilayer network but face certain challenges. Firstly, they rely on multiple unique databases and often examine each layer in isolation, resulting in a biased estimation of systemic risk. Secondly, they tend to use traditional centrality measures like Closeness, Betweenness, Eigenvector, and node degree to analyze the role of firms in risk transmission. While these centrality measures shed light on certain aspects of firms' roles, they are insufficient to assume the probability of risk transmission, identify potential crisis pathways, and provide a tool to control systemic risk via network structure.

This paper addresses these gaps by presenting a multilayer network designed to analyze the impact of network structure on systemic risk. In this analysis, we examine a sample of financial companies listed in the $S\&P500$ index from 2007 to 2023, creating quarterly dynamic multi-layer networks using Euclidean, Correlation, ARIMA model distances, and Variance decomposition layers. Each layer highlights different structures that capture various aspects of firm relations. The multi-layer network demonstrates that a node has different neighbours in each layer with different transmission probabilities, highlighting the insufficiency of a single layer for understanding the financial system.

Another contribution of our paper is introducing the *Influence* measure with time-dependent probability as a new centrality measure. We introduce the Influence measure as a centrality measure for evaluating the influence of firm positions in risk propagation within the network. The proposed centrality measure aims to identify the most influential companies in the market based on their contributions to systemic risk. While centrality measures in the current literature remain static and rely solely on network topology, we introduce *Influence* as a dynamic measure with flexible probability for the connection to capture the evolving nature of risks. Leveraging this concept from network theory, we aim to develop a novel centrality measure to quantify systemic risk. By incorporating time-dependent probabilities for connections, we enhance the prediction of systemic risk by introducing flexible Influence in our approach. We find that our proposed measure suggests that the companies in the central positions are more exposed to systemic risk. This can provide insights into the key points of vulnerability within the network.

Finally, we use the Influence Maximization model to identify sets of influential companies. This model goes beyond traditional centrality measures and risk rankings, focusing on identifying vulnerable companies that play a vital role in transmitting risk. Following Mirzasoleiman et al. (2012) we can effectively monitor network dynamics using our proposed Influence Maximization model to maximize joint influence and joint loss among potential crisis-involved companies. The research aims to uncover companies that, when affected by risk, can have far-reaching ripple effects. This understanding can help in comprehending risk propagation dynamics and enable regulators to control risk by placing these companies on a watch list.

We propose a new approach that provides a framework for understanding and addressing various crises resulting from different sources of shock. Our proposed centrality measure helps in identifying the role of firms and the transmission of risk across the network. Our model suggests that traditional centrality measures focusing on one type of relations are inadequate for effective market regulation. Crises, being rare events, can have substantial impacts on the economy, leading to significant losses. Identifying crucial sets of companies and predicting crisis paths in a network equips policymakers and regulators with effective tools to manage systemic risk from a new perspective. Investors can also use our findings to optimise their portfolios and mitigate risks associated with rare events. Ultimately, this work contributes to enhancing the understanding and management of systemic risk in financial networks, bolstering the resilience of the global financial network.

The rest of this work is organized as follows: section 2 is an overview of the data and methodology applied in this study, which covers stock similarity, sample and data,centrality measures, Influence Maximization, and risk estimation. Additionally, the results and relationship between centrality measures and firm characteristics is discussed in Section 3. Lastly, Section 4 provides a summary of the findings.

2. Data and methodology

2.1. Sample and data

Our sample includes the financial companies in the $S\&P500$ index between 2006 and 2023. The selected companies are with code 40 in the Global Industry Classification Standard in Banks, Insurance, and Financial Services industries. The sample covers the most important financial companies in the US market, making it a reliable representation of the US market. Our study period also includes three major crisis events: the US crisis of 2007-2009, the debt crisis in the EU (2010), and the COVID-19 pandemic (2020), making it an excellent sample for analyzing the relationship between systemic risk and network structure. For statistical reliability, we have set criteria to process our dataset. First, we removed stocks with trading suspensions lasting over one consecutive quarter. Second, we excluded stocks not listed at the beginning of the study period. Third, we eliminate any stocks that delisted before the period ended. As a result, we are left with 69 companies in $S\&P500$ to analyze. All data utilized in this study is sourced from Compustat and Factset.

2.2. Stock similarity measurement

When measuring similarity across stocks, one approach involves calculating the distance between the stocks' time series. Different aspects of their relations can be determined through these distances. According to Maharaj et al. (2019), there are various approaches to calculate distance, including raw-data-based, feature-based, and model-based methods. For instance, raw data can show dissimilarities in temporal data, particularly when time series have different lengths, with the Euclidean distance being commonly used in this category. Another approach involves computing distance based on correlations (Mantegna, 1999; Tumminello et al., 2010); auto-correlation models (D'Urso and Maharaj, 2009), periodograms(Caiado et al., 2020), and Hurst exponents (Cerqueti and Mattera, 2023; Lahmiri, 2016). Additionally, a model-based approach calculates dissimilarity across time series according to estimated parameters from forecasting models such as ARIMA (Piccolo, 1990), GARCH, (Otranto, 2008; D'Urso et al., 2016), measuring connectedness by variance decomposition models (Diebold and Yılmaz, 2014), or log-ARCH approach (Mattera and Otto, 2024).

In this study, four distances were employed to show dissimilarity across stocks: the Euclidean distance, the correlation approach introduced by Mantegna (1999), for the model-based approach we employ the log-ARCH estimation approach (Mattera and Otto, 2024), and the Generalized Variance Decomposition (GVD) approach (Diebold and Yılmaz, 2014) to quantify the extent of variations in one stock's time series can induce fluctuations in another stock's time series. In the first approach the distance across time series calculated as follows:

$$d_{ij} = \sqrt{\sum_{t=1}^{T}(x_{it} - x_{jt})^2}, \tag{1}$$

where x_{it} is the daily log return of stock i in time t, d_{ij} is the standard Euclidean distance between time series of stock i and j. For the second approach, ρ_{ij} as the correlation between stock i and j over time $t = 1, \ldots, T$ is estimated:

$$d_{ij} = \sqrt{2(1 - \rho_{ij})}. \tag{2}$$

We determine a connection between two stocks if they have high correlation. For the model-based approch, we define dissimilarity between stocks i and j by considering log-ARCH model. The distance between time series can define as follow (Piccolo, 1990):

$$d_{ij} = \sqrt{\sum_{p=1}^{\infty}(\gamma_{ip} - \gamma_{jp})^2}, \tag{3}$$

where γ_{ip} is the autoregressive coefficient of $AR(\infty)$ of order p of stock i. To avoid infinite sum in Equation 3 it is truncated at order p according to the Akaike or Bayesian information criterion. If the orders are different for stock i and j, we consider $p = max(p_1, p_2)$ and $\gamma_{ip} = 0$ for $p > p_1$ and $\gamma_{jp} = 0$ for $p > p_2$(Piccolo, 1990). These three distances convert to similarity with computing inverse of distances:

$$s_{ij} = \frac{1}{d_{ij}} \text{for all } i, j = 1, \ldots \text{n}, \tag{4}$$

where n is number of stocks and s_{ij} is similarity between stock i and j. Matrix S is dense and symmetric, which is directed with equal similarity in each direction. We choose the upper 90 percent of the highest values in the matrix to focus on important connections. Finally, according to the method introduced by Diebold and Yılmaz (2014), we build an adjacency matrix. This method uses the variance decomposition approach to describe the future values of the h-step ahead variance effect of stock i on stock j. The asymmetry of variance decomposition matrix allows us to construct directed links between stocks, enabling separate measurements of stock impact and vulnerability. The generalized variance decomposition matrix for H-step ahead $D^{(gH)} = [d_{ij}^{gH}]$ has entries (Diebold and Yılmaz, 2014):

$$d_{ij}^{gH} = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' \Theta_h \Sigma e_j)^2}{\sum_{h=0}^{H-1} (e_i' \Theta_h \Sigma \Theta_h' e_i)}, \tag{5}$$

where e_j is a selection vector with j^{th} element unity and zeros elsewhere, and e'_i is the transpose of e_i, Θ_h is the coefficient matrix multiplying the h-lagged shock vector in the infinite moving-average representation of the non-orthogonalized Vector Auto Regressive (VAR) model. Σ is the covariance matrix of the shock vector in the non-orthogonalized VAR, and σ_{jj}^{-1} is the j^{th} diagonal element of Σ. Sums of forecast error variance contributions are not necessarily unity. Hence, they base generalized connectedness indexes on $\tilde{D}^{gH} = [\tilde{d}_{ij}^{gH}]$, where $\tilde{d}_{ij}^{gH} = \frac{d_{ij}^{gH}}{\sum_{j=1}^{N} d_{ij}^{gH}}$. By construction, $\sum_{j=1}^{N} \tilde{d}_{ij}^{gH} = 1$ and $\sum_{i,j=1}^{N} \tilde{d}_{ij}^{gH} = N$. Using $\tilde{D}^{gH}$, generalized connectedness measures will calculate . The modified matrix $\tilde{D}^{gH}$ ensures that each row sums up to 1 and the sum of all entries in the matrix is equal to N(number of companies). Using $\tilde{D}^{gH}$, we can obtain generalized connectedness measures. From provided information, it can be inferred that this approach comprises directed weighted networks.

