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Analysing Network Dynamics: The Contagion Effects of SVB's Collapse on the US Tech Industry

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Abstract: The collapse of Silicon Valley Bank in 2023 was historically significant, and based on past experiences with similar banking sector shocks, it is widely expected to trigger domino effects among tech giants and startups. However, based on the analysis of risk spillover networks established by VARs estimation, we find little evidence of such a spread of risk contagion. We observe a clear downward trend in the total connectedness index of large-cap tech companies right after the the SVB collapse. Moreover, the market quickly responded in a way that isolated the financial services subcategory within the tech sector, forming a distinct community in the network. This explains how the risk contagion paths were cut off. We also provide visualised comparisons of contagion paths within the tech network before and after the SVB's collapse.

Keywords: LASSO VAR; network analysis; financial contagion; shock spillover; bankruptcy

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1. Introduction

On 10 March 2023, the Silicon Valley Bank (SVB) announced its collapse, marking the third largest bank failure in US history[1]. Within the same week, both Silvergate Bank and Signature Bank also triggered the rescue scheme under the Federal Deposit Insurance Corporation (FDIC) and Treasury. Even after the attempt through the newly formed bridge bank, the failure was not fully entailed. Founded on 17 October 1983 in Santa Clara, California, SVB had a distinct focus on supporting innovation and entrepreneurship in the technology and life science sectors. For instance, SVB's client base is heavily concentrated in venture capital-backed and early-stage startup firms; approximately 51% of its clients were from the early-stage technology and technology sectors[2]. SVB invested deposits from tech companies in long-term treasury bonds, which are very sensitive to interest rate changes. Hence, it is believed that the sharp rise in the Federal Reserve's interest rate resulted in significant losses from bond sales[3], eventually leading to the collapse of the SVB (Ali et al. 2024; Sanderson 2023; Yousaf and Goodell 2023).

SVB's failure has become the largest banking crisis since the 2007–2008 liquidity crisis. It was believed that this event would signal a butterfly effect across the US market, even the global financial market, leading to a series of studies. For example, Yousaf and Goodell (2023) explored the impact of SVB's collapse on all stock sectors in the US using an event study and only noted a significant drop in the return of the financial sector during the event. Pandey et al. (2023) further examined the impact on global stock markets and concluded that developed markets were more significantly affected, responding with higher abnormal volatility in the short term. Naveed et al. (2024) highlighted that the cryptocurrency market experienced a negative abnormal return on the day when SVB declared bankruptcy. Liu et al. (2024) investigated the market reaction of SVB's publicly traded depositors and borrowers and found that borrowers have more negative abnormal returns than depositors. Ali et al. (2024) focused on banking and tech firms in the US, Europe, and China. They concluded that the banking sector experienced a significant negative return, while tech firms remained largely unaffected on the day of SVB's collapse. As suggested by these studies, different sectors experienced varying degrees of influence and responded at different paces. Consequently, a series of studies analysed pre- and post-event contagion in the global market to investigate structural changes within the system, particularly the shifts in connections among the financial or banking sector and other sectors. Akhtaruzzaman et al. (2023) explored SVB's influence on contagion between financial and non-financial sectors. The study concluded that banks played the most significant role in spreading financial contagion. Banerjee et al. (2024) collected 60-minute interval data on ETFs to examine the connectedness between 17 FinTech and traditional financial sector ETFs before and after the 2023 bank crisis. Traditional financial ETFs were found to be net risk transmitters.

As a regional bank in the San Francisco Bay Area, SVB's failure raised concern about exacerbating the downturn of the tech industry, which offers a unique scenario to investigate how volatility risk propagates within the tech sector. Immediately after the collapse, the industry and market have clearly reported significant and direct loss in capital (e.g., Roblex) across the globe[4]. Given SVB's geographic focus and industry specialisation, technology firms should be the first to respond to this news, potentially acting as the trigger for broader market vibrations. However, this perspective has not been well explored in research on the impact of SVB collapse. Despite regulatory intervention by FDIC, etc., that aimed to stabilise the market through the bridge bank, it is important to understand how the SVB collapse directly affect the tech companies and whether there has been volatility risk contagion. While the banking and technology sectors mutually influence each other, with SVB acting as a crucial source of funding for tech startups and tech companies contributing to the bank's deposit, disruptions in the tech sector can affect SVB's financial health. However, this study mainly focuses on how SVB's failure impacts tech companies. This would further provide an explanation on why the FDIC's rapid responses through the bridge bank are partially effective: On the one hand, the swift intervention prevented the contagion risk spill among the tech industry due to the guarantee of retracing the "sunk" funds of these tech firms held in the three large troubled banks, hence practically controlling the banking crisis. However, on the other hand, the bank failure was fully entailed because the contagion risk rapidly cascaded from SVB to Signature and Silvergate, as well as the wider banking sector.

In light of this, our study aims to answer the following research question: How does the volatility risk contagion change among tech companies after SVB's collapse? We also take the view to treat the financial market as a complex network and believe the risk transmission mechanism through which financial shocks spread needs to be modelled with a systematic view. To the best of our knowledge, this is the first study that sheds light on shock contagions among US technology companies responding to the SVB collapse, providing different angles to the existing literature Ali et al. (2024), which only focus on several tech companies in different countries, whereas we consider tech companies on a system-wide level. Additionally, our study is also distinguished from the studies mentioned previously, which only focus on testing the abnormal returns of different equities. By modelling the complex pathways of volatility shock spillover among these companies, investors can better assess their portfolios, and regulators can take relevant steps to regulate the risk arising from similar failures.

We use the network approach to analyse contagion in the tech industry, a method that provides a perfect ground to understand financial contagion within a complex system, and such research has been growing rapidly in the literature to simplify complex financial systems, with significant contributions from studies like (Allen and Gale 2000; Gai and Kapadia 2010). And some recent studies continue to explore the contagion dynamics in the financial market (Ahelegbey and Giudici 2022; Liu et al. 2017; Lyócsa et al. 2019; Tong et al. 2018). The network topology often offers both technically and visually powerful indicators and analytical tools that demonstrate how the financial system (network structure) evolves and how the different components relate to one another dynamically, hence revealing the contagion clusters within the financial system and features such as network centrality where the spillover ignites (Barigozzi and Hallin 2017; Long et al. 2017; Lyócsa et al.