By integrating these diverse layers of interdependence, our multiplex network captures the richness of financial interactions and offers a framework for analysis. This approach enables us to capture cross-layer connections, providing a deeper understanding of relationships within financial network. Lastly, we measure systemic risk spillovers ($\Delta CoVaR$) that can describe the spillover risk on the entire market. Given this information, we construct a dynamic network model to estimate systemic risk of financial companies listed in $S\&P500$. In the following subsections, we present the Sample and network centralities.

2.3. Network centrality measures

To examine the interaction between the constructed multiplex network and risk spillovers, we employ centrality measures as variables to present their impact on the extent and pathways of risk contagion. Our study adopts various centrality measures, including Eigenvector centrality, Closeness centrality, and the Influence, to comprehensively assess the network's structural effects.The closeness centrality quantifies the proximity of each node to others in the network by determining the shortest path between a stock and all other accessible stocks. The equation is as follows:

$$CC_i = \frac{n-1}{\sum_{j=1}^{n} d(i,j)}, \tag{6}$$

where $\sum_{j=1}^{n} d(i,j)$ is the sum of all distances between stock i and other stocks. The importance of a stock in a network is quantified by the eigenvector centrality, which assesses its connections to other stocks. According to Billio et al. (2012) the equation is as follows:

$$EC_i = \frac{1}{\lambda}\sum_{j=1}^{n} a_{ji} EC_j, \tag{7}$$

where λ is the largest eigenvector of the adjacency matrix and a_{ji} is indicator of connection between stock j and i.

To estimate the Influence of each company in the network, we use the Independent Cascade Model which is used to model influence propagation for networks. It is a probabilistic model, assumes that each company has a threshold for activation and that once activated, it can activate its neighbors with a certain probability

(Easley et al., 2010). In the Independent Cascade Model:

$$P(A_t|A_{t-1}) = 1 - \prod_{v \in A_{t-1}} (1 - p_{vu}), \tag{8}$$

where A_t is the set of active companies at time t, A_{t-1} is the set of active companies at time $t-1$, and p_{vu} is the probability that company v activates company u. To calculate the Influence of each company in the Independent Cascade Model, one possible method is to use Monte Carlo simulation. This method involves running multiple simulations of the diffusion process, starting from a given seed set of companies and recording the number of companies that are activated for each simulation. The average number of activated companies across all simulations is then the Influence score for the seed set (Kempe et al., 2003). Our research find that while the flexible probability approach has advantages over other centrality measures, it can be limited by the fixed nature of the probability during different time periods. To address this limitation, we propose a time-varying probability approach that is based on the strength of the connection between each pair of companies. Under this approach, the higher the strength of the relationship between two companies, the higher the probability of risk transmission. Unlike the former approach that assumes equal probability for all edges in all quarters ($p_{uv} = p_{sw}$) (Easley et al., 2010), we consider different probabilities for each edge base on intensity of the connection, with $p_{uv}(t) \neq p_{sw}(t)$. In the proposed approach, the Independent Cascade model can be written as:

$$P(A_t|A_{t-1}) = 1 - \prod_{v \in A_{t-1}} (1 - p_{vu}(t)). \tag{9}$$

From a regulatory standpoint, monitoring all companies within a network to avoid substantial losses is a challenge. To address this issue, an appropriate approach involves identifying Influential sets using the Influence Maximization method, which will be discussed in the sub-section 2.4.

2.4. *Influence maximization*

Adopting a risk-based approach to effective supervision within the financial market becomes sensible. This strategy involves examining the key elements, like stocks, clusters, or sectors. As we will discuss subsequently, it's worth noting that the most vital stocks aren't solely those with the highest individual risk or those that have the most significant centrality across the network. Instead, we introduce a new approach by using the Influence Maximization approach that finds the set of stocks that have high systemic risk and simultaneously can transmit it to the largest portion of the network. This implies that if these key stocks were to encounter distress, they could impact a substantial number of companies (Chen et al., 2009).

The pioneering study by Domingos and Richardson (2001) marked one of the initial attempts to deep Influence Maximization is an algorithmic problem, utilizing probabilistic approaches. Following that, Kempe et al. (2003) framed the problem as a discrete optimization challenge, for subsequent research in this field.

They explore three cascade models: the independent, and the weight cascade models, and the linear threshold model. They explain that this problem is NP-hard. To tackle this challenge, they propose a greedy approximation algorithm for all three cascade models. The algorithm ensure that the Influence spread achieved is within a factor of $(1 - 1/e - \epsilon)$ of the optimal influence spread (where e is the base of the natural logarithm and ϵ is any positive real number). They also show that their algorithm outperforms classic degree and centrality-based heuristics in terms of influence spread. Let n be the number of companies, m be the number of connections, and S be the subset of companies selected to initiate the influence propagation, which is called the seed set. Let R number of rounds of simulations. The process of influence cascade from the seed set S is denoted as $RanCas(S)$, which results in a random set of companies being influenced by S. The goal is to take the input graph G and a number k and obtain a seed set S of size k. The primary objective is to maximize the expected number of companies activated by the seed set S. In summary, the algorithm aims to find an optimal seed set that maximizes the influence by selecting k companies from the graph G to initiate the influence cascade process.

The process of $RanCas(S)$ in the independent cascade (IC) model is as follows: consider A_i is the set of active companies in the i^{th} round, with A_0 initially set to the seed set S. For the connection $\overline{uv} \in E$, where u is in A_i and v has not yet been activated, v is activated by u in the $(i+1)^{th}$ round with an independent probability p. This is considered as the propagation probability. In other words, if there are neighbors of v that are already activated in A_i, v is added to A_{i+1} with a probability of $1 - (1-p)^l$ (l is the number of neighbors of v in A_i). This algorithm continues until $A_{i+1} = \emptyset$. It should be mentioned that in the random process $RanCas(S)$, each connection $\bar{uv}$ is determined once, either from u to v or from v to u, on whether the influence is propagated through this connection, but we consider two-way propagation and test it in both directions.

While this approach identifies the stocks that are vital for transmitting information within the network, it disregards the potential loss associated with these stocks. We propose an updated version of the Influence Maximization model that identifies the stocks that maximize potential loss (based on cumulative sum of firms' size) and influence simultaneously based on network topology.

In this new approach, the set of stocks that maximizes the interaction between the potential loss of each stock and its influence is chosen. This innovative method aims to optimize the selection process.

2.5. Risk estimation

To assign risk to each company dynamically, we estimate CoVaR based on the method proposed in Adrian and Brunnermeier (2016) and calculate $\Delta CoVaR$ to measure systemic risk and contribution of each company in the crisis in the market. Here, we calculate CoVaR of the market using $VaR_\alpha, \alpha = 95\%$ of market index or system (sys) and desired equity i.

Assuming stock i is distressed, its distress leads to a change in the VaR of the market. The CoVaR of system (sys) related to firm i is defined as:

$$Pr(R_s \leq CoVaR^{(sys|i)} \mid R_i = VaR^i) = q, \tag{10}$$

where R_s is the return of the market or system. Further, if a company falls into crisis, its risk spillover to the system is as follows:

$$\Delta CoVaR_{\alpha}^{(sys|i)} = CoVaR_{\alpha}^{(sys|VaR_{\alpha}^{i})} - CoVaR_{\alpha}^{(sys|VaR_{50\%}^{i})}. \tag{11}$$

3. Result and discussion

3.1. Summary statistics

We present the summary statistics in Table 1. The dependent variable, $\Delta CoVaR$, measures systemic risk, while the independent variables explain the network structure and control variables. The table also includes definitions, summary statistics, and sources of all the variables used in the analysis. The firms we studied exhibited an average systemic risk contribution, as measured by $\Delta CoVaR$, of 1.26. Regarding network centrality for the Euclidean layer, the average Closeness Centrality (CC) and Eigenvector Centrality EG are 0.24 and 0.07, respectively. The average Influence of fixed and time-varying probability were from 1.08 to 1.03. Moreover, the average firm had a market capitalization natural logarithm of 9.86, a return on assets of 2.71, a β of 1.29, a debt-to-equity ratio of 1.23, and a VaR of 3.34. Table 2 presents the correlation matrix for the firm-level variables and centrality measures of the correlation layer utilized in our analysis. A notable correlation of 0.62 between the systemic risk measure $\Delta CoVaR_t$ and VaR, suggests that companies with higher risk profiles may exert a more substantial impact on the market. Additionally, the network centrality measures exhibit significant correlations, averaging around 0.71. This indicates that these measures are not perfectly correlated, capturing distinct aspects of connections. The systemic risk measure $\Delta CoVaR_t$ exhibits positive correlations with CC_{t-1}, EG_{t-1}, and Influenc$_{t-1}$. This implies that firms with higher scores in centrality metrics are likely to contribute more to future systemic risk.

3.2. Network construction

For capturing the stocks' interdependency, we create 64 quarterly directed weighted networks for each layer using Euclidean, Correlation, and ARIMA distances, as well as Variance Decomposition. To identify the stationarity of the time series of stocks the ADF test is performed. Subsequently, networks of connections were constructed, where stocks serve as nodes and their similarity (inverse of the distance of each pair of stocks) serves as the weight of the edge between them. It is crucial to select the optimal number of edges to eliminate redundant connections in order to establish the network. This paper emphasizes the use of the 90% percentile as a criterion to consider the most similar stocks and to avoid less reliable edges.

The significant and increase in the number of edges can be a clear signal for systemic risk (Billio et al., 2012). To capture similarity between stocks, we employ lines connecting two stocks, color-coded based on the intensity of the edge weights between two stocks in quarter t signifying substantial similarity to another stock's log return series. We plot the fluctuation in the number of connections within ARIMA and Variance Decomposition layers throughout our sample period, providing a visual depiction of connection dynamics during pre-crisis (2007Q1, 2019Q2), post-crisis (2009Q3, 2020Q3) periods and two recession periods (2008Q4, 2020Q1) identified by NBER in the sample. The data clearly shows a substantial increase in the number of edges and the intensity of connections during crisis periods as compared to other periods, indicating a significant rise in network co-movement during crises (Figures 2, 3). It is evident from the figures that each layer responds differently to crises, with some reacting more stronger than others. For instance, the Variance Decomposition layer experiences a significant increase in the number and intensity of connections during the 2008 financial crisis, but the ARIMA layer has a smother response to this crisis while, in Covid-19, the ARIMA layer has more significant changes during the crisis compared to Variance Decomposition Layer. These findings highlight the dynamics of each layer and their ability to shed light on different aspects of the impact of crises on company relations. It can be concluded that an increase in connections is a clear indicator of market crises. The dynamic topological features of the network effectively capture the time-varying interactions among stocks, prominently highlighting the peaks during significant financial crises. These outcomes align with the observations in Billio et al. (2012); Huang et al. (2023) supporting the notion that financial market interconnectedness experiences a substantial surge during periods of crisis.

Our analysis involves the creation of a multi-layer network at quarterly intervals, capturing the dynamic nature of interactions among entities. Within each quarter, we compute key centrality measures: Influence, Closeness, and Eigenvector. These centrality metrics serve as tools for gauging companies' significance and their evolving roles across distinct quarters.

The relationship between network centralities and systemic risk is previewed in Figure 1, which displays $\Delta CoVaR$ against network centralities in each of the four layers. The weighted average of systemic risk indicator and centrality measures was computed based on market cap values, and the average values were plotted against quarters. The Euclidean layer, Correlation layer, ARIMA layer, and Variance decomposition layer are described in (a) to (d) of Figure 1, each with its own unique structure and dynamics. Clear jumps coinciding with the increase in systemic risk are observed in the layers. It is observed that "Influence" centrality aligns significantly with changes in ΔCoVaR across all layers, indicating its effectiveness in predicting systemic risk. In the ARIMA layer, Closeness centrality not only correlates with ΔCoVaR but also displays a notable response to the COVID-19 pandemic, more so than to other crises. Additionally, the study emphasizes how Eigenvector centrality demonstrates significant fluctuations during crises. These four layers have two distinct surges corresponding to the 2008 crisis and the COVID-19 crisis. Overall, these figures highlight a strong relationship between network centrality measures and systemic risk. Multiplex networks holds the potential to provide a greater amount of information compared to the single-layer networks. Each layer is unique in its relationship between network centrality and systemic risk, suggesting that each layer can aid in predicting systemic risk with greater precision. Variations observed in the topological structures serve as indicators that the phenomenon of risk spillover among companies is not static; it evolves over time.

3.3. Network centrality and risk spillover

During periods of company crisis, there is a possibility of creating a ripple effect that spreads through different layers of interconnected entities. This could potentially lead to a chain reaction of crises or shocks throughout the network. To determine the risk of spillover through risk contagion and shock transmission channels, we analyze the relationship between individual risks and the network topology using panel regression, as expressed in the Equation 12:

$$\Delta CoVaR^{\alpha}_{i,t} = \gamma CM_{i,t-1} + \nu VaR^{\alpha}_{i,t-1} + \Sigma_k \zeta_k X_{i,t-1} + \mu_i + \epsilon_{i,t}, \tag{12}$$

where $CM_{i,t-1}$ identifies a network centrality measure, includes $EG_{i,t-1}, CC_{i,t-1}, Inf_{i,t-1}, Inf^{D}_{i,t-1}$ are Eigenvector, Closness, Influence with fix contagion probability and Influence with Dynamic contagion probability as multiplex network centrality indicators respectively. Additionally, $VaR^{\alpha}_{i,t-1}$ denotes Value at Risk for company i and $\alpha = 0.95$, $X_{i,t-1}$ is firm-specific variables includes Size, ROA, β, Debt to equity and EPS growth, μ_i is firm fixed effects and $\epsilon_{i,t}$ is an error term, β_0 is a constant. In addition, as a result of the quarterly report of financial ratios, we calculate $\Delta CoVaR^{\alpha}_{i,t}$ based on average daily of $\Delta CoVaR^{\alpha}_{i,t}$ in each quarter. The results of the panel regressions, spanning the period from 2007 to 2023, are reported in Table 3.

Table 3 presents the regression results for the Euclidean layer in columns 1 to 4 and the Correlation layer in columns 5 to 8. The Variance decomposition layer is presented in the latter half of the table, in columns 1 to 4, and the ARIMA layer results in columns 5 to 8. $\Delta CoVaR$ is the dependent variable in all tables.

As Table 3 highlights a significant link between centrality measures and systemic risk, suggesting stocks in more central positions could play a larger role in spreading risk through the network in the next quarter. Considering the correlation between Influence centrality and $\Delta CoVaR$, both suggested measures of Influence (Dynamic and Static) are remarkably significant across all layers. Additionally, the coefficients of Dynamic Influence exceed those of the static measure, suggesting improved predictive abilities for this centrality measure. While the Closeness centrality has main role in Correlation and Euclidean layers reflected by adjusted R^2 values of to 25% and 21% respectively, its impact diminishes in the ARIMA layer, where the adjusted R^2 drops to 13%. In the Variance Decomposition layer, this centrality measure is not significant. This can be attributed to the different structure of this layer compared to the others, as it is computed based on the VAR model rather than the distance of the log return series. Like the Closeness centrality, Eigenvector centrality plays an important role in the Correlation and Euclidean layers, with adjusted R^2 equal to 21% and 14% respectively. This indicates that firms are connected through many centrally positioned firms. Such firms can transmit their firm-specific risk to more firms and are more likely to play a role in future systemic events. However, this centrality measure is not significant in other layers.

The number of edges in the correlation layer being higher than in other layers means that the centrality measure coefficients are also more significant in this layer compared to others. This extensive network of connections is linked to an increase in $\Delta CoVaR$. The more interconnected the network is, the greater the chance of spreading financial distress and the higher the systemic risk vulnerability. Conversely, elevated $\Delta CoVaR$ levels could encourage a more interconnected network. Firms facing increased risks might transmit these to the network, thus potentially seeking to establish more connections with partners. This strategy may aim at risk diversification, securing more funding, or enhancing overall resilience. This finding is align with the research of Billio et al. (2012).