2019; Zhang et al. 2020). The most widely used method for measuring the contagion connectedness network in the financial markets was proposed in Diebold and Yilmaz (2009) and enhanced by Diebold and Yilmaz (2012) and Diebold and Yılmaz (2014). We refer to it as the Diebold–Yilmaz connectedness approach for simplicity. For example, the Diebold–Yilmaz connectedness approach is used in analysing the spillover of the stock markets (Cheng et al. 2022; Mensi et al. 2018; Shen et al. 2022), cross-markets (Husain et al. 2019; Ma et al. 2019), and cryptocurrency markets (Guo 2024; Ji et al. 2019), etc. We also use this method in this study due to its advantage in both modelling the connectedness level of shock spillover and identifying risk transmitters and receivers. It effectively accounts for how shock propagates through the system, which cannot be evaluated by methods with lower computational complexity, such as correlation analysis (Forbes and Rigobon 2002), the copula approach (Rodriguez 2007), and Granger causality (Billio et al. 2012). Comparing with other risk contagion modelling techniques, such as GARCH-BEKK, DCC-GARCH, etc., the Diebold–Yilmaz approach can capture the overall and directional spillover among the variables and is computationally more efficient.

To explore the changes in shock contagion relationships within the tech industry after the SVB collapse, we include the top 30 tech companies in the US by market capitalisation in a network analysis. The econometric technique underlying the Diebold–Yilmaz approach is the vector autoregression (VAR) model, which identifies directed links within the contagion network. When constructing the network of a sector, challenges arise in the parameter estimation of the VAR model due to the large number of nodes involved. It is also obvious that we can only use short-term time series samples in such an event study. There are a few techniques to solve this issue: for instance, the large Bayesian VARs (Korobilis and Yilmaz 2018) and the LASSOed VARs (Demirer et al. 2018) are both proposed to handle high-dimensional datasets. We adopt the latter approach in this study.

In general, our study makes several contributions to the literature. First, we extend the shock contagion literature by investigating the volatility contagion network in the US tech industry under the context of SVB's collapse. Second, we contribute to the literature on network analysis in modelling financial shock contagion, particularly in the context of high-dimensional data modelling, while most existing studies do not target a large number of variables. Third, we apply the direct Louvain algorithm for the community detection in the shock contagion networks, which provides a better understanding to compare the structure of the shock contagion networks.

In the subsequent sections of the paper, we proceed as follows. Sections 2 and 3 provide the methodology applied and a detailed description of the data used for analysis. Section 4 summarises the results, and we conclude the paper in Section 5.

2. Methodology

The Diebold–Yilmaz connectedness measure and network approach are typical methods applied in financial contagion studies, associating interconnections among stocks to shock spillovers across the entire financial system (Ahelegbey et al. 2021). Our aim is to explore the changes in volatility shock contagion effects among the largest 30 US tech companies under the context of the SVB collapse. We examine both static and dynamic connectedness. Static connectedness is estimated based on a long-term network structure spanning from 2019 to 2023, covering a total of 5 years. Dynamic connectedness captures the changes of connectedness based on short-term networks calculated using 6-month rolling windows. In addition to analysing the overall network connectedness, we also explore the properties of shock spillover networks before and after the SVB collapse, as well as changes in community and clustering structures in response to this event.

2.1. Constructing Shock Contagion Networks

In this study, we focus on the volatility connectedness among the large-cap tech sector. The daily volatility σ_{it} for equity i on day t is calculated using Parkinson's method (Parkinson 1980):

$$\sigma_{it} = \sqrt{\frac{1}{4\ln(2)} \ln\left(\frac{H_{it}}{L_{it}}\right)^2}, \tag{1}$$

where H_{it}, L_{it} are the high price and low price of market i on day t, respectively. The advantage of using Parkinson's volatility is that it considers intraday information. This volatility time series data are used to construct shock contagion networks and calibrate connectedness.

We establish directed networks of shock spillovers among the tech companies. The network G is written as a duplet (V, E). $V = \{v_i : i = 1, 2, ..., K\}$ is the vertices set, represented by K tech companies.

$$E = \begin{pmatrix} e_{1,1} & e_{1,2} & e_{1,3} & \cdots & e_{1,K} \\ e_{2,1} & e_{2,2} & e_{2,3} & \cdots & e_{2,K} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ e_{K,1} & e_{K,2} & e_{K,3} & \cdots & e_{K,K} \end{pmatrix}$$

is an asymmetric weighted adjacency matrix, in which $e_{i,j}$ represents the strength of spillover effect from v_i to v_j. According to the Diebold–Yilmaz network approach, the asymmetric weighted adjacency matrix E is derived from the forecast error decomposition of a VAR model (see the initial work of Diebold and Yilmaz (2009)). We briefly recap the method here.

2.1.1. The Diebold–Yilmaz Network

The construction of the shock contagion network starts with the VAR(p)model:

$$y_t = \mu + \sum_{i=1}^{p} A_i y_{t-i} + u_t, \quad u_t \sim \mathcal{N}(0, \Omega), \tag{2}$$

where y_t is a $K \times 1$ vector of volatility at time t, A_i is the $K \times K$ transition matrix on lag-i, and u_t is a K-dimensional multi-variate normal residual with zero mean and time-independent covariance matrix $\Omega = (\sigma_{ij}^2)_{i=1,2...,K; j=1,2,..,K}$. We estimate the VAR model over both fixed periods and rolling windows to obtain the dynamics of volatility connectedness.

A stationary VAR model has the following moving average representation MA(h), where y_t can be represented as a weighted sum of past and present errors and a constant term,

$$y_t = \mu + \sum_{i=0}^{h} \Phi_i u_{t-i}, \tag{3}$$

where $\Phi_i = A_1\Phi_{i-1} + A_2\Phi_{i-2} + \cdots + A_h\Phi_{i-h}$ and Φ_0 is the identity matrix.