Based on Table 3, when it comes to crisis, the larger the size of the firm, the more contribution in transmitting system risk, due to Table 2, the correlation between centrality measures and size shows that larger firms have more connections and they have more tendency to join domino effect in crisis. The increase in idiosyncratic risk of the firms (Value at Risk) leads to more possibility of triggering systemic risk or playing a major role in transmitting it to the network. According to our analysis, this variable is the most important parameter in predicting upcoming systemic risk situations. When the financial performance, notably ROA (Return on Assets) and EPS (Earnings Per Share) growth, of firms shows improvement, their contribution to systemic risk tends to decrease. This correlation may be attributed to a stronger financial structure within these companies, which reduces their inclination to accumulate debt. Firms burdened with higher levels of debt are more susceptible to being part of a cascading failure, a domino effect where the financial distress of one firm can lead to the downfall of others.

Furthermore, β, a parameter that describes the relationship between a stock's return and the market index, emerges as a significant predictor of risk. A higher dependency on the market index signals a greater potential for a firm to be involved in a network crash. The more a firm's stock return is influenced by market movements, the more likely it is to contribute to systemic instability. These results highlight the role of central firms in the network that can absorb and transmit risk to the whole market.

To better understand the relationships between firms in a multiplex network, we consider all aspects of their relations simultaneously. The results obtained for analyzing a single layer network are appropriate, but not sufficient. Following the approach suggested by Hmimida and Kanawati (2015), we can aggregate the centrality measures of our layers by using an entropy-like aggregation function as follows:

$$CM_i^{multi} = -\Sigma_{m=1}^{M} \frac{CM_i^m}{CM_i^T} ln(\frac{CM_i^m}{CM_i^T}). \tag{13}$$

The index of multilayer centrality for firm i after aggregation is represented by CM_i^{multi} in this Equation. CM_i^m indicates the centrality measure of layer m for firm i, while $CM_i^T = \Sigma_{m=1}^{M} CM_i^m$ is the sum of centrality measures in all layers for firm i, T stands for Total. The CM_i^{multi} will reach its maximum value if a firm is equally connected in each layer, and it will be null if it is only connected in one layer. Hence, the more connected a firm is in different layers, the more impactful it becomes. To further analyze the relation between centrality measures and systemic risk, the panel regression is conducted as follows:

$$\Delta CoVaR_{i,t}^{\alpha} = \gamma CM_{i,t-1}^{multi} + \nu VaR_{i,t-1}^{\alpha} + \Sigma_k \zeta_k X_{i,t-1} + \mu_i + \epsilon_{i,t}. \quad (14)$$

Table 4 presents the results of the regression analysis based on Equation 14. The findings from the table underscore the significant impact of centrality measures on ΔCoVaR within an aggregated network framework. Notably, a unit change in both Dynamic and Static Influence measures, with coefficients of 0.421 and 0.413 respectively, triggers more pronounced alterations in ΔCoVaR compared to similar changes in Closeness and Eigenvector centralities, which have coefficients of 0.276 and 0.203 respectively. A key advantage of leveraging Influence centrality is its foundation on the contagion probabilistic model, lending it heightened sensitivity to network structure and enabling it to account for varying scenarios of propagation with dynamic probability through simulations in the Independent Cascade model. Parallel to observations made in single-layer networks, both Return on Assets (ROA) and the Growth of EPS manifest a reducing impact on systemic risk. Furthermore, the aggregated data analysis is inline with findings from single-layer panel regressions regarding firm size, idiosyncratic risk, the β coefficient, and the debt-to-equity ratio, all of which are identified as factors contributing positively to systemic risk. Taken together, by integrating different layers, our approach capture various dimensions of stock interrelations to construct a predictive model for systemic risk, tailored to address crises originating from diverse sources. This model leverages aggregated centrality measures to enhance informational depth for more accurately predicting ΔCoVaR.

To assess the robustness of our main results, we conducted a test using panel regression analysis in two periods: during recession and during normal times. The results, which are presented in Table 5, show that the coefficients of centrality variables mostly remained unchanged between the two periods, indicating that the multi-layer network structure has a stable and long-term effect on systemic risk. During the Recession period, the estimated coefficients of centrality measures are larger (about two times and more) than those in the normal period, suggesting that the centrality measures play a more important role during crises. Similar to the whole sample period, the increase in VaR and β and firm's size impact the systemic risk positively.

3.4. Influence adjusted loss

An important application of Influence Centrality through the Influence Maximization method is the ability to compute the joint influence of a set of stocks. This capability is unique to Influence Maximization and is not achievable with other centrality measures such as Closeness or Eigenvector centrality. we employ an Influence Maximization algorithm to identify sets of influential stocks within a network. These stocks possess the capacity to initiate shocks, and if they become distressed simultaneously, they have the potential to propagate risk across a substantial portion of the network, potentially resulting in significant losses.

Traditionally, Influence Maximization focuses on identifying the most influential nodes based on their ability to disseminate information. We extend this approach to uncover the most dangerous sets of nodes—those capable of transmitting risk to the highest number of nodes and causing the greatest total cumulative loss, considering the size of the companies involved. By identifying these nodes, regulators can effectively immunize the network by targeting these critical nodes for enhanced monitoring and risk management. Ensuring the financial health of these key nodes enables regulators to manage systemic risk more effectively. Within each time period, we select five companies through this algorithm, assigning a distinct level of importance to each company in a specific order. The foremost company, seed 1, holds the highest importance, followed by the sequentially less important companies up to seed 5. Figure 4a illustrates the nodes selected through our revised Influence Maximization algorithm 2020Q1 in Euclidean layer. In this figure, the size of the nodes corresponds to their market value, with the selected stocks highlighted in orange. The companies selected include JP Morgan (bank), CME Group (financial services), Prologis (real estate), Ventas (real estate), and Black Rock (financial services). These selected stocks belong to diverse sectors and vary in size, demonstrating the algorithm's ability to identify influential nodes across different industry groups. Figure 4b describes the influential set of stocks in the correlation layer for the same period (2020Q1). Here, the selected stocks highlighted in orange are JP Morgan (bank), CME Group (financial services), Prologis (real estate), Ventas (real estate), and Equifax (financial services). Notably, four companies—JP Morgan, Prologis,CME Group and Ventas—are present in both layers, underscoring their significance from multiple perspectives.

The consistent selection of JP Morgan, Prologis, and Ventas across different layers highlights their critical positions within the network. This finding emphasizes the importance of these companies in maintaining systemic stability. By immunizing these key stocks, the risk originating from any other stock can be contained within local neighborhoods, preventing its propagation to other parts of the network.

As depicted in these figures, our approach selects stocks based on a combination of their central position within the network and the cumulative summation of companies' market size that will involve a domino effect. This dual criterion ensures that the chosen nodes are not only well-positioned to transmit risk but also represent significant economic entities. This comprehensive strategy enables a more effective identification of critical nodes, enhancing the ability to manage and mitigate systemic risks.

When compared to alternative approaches, such as selecting stocks based on their network position (e.g., nodes with the highest centrality measures like Closeness and Eigenvector centrality), our proposed method offers a more comprehensive solution.

In Table 6, it is evident that in the Euclidean layer, four nodes—JPM, BAC, PNC, and USB—appear in both Closeness and Eigenvector centrality measures. These nodes are close neighbors (see Figure 4a), and immunizing them would only protect a portion of the network rather than the entire network. This pattern repeats in the correlation layer, where Closeness and Eigenvector centralities have four common stocks—C, BAC, JPM, and AMP—with three of them (C, BAC, JPM) being close neighbors (see Figure 4b). As a result, immunizing these nodes would again only mitigate risk for a portion of the network. By integrating both Influence centrality and firm sizes, our approach identifies stocks that are critical both in terms of their potential to propagate risk and the magnitude of the impact they could have if distressed.

Our analysis across different quarters confirms the effectiveness of this approach. It consistently selects nodes that play a pivotal role in the network, thereby providing regulators with targeted insights into which companies to monitor closely. This strategic focus on the most dangerous nodes allows for more efficient and effective risk management, ultimately contributing to greater systemic stability.

4. Conclusion

In conclusion, our study develops a multi-layer network designed to capture various facets of risk contagion. This complex network encompasses distinct risk channels, including Correlation, Euclidean and ARIMA distances, and variance decomposition layers. A notable feature introduced is the Influence measure, which serves as a centrality metric that is able to utilize the probability of contagion for each connecting edge to estimate how a single stock might affect others on average. This Influence measure is adaptable to changing probabilities of contagion based on the intensity of the connection, enhancing the ability to predict systemic risk. In an effort to gauge the predictive capability of this centrality in relation to systemic risk, the study establishes a network comprising four layers, setting the scene for a comparison between Closeness, Eigenvector, and Influence centrality measures. Aggregating these centrality measures, lead to obtain different aspects of connections across stocks. By calculating centrality and estimating $\Delta CoVaR$ for each company, utilizing panel regression, yielding compelling evidence that our innovative multi-layer network possesses a remarkable predictive power for $\Delta CoVaR$. Evidently, Influence emerges as the most pivotal centrality measure within this predictive framework. We undertake an analysis to ascertain whether influential companies propagate risk to neighboring counterparts. Our findings demonstrate that strategically positioned influential companies have the ability to both propagate and alleviate risk.

Aiming to deliver practical tools for regulators and investors, we formulate a new version of Influence Maximization model. This model systematically identifies companies with major Influence with the largest possible loss, capable of transmitting risk or information extensively across the network. The results of our model demonstrate its significant utility in identifying and mitigating systemic risks within financial networks. By focusing regulatory efforts on the healthiness of the top five most critical stocks, we can greatly enhance the robustness and resilience of the entire network. This proactive approach not only helps in averting potential crises but also in ensuring sustained economic stability. By incorporating these companies, regulators can adopt a risk-based approach strategy that avoids exhaustive scrutiny of all companies of the network.

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Algorithm 1 Influence Maximization in Financial Networks

$G \leftarrow$ Financial network graph

$K \leftarrow$ Number of seed nodes

Iterations $\leftarrow$ Number of simulations in IC model

$p \leftarrow$ Propagation probability

$S \leftarrow \emptyset$ ▷ Initialize the seed set

$Size \leftarrow$ Normalized firm's size

while $|S| < K$ **do**

  $M \leftarrow []$ ▷ For storing node scores

  for $u \in S$ **do**

    for $v \in G$ *and* $v \notin S$ **do**

      $S' \leftarrow S \cup \{v\}$

      $influence \leftarrow \text{avgSize}(G, S', p, \text{Iterations})$

      $loss \leftarrow \sum_{u \in S'} \text{Size}(u)$

      $score \leftarrow influence \times loss$

      append $(v, score)$ **to** M

    end

    $M \leftarrow$ Sort M by score in descending order

    $v \leftarrow$ Node with highest score in M

    append v **to** S

  end

end

Output: S ▷ Final set of seed nodes

Algorithm 2 Influence Maximization Functions

avgSize function:

Input: $G \leftarrow$ Graph, $S \leftarrow$ Seed set, $p \leftarrow$ Propagation probability, $iterations \leftarrow$ Number of iterations

$avg \leftarrow 0$

for $i \leftarrow 1$ *to iterations* **do**

$result \leftarrow \text{runIC}(G, S, p)$

$avg \leftarrow avg + \frac{\text{length}(result)}{iterations}$

end

Output: avg ▷ Average number of influenced nodes

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runIC function

Input: $G \leftarrow$ Graph, $S \leftarrow$ Seed set, $p \leftarrow$ Propagation probability

$T \leftarrow$ Deep copy of S ▷ Copy already selected nodes

$i \leftarrow 0$

while $i < length(T)$ **do**

for $v \in$ *neighbors of* $T[i]$ **do**

if $v \notin T$ **then**

▷ If v wasn't selected yet

$w \leftarrow G.\text{number\_of\_edges}(T[i], v)$ ▷ Count the number of edges between two nodes **if**

$random.uniform(0, 1) < 1 - (1 - p)^w$ **then**

▷ If at least one edge propagates influence

append v to T

end

end

end

$i \leftarrow i + 1$

end

Output: T ▷ Set of influenced nodes

Table 1: Summary statistics and variable definitions

Variables	Definition	# obs	Mean	25	50	75	S.d.	Source
Dependent Variable:								
ΔCoVaR	Systemic risk measure	4322	1.26	0.74	1.08	1.57	0.76	Author calculations
Network centralities:								
CC	Closeness centrality	4322	0.24	0.020	0.29	0.36	0.16	Author calculations
EG	Eigenvector centrality	4322	0.07	0.000	0.013	0.15	0.09	Author calculations
Influence	Influence with fix probability	4322	1.08	1.01	1.05	1.13	0.08	Author calculations
Influence$_D$	Influence with dynamic probability	4322	1.03	1.00	1.02	1.05	0.03	Author calculations
Control variables:								
Size	Natural logarithm of firm size	4322	9.86	9.15	9.79	10.48	1.04	Compustat database
ROA	Return on Asset	4322	2.71	0.62	1.30	3.32	4.41	Compustat database
β	Systematic risk using $S\&P500$ index	4322	1.29	0.75	1.09	1.42	0.56	Compustat database
D2E	Debt to Equity ratio	4322	1.23	0.36	0.84	1.51	2.969	Compustat database
VaR	Value at Risk at 5%	4322	3.34	1.99	2.60	3.70	2.40	Author calculations
GEPS	Growth rate of Earning Per Share	4322	0.67	-33.66	-1.54	22.22	624.15	Compustat database

Table 2: Correlation matrix of variables used in the regression

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\Delta CoVaR_t$	1									
$Size_{t-1}$	0.187	1								
ROA_{t-1}	-0.071	0.008	1							
β_{t-1}	0.226	-0.043	-0.161	1						
$D2E_{t-1}$	0.041	0.117	-0.132	0.021	1					
VaR_{t-1}	0.619	-0.290	-0.180	0.383	0.041	1				
$GEPS_{t-1}$	-0.010	0.011	0.032	-0.006	-0.001	-0.023	1			
CC_{t-1}	0.111	0.193	0.0793	-0.184	0.012	0.20	-0.0184	1		
EG_{t-1}	0.066	0.109	0.084	-0.115	-0.002	0.113	-0.015	0.655	1	
Influence$_{t-1}$	0.062	0.115	0.041	-0.19	0.005	0.153	-0.025	0.695	0.796	1