Considering a shock $\delta = (\delta_1, \delta_2, \cdots, \delta_K)'$ occurring at time t, Koop et al. (1996) and Pesaran and Shin (1998) define the generalised impulse response function that measures the impact of each variable in response to a shock $\delta_j = \sqrt{\sigma_{jj}}$ on the j-th element:

$$\begin{aligned} \mathrm{GIRF}_{jt}(h) &= \mathbb{E}(y_{t+h} \mid u_{jt} = \delta_j, \mathcal{F}_{t-1}) - \mathbb{E}(y_{t+h} \mid \mathcal{F}_{t-1}) \\ &= \left(\frac{\Phi_h \Omega b_j}{\sqrt{\sigma_{jj}}}\right)\left(\frac{\delta_j}{\sqrt{\sigma_{jj}}}\right) \qquad , h = 1, 2, ... \\ &= \sigma_{jj}^{-\frac{1}{2}} \Phi_h \Omega b_j \end{aligned} \tag{4}$$

where $\mathcal{F}_{t-1}$ is the state of the past information until $t-1$, and b_j is the j-th column of the $K \times K$ identify matrix.

This leads to the definition of generalised forecast error variance decomposition in the Diebold–Yilmaz approach:

$$\Theta^g_{i,j}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (b_i' \Phi_h \Omega b_j)^2}{\sum_{h=0}^{H-1} (b_i' \Phi_h \Omega \Phi_h' b_i)}. \tag{5}$$

Because $\sum_{i=1}^{K} \Theta^g_{ij} \neq 1$, to normalise the variance decomposition matrix, Diebold and Yilmaz (2012) suggested

$$\tilde{\Theta}^g_{ij}(H) = \frac{\Theta^g_{ij}(H)}{\sum_{j=1}^{K} \Theta^g_{ij}(H)}, \tag{6}$$

such that we have $\sum_{j=1}^{K} \tilde{\Theta}^g_{ij}(H) = 1$ and $\sum_{i,j=1}^{K} \tilde{\Theta}^g_{ij}(H) = K$. $\tilde{\Theta}^g_{ij}(H)$ measures the cumulative shock spillover from equity i to equity j over H time periods following the shock. The total spillover index, also referred to as the total connectedness index (TCI), measuring the overall connectedness in a network is defined as:

$$TCI(H) = \frac{\sum_{i,j=1;i\neq j}^{K} \tilde{\Theta}^g_{ij}(H)}{\sum_{i,j=1}^{K} \tilde{\Theta}^g_{ij}(H)} = \frac{\sum_{i,j=1;i\neq j}^{K} \tilde{\Theta}^g_{ij}(H)}{K} \tag{7}$$

We know that, for any $H \in \mathbb{Z}^+$, $TCI(H)$ is bounded between 0 and 1[5]. A larger TCI means the shocks in one company are more likely to spread to other companies, suggesting a potentially higher risk contagion. In addition to TCI, directional connectedness provides more details on how shocks are transmitted from one company to all other companies and vice versa. We can calculate the directional volatility connectedness from others to equity i as

$$S^g_{i\leftarrow\bullet}(H) = \frac{\sum_{j=1;j\neq i}^{H} \tilde{\Theta}^g_{ij}(H)}{K}, \tag{8}$$

similarly, the directional volatility connectedness to others from equity i is

$$S^g_{\bullet\leftarrow i}(H) = \frac{\sum_{j=1;j\neq i}^{K} \tilde{\Theta}^g_{ji}(H)}{K}, \tag{9}$$

and the net pairwise connectedness is

$$S^g_{ij}(H) = \frac{\tilde{\Theta}^g_{ij}(H) - \tilde{\Theta}^g_{ji}(H)}{K}, \tag{10}$$

which captures the net directional volatility spillover between two companies. These connectedness measures can be organised into a connectedness table (see Table 1).

Table 1. Connectedness table.

	y_1	y_2	$\cdots$	y_K	$S^g_{i\leftarrow\bullet}(H)$
y_1	$S^g_{11}(H)$	$S^g_{12}(H)$	$\cdots$	$S^g_{1K}(H)$	$\frac{\sum_{j=1;j\neq 1}^{K} \tilde{\Theta}^g_{1j}(H)}{K}$
y_2	$S^g_{21}(H)$	$S^g_{22}(H)$	$\cdots$	$S^g_{2K}(H)$	$\frac{\sum_{j=1;j\neq 2}^{K} \tilde{\Theta}^g_{2j}(H)}{K}$
$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\vdots$
y_K	$S^g_{K1}(H)$	$S^g_{K2}(H)$	$\cdots$	$S^g_{KK}(H)$	$\frac{\sum_{j=1;j\neq K}^{K} \tilde{\Theta}^g_{Kj}(H)}{K}$
$S^g_{\bullet\leftarrow i}(H)$	$\frac{\sum_{j=1;j\neq 1}^{K} \tilde{\Theta}^g_{j1}(H)}{K}$	$\frac{\sum_{j=1;j\neq 2}^{K} \tilde{\Theta}^g_{j2}(H)}{K}$	$\cdots$	$\frac{\sum_{j=1;j\neq K}^{K} \tilde{\Theta}^g_{jK}(H)}{K}$	$\frac{\sum_{i,j=1;i\neq j}^{K} \tilde{\Theta}^g_{ij}(H)}{K}$

This connectedness table allows us to track pairwise connectedness between all pairs of companies as well as system-wide connectedness. We follow Diebold and Yılmaz (2014) to construct the NPDC (net pairwise directional connectedness) matrix E as the asymmetric weighted adjacency matrix in our shock contagion networks. Denote the connectedness matrix $\mathcal{S}$ as

$$\mathcal{S} = \begin{bmatrix} S^g_{11}(H) & S^g_{12}(H) & S^g_{13}(H) & \cdots & S^g_{1K}(H) \\ S^g_{21}(H) & S^g_{22}(H) & S^g_{23}(H) & \cdots & S^g_{2K}(H) \\ S^g_{31}(H) & S^g_{32}(H) & S^g_{33}(H) & \cdots & S^g_{3K}(H) \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ S^g_{K1}(H) & S^g_{K2}(H) & S^g_{K3}(H) & \cdots & S^g_{KK}(H) \end{bmatrix}, \tag{11}$$

where $S^g_{i,j}(H) \neq S^g_{j,i}(H)$. Then,

$$E = \max[\mathcal{S} - \mathcal{S}^T, 0]. \tag{12}$$

2.1.2. LASSO-VAR Estimation

In the model calibration, we find that the VARs parameter set is much larger than the number of observations. This leads to a high dimensionality issue in parameter estimation. We follow the LASSO-VAR technique documented in Demirer et al. (2018), which addresses this challenge by LASSO regularisation. The idea is to penalise the parameters that are only slightly informative and shrink them towards zero.