Table 3: The impact of network structure on systemic risk

	Euclidean layer				Correlation layer			
Independent variables	$\mathbf{CC_{t-1}}$	$\mathbf{EG_{t-1}}$	$\mathbf{INF_{t-1}}$	$\mathbf{INF^{D}_{t-1}}$	$\mathbf{CC_{t-1}}$	$\mathbf{EG_{t-1}}$	$\mathbf{INF_{t-1}}$	$\mathbf{INF^{D}_{t-1}}$
CM_{t-1}	0.5078***	0.3824***	0.5407***	1.3052***	0.6499***	0.7660***	0.7851***	1.9172***
	(20.88)	(9.89)	(11.78)	(10.94)	(26.92)	(21.20)	(19.30)	(16.77)
$Size_{t-1}$	0.0142***	0.0239***	0.0229***	0.0226***	0.0148***	0.0248 ***	0.0227***	0.0228***
	(3.90)	(6.39)	(6.16)	(6.07)	(4.22)	(6.94)	(6.28)	(6.23)
ROA_{t-1}	-0.4526***	-0.2887***	-0.2824***	-0.2781***	-0.5546***	-0.4878***	-0.4415***	-0.3940***
	(-5.72)	(-3.54)	(-3.49)	(-3.42)	(-7.21)	(-6.16)	(-5.54)	(-4.92)
$Beta_{t-1}$	0.1808***	0.1798***	0.1846***	0.1826***	0.1415***	0.1472***	0.1554***	0.1590***
	(24.92)	(23.88)	(24.59)	(24.29)	(19.70)	(19.88)	(20.97)	(21.25)
VaR_{t-1}	0.0242***	0.0452***	0.0423***	0.0455***	0.0552***	0.0542***	0.0542***	0.0542***
	(6.35)	(11.96)	(11.17)	(12.19)	(16.17)	(15.40)	(15.28)	(15.14)
$D2E_{t-1}$	0.003**	0.0045***	0.0044***	0.0043***	0.0038***	0.0038**	0.0043***	0.0042***
	(2.96)	(3.70)	(3.64)	(3.56)	(3.36)	(3.27)	(3.70)	(0.0003)
$GEPS$	-0.0011*	-0.0012*	-0.0011*	-0.0012*	-0.0012*	-0.0013*	-0.0011*	-0.0012*
	(-2.04)	(-2.24)	(-2.10)	(-2.14)	(-2.18)	(-2.49)	(-2.06)	(-2.15)
R^2	21%	14%	15%	15%	25%	21%	19%	18%
# of obs	4322	4322	4322	4322	4322	4322	4322	4322
	VAR layer				**AR layer**			
Independent variables	$\mathbf{CC_{t-1}}$	$\mathbf{EG_{t-1}}$	$\mathbf{INF_{t-1}}$	$\mathbf{INF^{D}_{t-1}}$	$\mathbf{CC_{t-1}}$	$\mathbf{EG_{t-1}}$	$\mathbf{INF_{t-1}}$	$\mathbf{INF^{D}_{t-1}}$
CM_{t-1}	-0.1260	-0.0083	0.3094***	0.3190***	0.1321***	0.0427	0.1360**	0.1562**
	(-2.02)	(-0.15)	(13.30)	(13.40)	(3.59)	(1.17)	(2.61)	(2.81)
$Size_{t-1}$	0.0265***	0.0265***	0.0206***	0.0205***	0.0268***	0.0270***	0.0268***	0.0269***
	(6.90)	(6.89)	(5.43)	(5.40)	(7.13)	(7.17)	(7.13)	(7.16)
ROA_{t-1}	-0.2231**	-0.2180**	-0.3406***	-0.3434***	-0.1785*	-0.1812*	-0.1804*	-0.1764*
	(-2.65)	(-2.59)	(-4.11)	(-4.14)	(-2.18)	(-2.21)	(-2.20)	(-2.16)
$Beta_{t-1}$	0.1755***	0.1757***	0.1599***	0.1597***	0.1783***	0.1796***	0.1794***	0.1789***
	(22.71)	(22.72)	(20.88)	(20.86)	(23.41)	(23.57)	(23.57)	(23.48)
VaR_{t-1}	0.0539***	0.0538***	0.0550***	0.0550***	0.0544***	0.0546***	0.0547***	0.0545***
	(14.48)	(14.43)	(15.08)	(15.09)	(14.73)	(14.76)	(14.81)	(14.76)
$D2E_{t-1}$	0.0036**	0.0036**	0.0030*	0.0030*	0.0047***	0.0047***	0.0047***	0.0047***
	(2.60)	(2.62)	(2.22)	(2.22)	(3.86)	(3.87)	(3.88)	(3.89)
$GEPS$	-0.0016**	-0.0016**	-0.0015**	-0.0015**	-0.0013*	-0.0013*	-0.0013*	-0.0013*
	(-2.71)	(-2.69)	(-2.64)	(-2.67)	(-2.36)	(-2.39)	(-2.38)	(-2.40)
R^2	12%	12%	16%	16%	13%	12%	13%	14%
# of obs	4158	4158	4158	4158	4322	4322	4322	4322

Note: This table shows the panel regression results for an unbalanced panel of financial companies listed in $S\&P500$ over the period of 2007–2023. The t-statistics of the parameters are reported in parentheses. Firm fixed effects are included in all regressions. The $*, **, and ***$ indicate significance at the levels of 0.1, 0.05, and 0.01, respectively.

Table 4: The impact of aggregated network structure on systemic risk

Independent variables	$\mathbf{CC_{t-1}}$	$\mathbf{EG_{t-1}}$	$\mathbf{INF_{t-1}}$	$\mathbf{INF^{D}_{t-1}}$
CM^{multi}_{t-1}	0.2757***	0.2033***	0.4130***	0.4208***
	(19.09)	(18.73)	(5.79)	(5.91)
$Size_{t-1}$	0.0213***	0.0210***	0.0268***	0.0269***
	(5.89)	(5.77)	(7.16)	(7.16)
ROA_{t-1}	-0.4134***	-0.3923***	-0.1997*	-0.2005*
	(-5.20)	(-4.94)	(-2.44)	(-2.46)
$Beta_{t-1}$	0.1713***	0.1564***	0.1777***	0.1776***
	(23.38)	(21.06)	(23.39)	(23.39)
VaR_{t-1}	0.0456***	0.0462***	0.0546***	0.0545***
	(12.73)	(12.89)	(14.81)	(14.81)
$D2E_{t-1}$	0.0041***	0.0033**	0.0045***	0.0045***
	(3.51)	(2.75)	(3.70)	(3.69)
$GEPS_{t-1}$	-0.0011*	-0.0013*	-0.0014*	-0.0014*
	(-2.06)	(-2.38)	(-2.41)	(-2.40)
R^2	19%	19%	14%	14%
# of obs	4322	4322	4322	4322

Note: This table shows the panel regression results of aggregated centrality measures for an unbalanced panel of financial companies listed in $S\&P500$ over the period of 2007–2023. The t-statistics of the parameters are reported in parentheses. Firm fixed effects are included in all regressions. The $*, **, and ***$ indicate significance at the levels of 0.1, 0.05, and 0.01, respectively.

Table 5: The impact of network structure on systemic risk

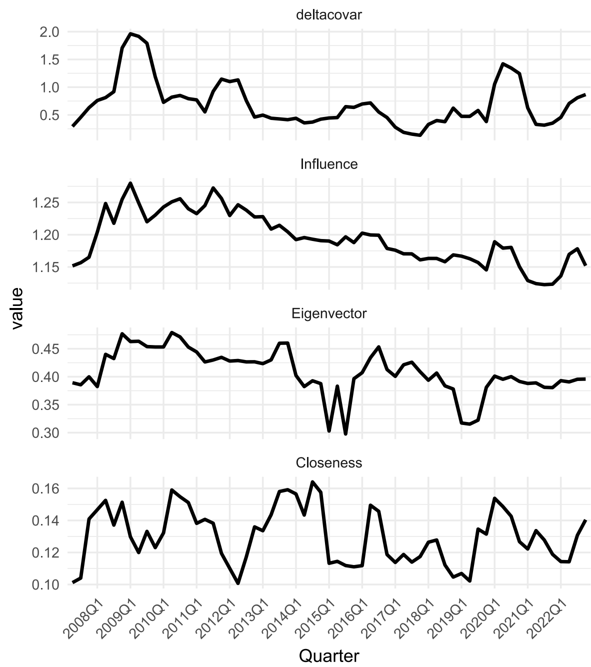
	Normal				Recession			
Independent variables	$\mathbf{CC_{t-1}}$	$\mathbf{EG_{t-1}}$	$\mathbf{INF_{t-1}}$	$\mathbf{INF^{D}_{t-1}}$	$\mathbf{CC_{t-1}}$	$\mathbf{EG_{t-1}}$	$\mathbf{INF_{t-1}}$	$\mathbf{INF^{D}_{t-1}}$
CM^{multi}_{t-1}	0.2524***	0.1894***	0.3524***	0.3583***	0.4948***	0.4***	1.2123**	1.2645**
	(18.62)	(18.98)	(5.39)	(5.49)	(7.32)	(6.46)	(2.69)	(2.82)
$Size_{t-1}$	0.0203***	0.0192***	0.0255***	0.0255***	0.0294*	0.034*	0.0342*	0.0345*
	(5.77)	(5.46)	(6.96)	(6.96)	(2.21)	(2.54)	(2.48)	(2.50)
ROA_{t-1}	-0.3439***	-0.3324***	-0.1220	-0.1225	-0.6421*	-0.5928*	-0.4653	-0.4699
	(-4.33)	(-4.20)	(-1.49)	(-1.50)	(-2.49)	(-2.28)	(-1.74)	(-1.76)
$Beta_{t-1}$	0.1594***	0.1466***	0.1679***	0.1679***	0.2639***	0.2230***	0.2362***	0.2356***
	(22.78)	(20.75)	(23.07)	(23.08)	(8.64)	(7.26)	(7.50)	(7.49)
VaR_{t-1}	0.0369***	0.0378***	0.0455***	0.0455***	0.0752***	0.0708***	0.0840***	0.0839***
	(10.08)	(10.36)	(12.03)	(12.02)	(6.75)	(6.23)	(7.31)	(7.31)
$D2E_{t-1}$	0.0032**	0.0022	0.0035**	0.0035**	0.0068	0.0068	0.0076	0.0075
	(2.83)	(1.93)	(2.95)	(2.94)	(1.61)	(0.11)	(1.75)	(1.72)
$GEPS$	-0.0014**	-0.0017**	-0.0017**	-0.0017**	0.0004	0.0007	0.0007	0.0007
	(-2.72)	(-3.15)	(-3.14)	(-3.13)	(0.21)	(0.35)	(0.32)	(0.35)
R^2	21%	22%	15%	15%	18%	17%	12%	12%
# of obs	3713	3713	3713	3713	609	609	609	609

Note: This table shows the panel regression results for an unbalanced panel of financial companies listed in $S\&P500$ over the period of 2007–2023. The t-statistics of the parameters are reported in parentheses. Firm fixed effects are included in all regressions. The $*, **, and ***$ indicate significance at the levels of 0.1, 0.05, and 0.01, respectively.

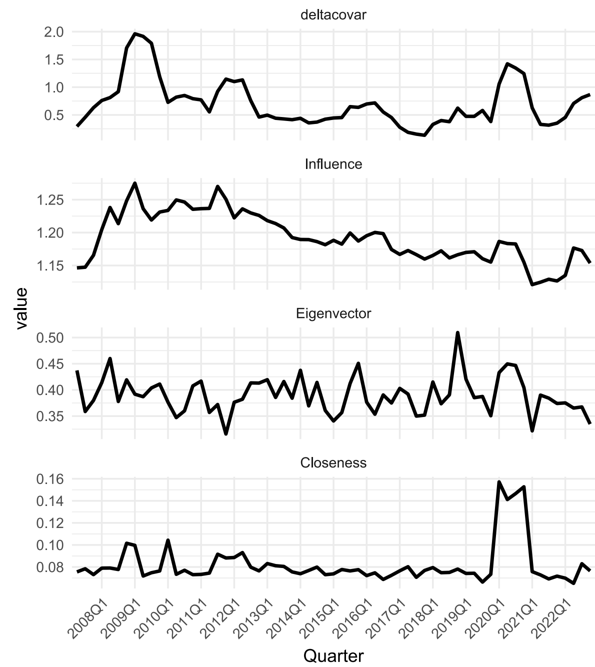
Table 6: The Most Central Nodes

	Euclidean layer			Correlation layer		
Node	**InfMax**	**CC**	**EG**	**InfMax**	**CC**	**EG**
1	JPM	BAC	PNC	JPM	AMP	C
2	CME	JPM	BAC	CME	LNC	BAC
3	PLD	PNC	JPM	PLD	JPM	JPM
4	VTR	GS	USB	VTR	C	PNC
5	BLK	USB	HBAN	EFX	BAC	AMP

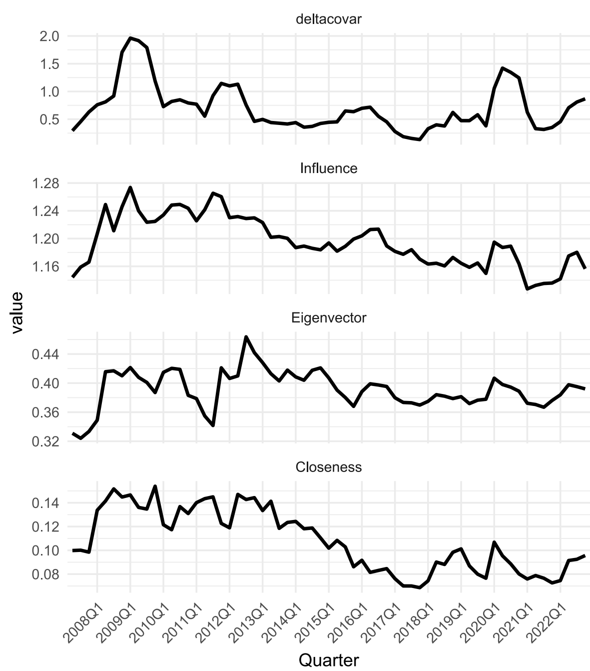
Note: This table shows the set of 5 nodes (Ticker ID) selected by the Influence Maximization (InfMax) and the most central nodes according to Closeness (CC), and Eigenvector Centralities (EG)) for Euclidean and Correlation layers in 2020Q1



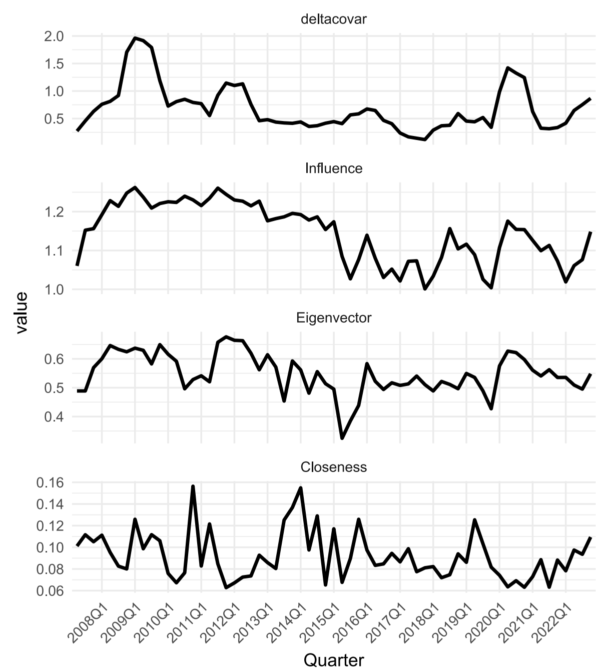
(a) Euclidean Layer



(b) ARIMA Layer

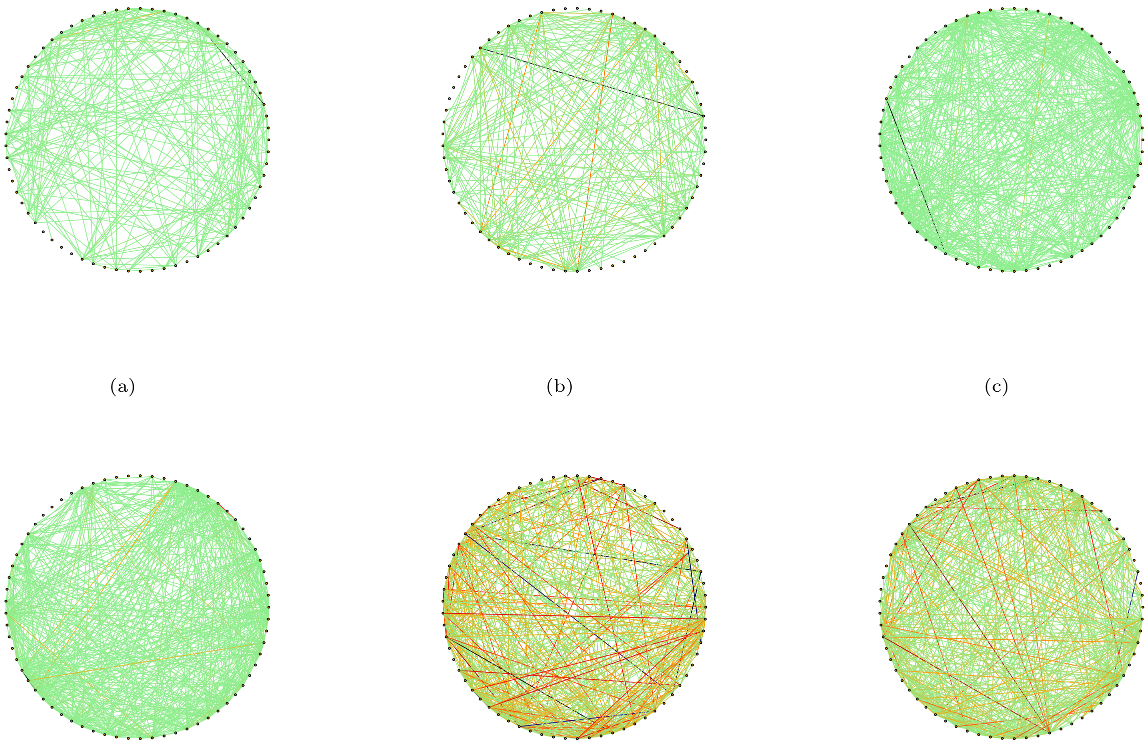


(c) Correlation Layer



(d) Variance Decomposition Layer

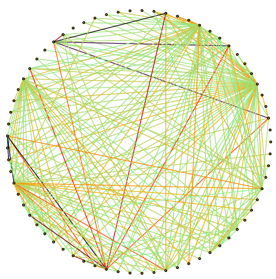
Figure 1: Centrality measures and Systemic Risk. This figure plots the ΔCoVaR, Influence, Eigenvector and Closeness from top to down, for financial companies listed in S&P500 from 2007Q1-2022Q4. (a) Risk and Centrality measures for Euclidean Layer, (b) ARIMA Layer, (c) Correlation Layer and (d) Variance Decomposition Layer



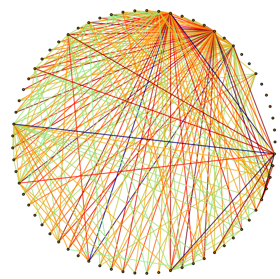
(a) (b) (c)

(d) (e) (f)

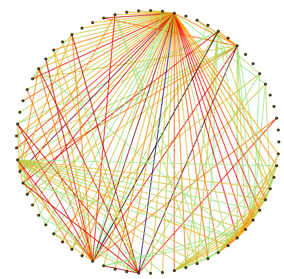
Figure 2: ARIMA networks in 2007Q1, 2008Q4, 2009Q3, 2019Q2, 2020Q1 and 2020Q3. (a) The netwotk in 2007Q1, (b) The netwotk in 2008Q4, (c) The netwotk in 2009Q3 (d) The netwotk in 2019Q2, (e) The netwotk in 2020Q1, The netwotk in 2020Q3.