The number of VAR parameters depends on the number of lags, so choosing the optimal lag order p is important. The number of parameters for the transition matrixes $A_1, \cdots, A_p$ that need to be estimated is $K^2 p + K$. LASSO estimation is used when the observation is less than the parameters that we need to estimate.

The $\mathcal{L}_1$ (LASSO) regularisation introduces a penalty term $\lambda \sum_{i=1}^{p} \|A_i\|^q$ in the ordinary least squares (OLSs) estimation:

$$(\hat{\mu}, \hat{A}_1, \cdots, \hat{A}_p)_{\text{LASSO}} = \underset{(\mu, A_1, \cdots, A_p) \in \mathbb{R}^{K(p+1)}}{\arg\min} \left[\sum_{t=1}^{T} \|y_t - \mu - \sum_{i=1}^{p} A_i y_{t-i}\|^2 + \lambda \sum_{i=1}^{p} \|A_i\| \right], \tag{13}$$

where λ controls the amount of penalisation. The optimal value for the regularisation parameter λ is important for the performance of the LASSO-VAR model, and λ is selected by a 10-fold cross-validation.

2.2. Network Analysis

As suggested by Diebold and Yılmaz (2014), the Diebold–Yilmaz connectedness approach marries VAR variance decomposition theory with network theory. Following the shock contagion networks construction in the previous section, we analyse network properties, including network density and distributions of in- and out-degrees, to compare the network structure before and after the SVB event. Additionally, we want to investigate whether, in general, the tech companies in the same sub-categories in the GICS classification show similar behaviours in propagating or receiving risk and how the community structure has been impacted by the collapse of SVB. To achieve this, we introduce the application of the direct Louvain algorithm to cluster the communities in the shock contagion network.

2.2.1. Network Properties

Network density, denoted as ρ, measures the connectivity in a network and is calculated as:

$$\rho = \frac{M}{K(K-1)}, \tag{14}$$

where M is the total number of edges in the network and K is the number of vertices in the network. It measures the actual connections between the vertices compared with the maximum possible connections, ranging from 0 to 1. A higher density indicates that the companies are more connected and there is greater risk spillover in the network. In contrast, a lower density suggests a sparser network with less risk contagion paths. We can have a general idea of the changes in the network structure by comparing the network density before and after the collapse of SVB.

The weighted in-degree of a vertex v_j is the sum of the weights of all incoming edges to v_j, which captures the net risk connectedness of vertex v_j transferred from other vertices. It can be represented as:

$$D_j^{in} = \sum_{i=1}^{K} e_{i,j}. \tag{15}$$

Similarly, the weighted out-degree of a vertex v_j is the sum of the weights of all outgoing edges from v_j and is given by:

$$D_j^{out} = \sum_{j=1}^{K} e_{j,i}. \tag{16}$$

The weighted in- and out-degrees indicate which vertices are most affected by the shocks and which are the key risk transmitters in the network. Vertices with significant changes in these measures may show their importance in the network.

2.2.2. Community Detection

To detect community in the network, a classical way is to find a partition of the vertices set that maximises the modularity; we adopt the direct Louvain algorithm proposed by Dugué and Perez (2022). Modularity measures the strength of the division of a network into communities. A higher modularity value indicates that there are more connections within the community rather than between them. A partition $\mathbb{C}$ of a network $G = (V, E)$ is a collection of disjoint subsets $\mathbb{C} = \{C_1, ..., C_n\}$ of vertices set V; every vertex $v_i \in V$ is included in exactly one subset community C_i. The modularity Q for this directed network is defined as

$$Q = \frac{1}{M} \sum_{v_i, v_j \in V} \left[A_{v_i v_j} - \frac{d_{v_i}^{in} d_{v_j}^{out}}{2M} \right] \delta(C_{v_i}, C_{v_j}), \tag{17}$$

where M is the total edges in the graph, and A is the adjacency matrix of network G, where

$$A_{v_i v_j} = \begin{cases} 1 & \text{if } \langle v_i, v_j \rangle \in E, \\ 0 & \text{if } \langle v_i, v_j \rangle \notin E. \end{cases}$$

v_j is a neighbouring vertex of v_i if $A_{v_i v_j} = 1$. $d_{v_i}^{in} = |\{v_j \in V : \exists(v_i, v_j) \in A\}|, d_{v_i}^{out} = |\{v_j \in V : \exists(v_j, v_i) \in A\}|$ are the in-degree and out-degree of v_i, respectively. $\delta(C_{v_i}, C_{v_j}) = 1$ if $v_i = v_j$; otherwise, it is 0. Louvain's algorithm computes gain modularity for the directed graph:

$$\Delta_Q = \frac{d_{v_i}^C}{M} - \left[\frac{d_{v_i}^{out} \sum_{v_j \in C} d_{v_j}^{in} + d_{v_i}^{in} \sum_{v_j \in C} d_{v_j}^{out}}{M^2} \right], \tag{18}$$

where $d_{v_i}^C = |\{v_j \in C : \exists(v_i, v_j) \in A\}|$ stands for the degree of vertex v_i in community C, $\sum_{v_j \in C} d_{v_j}^{in} \left(\sum_{v_j \in C} d_{v_j}^{out} \right)$ is the total number of in (out) edges to all vertices within community C. The algorithm starts from a singleton partition, where each vertex in the network is considered a separate community, and the modularity Q is calculated for each vertex in its own community. Next, for every vertex v_i, it assesses the impact on modularity if v_i

were to be removed from its current community and placed it into the community of its neighbouring vertices. The algorithm determines the changes in modularity (ΔQ) for each community C_i that vertex v_i is connected to. Vertex v_i is assigned to the community, which results in the highest increase in modularity among all its neighbouring communities, which is defined as communities that have at least one directed edge between vertices. If no increase is possible, vertex v_i stays in its original community (Dugué and Perez 2022). The modularity Q is then updated for the new community structure until the maximum Q is reached to ensure the network is well divided into communities.