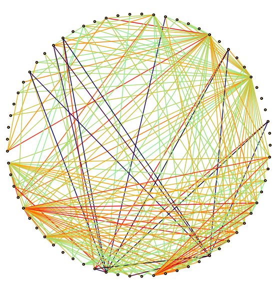
(a)



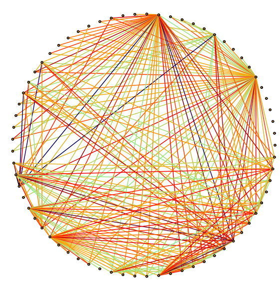
(b)



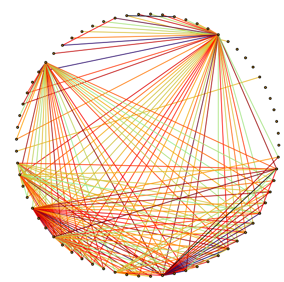
(c)



(d)

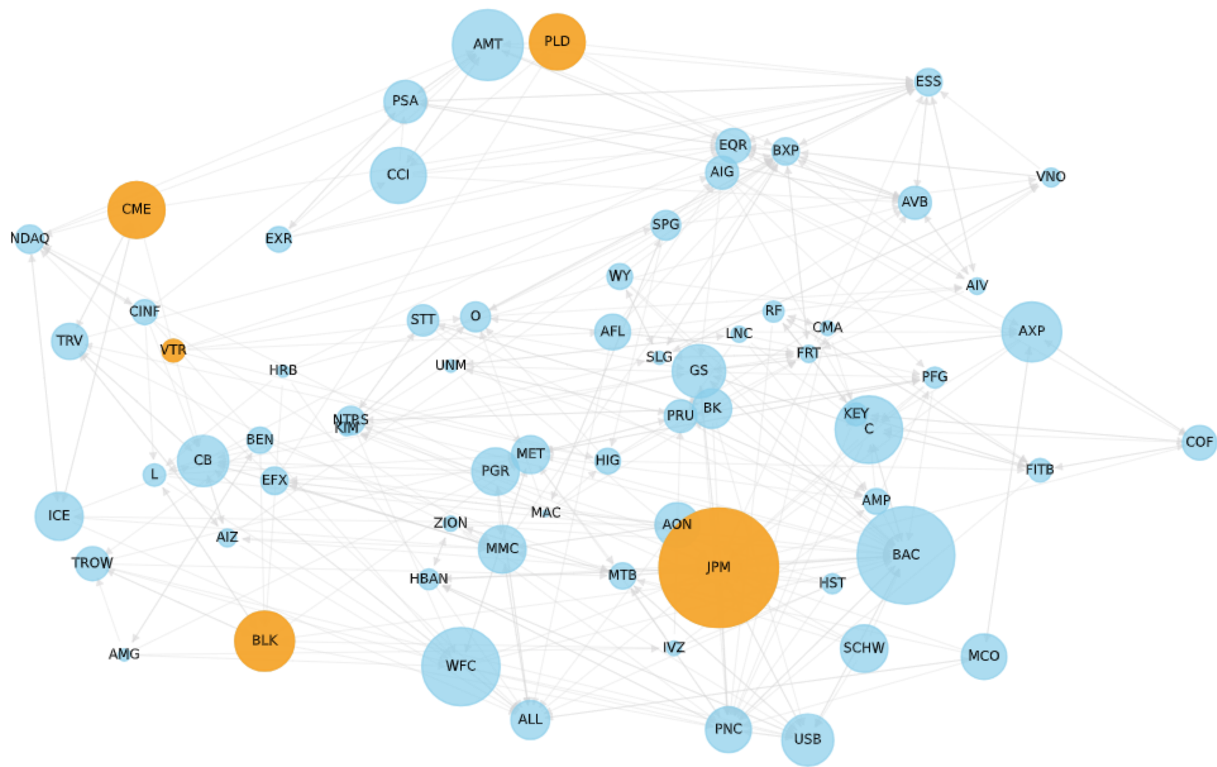


(e)

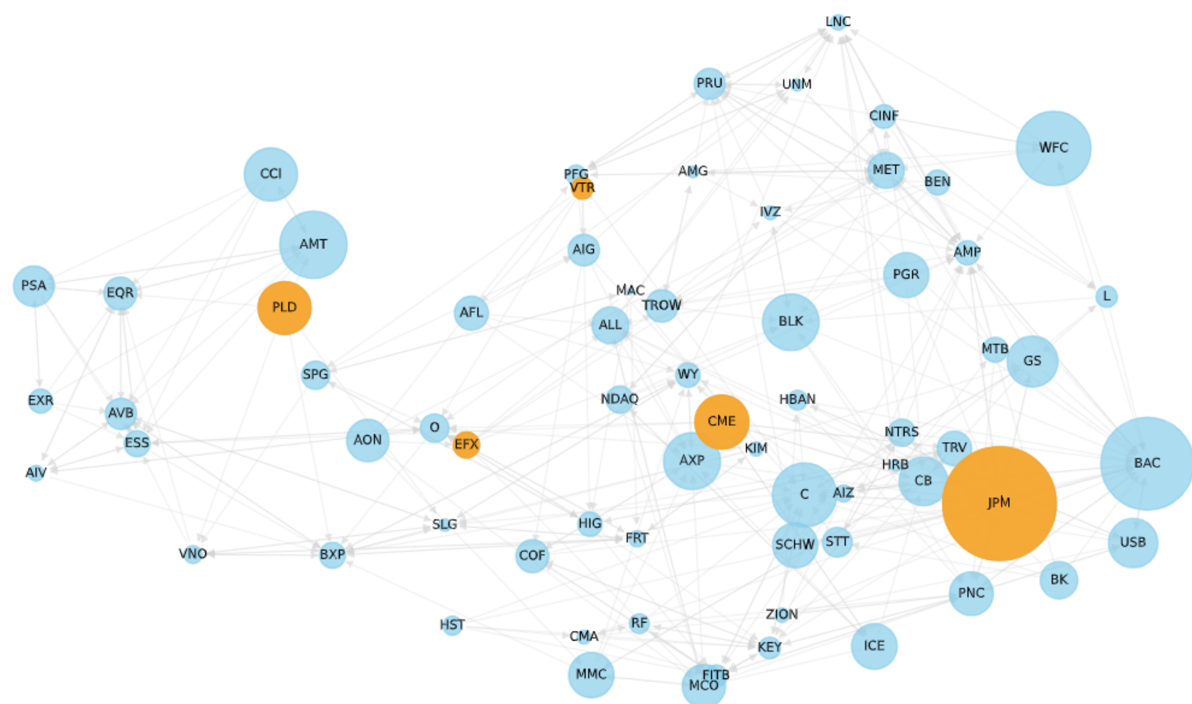


(f)

Figure 3: Variance Decomposition networks in 2007Q1, 2008Q4, 2009Q3, 2019Q2, 2020Q1 and 2020Q3. (a) The netwotk in 2007Q1, (b) The netwotk in 2008Q4, (c) The netwotk in 2009Q3 (d) The netwotk in 2019Q2, (e) The netwotk in 2020Q1, The netwotk in 2020Q3.



(a) This figure shows the network of the Euclidean Layer in 2020Q1. The stocks selected by the Influence Maximization method are highlighted in orange



(b) This figure shows the network of the Correlation Layer in 2020Q1. The stocks selected by the Influence Maximization method are highlighted in orange