3. Data

The Bloomberg United States Technology Large, Mid & Small Cap Price Return Index covers 99% of the market capitalisation for the tech industry, with an overall value of USD 15.17 trillion. We selected the top 30 tech companies based on the average market cap between 2021 and 2022 from this index. Large cap companies have greater liquidity and can reflect the market information more rapidly than the mid cap and small cap companies. The selected 30 tech companies serve as a representative sample of the US tech industry, constituting around 60% of the index with a market cap of USD 8.98 trillion, which has a significant influence on the entire industry. We collected daily high, low, open and closed data from Yahoo! Finance. Our data are from 1 January 2019 to 1 December 2023, totalling 1238 trading days. Table 2 lists detailed information about the companies, including their market capitalisations and GICS (Global Industry Classification Standard) codes. The inclusion of the GICS code provides a standard framework for the tech companies to be classified into their sub-categories. This code will provide insights into which sub-categories transfer or receive risk the most in the shock contagion network, and it will also be used for a subsequent community detection analysis to explore whether companies within the same sub-categories are interconnected with each other. Additionally, the descriptive statistics of the data are displayed in Table 3.

Table 2. List of technology companies, ticks, market capitalisation, and GICS code.

Companies	Ticks	Market Cap (USD Billion)	GICS Classification (Abbrv.)
Apple Inc.	AAPL	2405.896	Technology Hardware (TH)
Microsoft Corp.	MSFT	1976.938	Software (SW)
NVIDIA Corp.	NVDA	447.193	Semiconductors (SC)
Visa Inc.	V	360.405	Financial Services (FS)
Mastercard	MA	343.510	Financial Services (FS)
Adobe Inc.	ADBE	225.319	Software (SW)
PayPal Holding Inc.	PYPL	220.261	Financial Services (FS)
Salesforce Inc.	CRM	218.680	Software (SW)
Cisco System Inc.	CSCO	209.983	Communications Equipment (CE)
Intel Corp.	INTC	208.832	Semiconductors (SC)
Broadcom Inc.	AVGO	208.626	Semiconductors (SC)
Oracle Corp.	ORCL	206.621	Software (SW)
Accenture PLC	ACN	197.559	IT Services (IT)
Advanced Micro Devices Inc.	AMD	176.391	Semiconductors (SC)
Texas Instruments Inc.	TXN	174.146	Semiconductors (SC)
QUALCOMM Inc.	QCOM	143.234	Semiconductors (SC)
Intuit Inc.	INTU	136.708	Software (SW)
ServiceNow Inc.	NOW	129.568	Software (SW)
International Business Machines Corp.	IBM	120.036	IT Services (IT)
S&P Global Inc.	SPGI	113.735	Capital Markets (CM)
Applied Materials Inc.	AMAT	98.8077	Semiconductors (SC)
Automatic Data Processing Inc.	ADP	85.7765	Professional Services (PS)
Analog Devices Inc.	ADI	82.4632	Semiconductors (SC)
Lam Research Corp.	LRCX	75.7516	Semiconductors (SC)
Block Inc.	SQ	75.0931	Financial Services (FS)
Micron Technology Inc.	MU	72.746	Semiconductors (SC)

Table 2. *Cont*.

Companies	Ticks	Market Cap (USD Billion)	GICS Classification (Abbrv.)
Moody's Corp.	MCO	71.5542	Capital Markets (CM)
Fiserv Inc.	FI	67.4635	Financial Services (FS)
Fidelity National Information Services Inc.	FIS	66.4723	Financial Services (FS)
Microchip Technology Inc.	MCHP	63.2897	Semiconductors (SC)

Notes: This table provides information on the selected 30 tech companies, ranked by market capitalisation from highest to lowest.

Table 3. Descriptive statistics on volatilities for 30 tech companies.

Ticks	Min	Max	Mean	S.D.	Skewness	Kurtosis	ADF Test
AAPL	6.834	125.488	25.854	14.4	2.05	6.67	−5.255 **
MSFT	4.30	160.93	24.29	14.15	2.63	13.01	−4.804 **
NVDA	11.06	175.76	43.18	22.21	1.72	4.85	−5.301 **
V	5.28	127.12	22.73	13.54	2.68	11.53	−4.776 **
MA	6.04	137.64	25.48	15.3	2.62	11.1	−4.907 **
ADBE	5.73	173.93	30.15	16.69	2.47	11.16	−5.559 **
PYPL	8.55	141.02	35.21	18.27	1.65	4.45	−5.113 **
CRM	6.75	167.65	31.01	16.97	2.39	10.29	−5.619 **
CSCO	6.00	152.08	21.82	13.36	3.79	23.61	−4.902 **
INTC	6.19	206.96	29.68	16.72	2.96	18.01	−5.689 **
AVGO	5.99	262.91	29.29	18.78	5.09	44.39	−6.242 **
ORCL	5.09	163.35	23.73	14.46	3.30	19.39	−6.147 **
ACN	4.66	184.81	22.51	14.70	3.95	29.61	−4.966 **
AMD	14.14	151.91	46.84	21.89	1.37	2.30	−5.784 **
TXN	5.82	142.06	25.88	13.69	2.76	13.91	−5.306 **
QCOM	6.01	246.77	33.05	18.36	3.09	20.59	−5.662 **
INTU	6.59	163.21	31.06	17.17	2.05	7.15	−4.825 **
NOW	9.51	181.83	37.20	20.18	1.88	5.66	−5.314 **
IBM	4.41	140.93	20.44	12.27	3.17	16.88	−4.899 **
SPGI	5.49	184.59	24.37	14.53	3.56	23.27	−5.526 **
AMAT	7.51	168.80	36.79	18.92	2.26	9.34	−5.888 **
ADP	6.29	198.64	22.56	14.80	4.05	29.05	−5.364 **
ADI	7.40	187.18	28.63	15.57	3.57	24.44	−5.549 **
LRCX	8.50	207.28	37.88	20.13	2.55	12.33	−5.482 **
SQ	10.94	302.58	54.58	30.79	2.14	8.72	−5.239 **
MU	9.58	184.56	38.73	18.58	2.12	8.12	−5.226 **
MCO	6.51	153.37	25.26	15.81	3.19	16.12	−4.640 **
FI	6.16	180.16	26.16	15.69	3.07	17.38	−5.894 **
FIS	5.90	218.12	28.38	17.32	3.44	22.92	−6.037 **
MCHP	10.68	195.89	35.14	17.75	2.69	14.8	−5.618 **

Notes: This table reports summary statistics of the 30 selected tech companies. *, **, and *** indicate significance at the 5%, 1%, and 0.1% levels, respectively.

4. Empirical Results

The VAR model of the Diebold–Yilmaz connectedness approach assumes that the time series data input is stationary. Therefore, we used the augmented Dickey–Fuller (ADF) test to test the stationarity of our volatility time series. Table 3 presents the results of the ADF test, showing that all the volatility series are stationary at the 1% significance level, indicating they are ready for VAR estimation. Selecting the optimal lag length is important to capture the dynamics of the VAR model. To determine the optimal lag length, we choose to use Bayesian information criterion (BIC). Based on the BICs, we choose the optimal lag for our VAR as one. Then, we proceed to compute both the static and dynamic connectedness models for further analysis.

4.1. Full Sample Static Connectedness

The full sample static connectedness reflects the average level of connectedness among these 30 tech companies over a fixed period. We constructed the connectedness table (Table 4) below using the previously mentioned method (see Table 1) to show the average connectedness and identify the main risk receivers and transmitters. The average shock spillover is at a level of 86.10% among the 30 tech companies. If $S^g_{\bullet \leftarrow i}(H) - S^g_{i \leftarrow \bullet}(H) > 0$ (hereafter referred to as net volatility connectedness), it means the company propagates risk on others more than it is affected by them. Overall, we observe that 12 out of 30 tech companies are major risk transmitters, where they spread more risk to all other companies instead of being influenced by them. Additionally, software companies and semiconductor companies are significant contributors to risk transmission, with a total net volatility connectedness value of 19.78% and 13.7%, respectively. Similarly, professional services and communication equipment companies are also risk spreaders. In contrast, financial services companies tend to receive more risk from others, with a total net volatility connectedness value of −40.33%. The same pattern is observed in IT services, capital market, and technology hardware companies, where they also tend to absorb more risk from others rather than transmitting it.

Furthermore, the results show that MSFT has the highest net volatility connectedness value (28.34%), followed by TXN (25.26%) and ADI (22.92%), which means that these companies mainly play as risk transmitters, whereas FIS, AMD, and SQ are more affected by the average shocks in all other companies, with the lowest net volatility connectedness values of −33.09%, −18.17%, and −17.2%, respectively. The full sample static connectedness results provide a comparison baseline for the following analysis.

Table 4. Static connectedness table.

GICS Abbrv.	Ticks	$S^g_{i \leftarrow \bullet(H)}$	$S^g_{\bullet \leftarrow i(H)}$	$S^g_{\bullet \leftarrow i(H)} - S^g_{i \leftarrow \bullet(H)}$
TH	AAPL	85.22	80.79	−4.43
SW	MSFT	89.00	117.34	28.34
SW	ADBE	88.45	107.76	19.31
SW	NOW	87.25	84.46	−2.79
SW	INTU	86.66	82.72	−3.94
SW	CRM	86.84	79.59	−7.25
SW	ORCL	81.51	67.71	−13.80
SC	TXN	89.31	114.57	25.26
SC	ADI	87.85	110.76	22.92
SC	AVGO	86.80	100.11	13.32
SC	MCHP	88.22	100.72	12.49
SC	AMAT	87.46	92.21	4.75
SC	NVDA	86.52	83.91	−2.61
SC	LRCX	88.13	83.10	−5.03
SC	MU	84.67	76.04	−8.63
SC	INTC	83.60	68.64	−14.96
SC	QCOM	84.86	69.21	−15.64
SC	AMD	81.94	63.76	−18.17
FS	V	88.43	104.28	15.84
FS	MA	88.44	100.56	12.12
FS	PYPL	85.76	78.42	−7.34
FS	FI	84.87	74.21	−10.66
FS	SQ	84.51	67.31	−17.20
FS	FIS	79.09	46.00	−33.09
IT	ACN	88.62	101.10	12.47
IT	IBM	84.24	68.91	−15.32

Table 4. *Cont.*

GICS Abbrv.	Ticks	$S^g_{i\leftarrow\bullet(H)}$	$S^g_{\bullet\leftarrow i(H)}$	$S^g_{\bullet\leftarrow i(H)} - S^g_{i\leftarrow\bullet(H)}$
CM	SPGI	86.30	83.86	−2.44
CM	MCO	85.56	80.67	−4.89
PS	ADP	87.56	97.81	10.24
CE	CSCO	85.37	96.49	11.11
$TCI(H)$				86.10

Notes: This table displays the full sample connectedness result of the 30 tech companies along with their GICS abbreviations. The third column shows the volatility connectedness from other companies to company *i*. Conversely, the fourth column presents the volatility connectedness from company *i* to other companies. The final column provides the net volatility connectedness. A positive value indicates that the company is more likely to spread risk to other companies, whereas a negative value suggests that it mainly receives risk from other companies.

4.2. Rolling Window Dynamic Connectedness

While the above full-sample connectedness analysis provides the average directional and total connectedness, that does not account for the dynamic aspects of the connectedness. Therefore, in order to capture how the connectedness changes over time, we then perform a rolling window estimation analysis in this subsection. Dynamic connectedness measures how the average connectedness changes over time. We compute the dynamic network connectedness by estimating LASSO VAR over a specific rolling window.

Figure 1 plots the total connectedness index among 30 tech companies using a 120-day rolling window and a 5-day forecast horizon[6]. TCI (see Equation (7)) quantifies the average shock spillover of a single variable on all others. This index can be interpreted as an indicator of overall market risk. A large TCI suggests that the average transmission of a shock from one variable to all others is substantial, indicating a high market contagion risk. The graph features a highlighted red solid line, corresponding to 10 March 2023, the day that the shares of SVB declined by 60% when the market opened. We highlighted the data points for the beginning of each week across the time period from March 2022 to December 2023 to visualise a clear overall connectedness trend among tech companies before and after the collapse of SVB. Clearly, there is a downward trend in connectedness from over 85% to below 60%, indicating that, after the event, the risk of contagion in the tech industry decreases. This result is supported by the findings of (Ali et al. 2024), who conducted an event study on high-tech firms in the US, Europe, and China and found that there are insignificant abnormal returns for the high-tech companies on the event day. These insignificant abnormal returns suggest that the tech industry's reaction to the collapse of SVB was relatively muted. The collapse of SVB did not cause significant reactions across the tech industry, which perhaps prevented the risk contagion in the industry, supporting the observed drop in the total connectedness index.

It is worth mentioning that three days after the collapse of SVB, regulatory intervention by the FDIC and others stepped in on 13 March 2023 to mitigate the damage and enhance market confidence. They addressed the safety of the banking system and stabilised the market through the bridge bank. In addition, deposit insurance was put in place to protect deposits belonging to tech companies banking with SVB. The regulators swiftly announced that these deposits would be fully redeemable. Additionally, the Federal Reserve launched a new lending facility, enabling banks to post high-quality assets, thus allowing commercial entities to borrow at a generous rate. This ensured that credit remained available to tech companies. The guarantee of retracing the "sunk" funds of the tech companies prevented the contagion risk spread among the tech industry. Moreover, tech companies did not only bank with SVB, which means they are robust with multiple funding sources. For example, as reported by *Economics Times*[7], Roku had 26% of its cash with SVB, and Roblox had 5% of its cash held at SVB. The diversification of their banking relationships also helped reduce the shock transmission arising from one single bank failure. To conclude, these actions taken by regulators, together with the diverse banking of tech companies, suggested that

SVB's failure did not signal the contagion effect for the tech industry. Instead, we noticed a decrease in the risk of contagion.

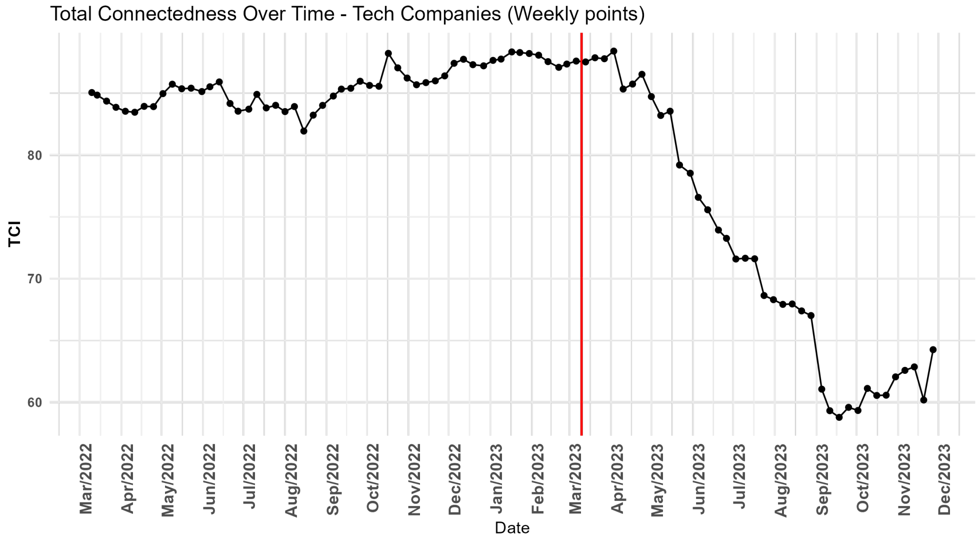

Figure 1. Total connectedness index. Notes: This figure shows the total connectedness trend among 30 tech companies using a 120-day rolling window and a 5-day forecast error horizon. The highlighted red line indicates the day of the SVB collapse.

4.3. Impact of the SVB Collapse on Shock Contagion Network Dynamics

4.3.1. Network Properties: A Comparison on Pre- and Post-SVB Collapse

We further created the net pairwise directional connectedness network for the periods before and after the SVB collapse, which allows us to observe the net risk transmission path clearly and offers more detailed insights into the comparison of directional risk transmission within the network of 30 tech companies. To accomplish this, we select two subsets of data to analyse and compare several network metrics before and after the SVB bank collapse. The first subset spans from 10 September 2022, to 10 March 2023, while the second covers the period from 13 March 2023, to 10 September 2023.

This allows us to compare changes in network structure associated with the event. Table 5 compares the net volatility connectedness changes for the individual companies. Several companies experienced significant changes. For example, FIS became less central in receiving risk from others, while MSFT shifted being a major risk transmitter to a risk receiver.

To make this transformation clearer, Figures 2 and 3 visualise the average net pairwise directional connectedness among 30 tech companies before and after the SVB collapse. The net risk transmission is unidirectional, which better reflects each asset's dominant position in transferring the risk (Demirer et al. 2018). Red nodes indicate net transmitters and green nodes indicate net receivers. The node size and edge width are adjusted based on the connectedness strength to visually distinguish between more and less connectedness entities.

We can notice that after SVB's collapse, network (Figure 3) becomes more sparse than before (Figure 2). We validate this by calculating the network density (see Equation (14)). The greater the network density, the more connections between the nodes. The network density shows a slight change, decreasing from 0.076 to 0.070. Furthermore, we consider centrality measures to find the important players in the network. We analyse degree centrality (see Equations (15) and (16)), which measures the number of edges connected to a node. Nodes with a high degree of centrality are considered influential within the network, indicating their importance in receiving or transmitting information flow.

Table 5. Net volatility connectedness of 30 tech companies.

Ticks	Net Volatility Connectedness	Before	After	Difference (After − Before)
FIS	−33.09	−43.10	−12.44	30.66
V	15.84	−10.25	12.29	22.54
MCO	−4.89	−19.19	3.15	22.34
INTU	−3.94	−13.39	8.49	21.88
NOW	−2.79	−5.04	15.54	20.58
ADBE	19.31	−6.55	11.75	18.30
SPGI	−2.44	−16.38	−1.21	15.17
FI	−10.66	−4.67	7.83	12.50
LRCX	−5.03	13.91	25.86	11.95
IBM	−15.32	−24.92	−16.76	8.16
CRM	−7.25	−22.03	−15.43	6.60
PYPL	−7.34	−21.77	−16.16	5.61
ORCL	−13.80	−13.92	−9.66	4.26
ACN	12.47	16.12	18.96	2.84
MA	12.12	16.98	19.64	2.66
NVDA	−2.61	−3.78	−1.43	2.35
SQ	−17.20	−15.04	−14.13	0.91
INTC	−14.96	−6.32	−12.76	−6.44
AVGO	13.32	4.09	−4.15	−8.24
TXN	25.26	26.75	16.40	−10.35
CSCO	11.11	0.19	−12.04	−12.23
MU	−8.63	−0.89	−14.38	−13.49
AMD	−18.17	5.05	−8.63	−13.68
AAPL	−4.43	−1.92	−15.84	−13.92
AMAT	4.75	23.06	8.98	−14.08
ADI	22.92	30.69	12.33	−18.36
QCOM	−15.64	20.20	0.64	−19.56
MCHP	12.49	36.09	15.33	−20.76
ADP	10.24	5.29	−15.81	−21.10
MSFT	28.34	30.74	−6.37	−37.11

Notes: This table demonstrates the net volatility connectedness estimated across the whole sample period of 30 tech companies, as shown in the second column. The third and fourth columns present the net volatility connectedness before and after the collapse of SVB. The last column calculates the difference between the values before and after the collapse.

Figures 4 and 5 compare the weighted in-degree and out-degree distributions. The weighted in-degree of a node is the sum of the weights of the edges leading into it, while the weighted out-degree is the sum of the weights leading out from it. Prior to the failure of SVB, most of the companies were distributed between a weighted in-degree and out-degree of 0 and 5, while a few had high weighted degrees. MCHP, MSFT, and ADI played as the main risk transmitters in the network, whereas FIS, IBM, and CRM acted as the major risk receivers. Following the collapse of SVB, the network structure changed, with the distribution becoming more dispersed and evenly spread across the nodes, leading to a diversification of risk. ADP, MU, and AAPL became the main risk receivers, with LRCX, CAN, and MA emerging as key risk transmitters.

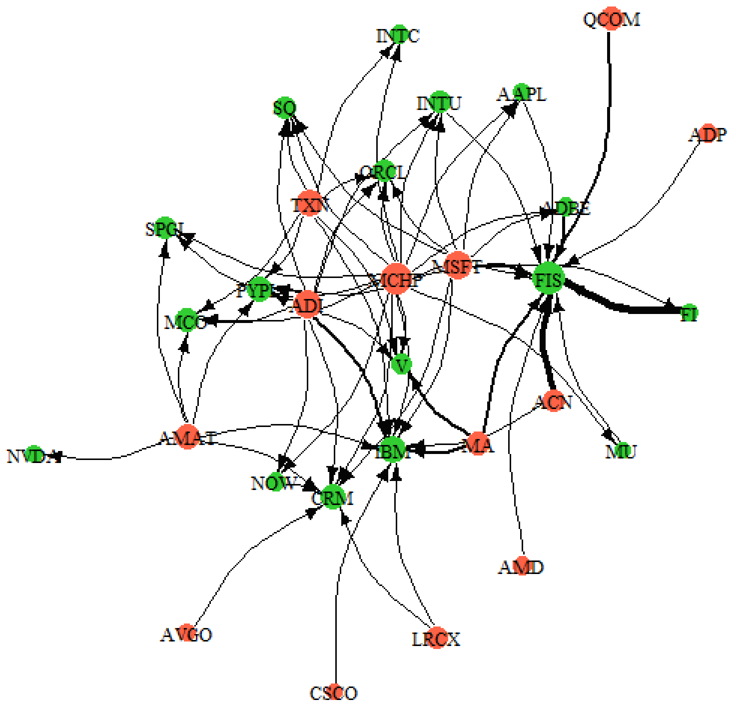

Figure 2. Network visualisation of net pairwise directional connectedness paths before SVB's collapse.

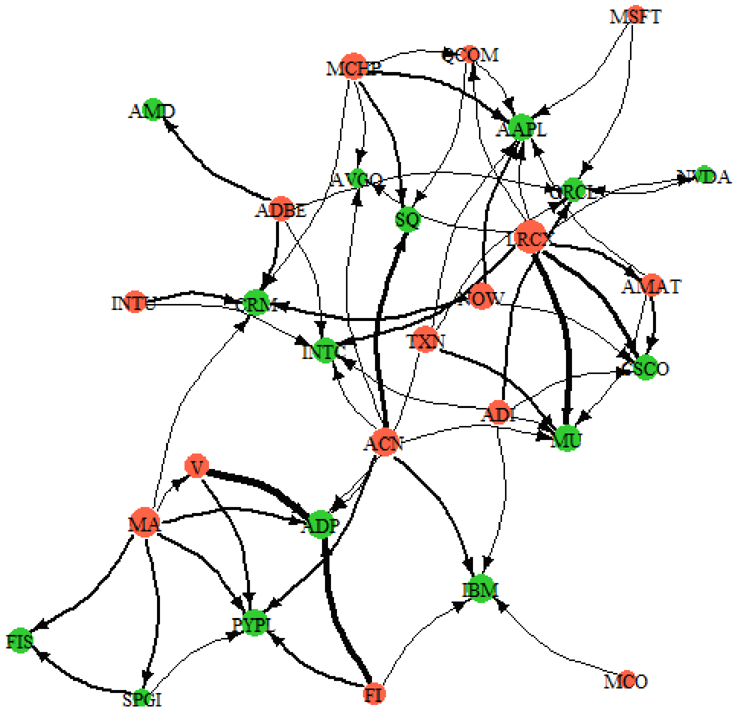

Figure 3. Network visualisation of net pairwise directional connectedness paths after SVB's collapse.

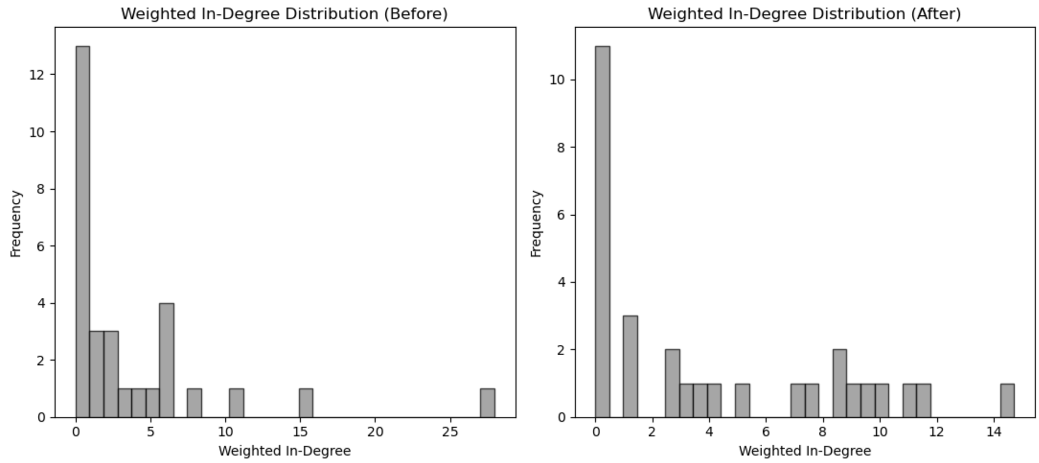

Figure 4. Weighted in-degree distribution before and after SVB's collapse.

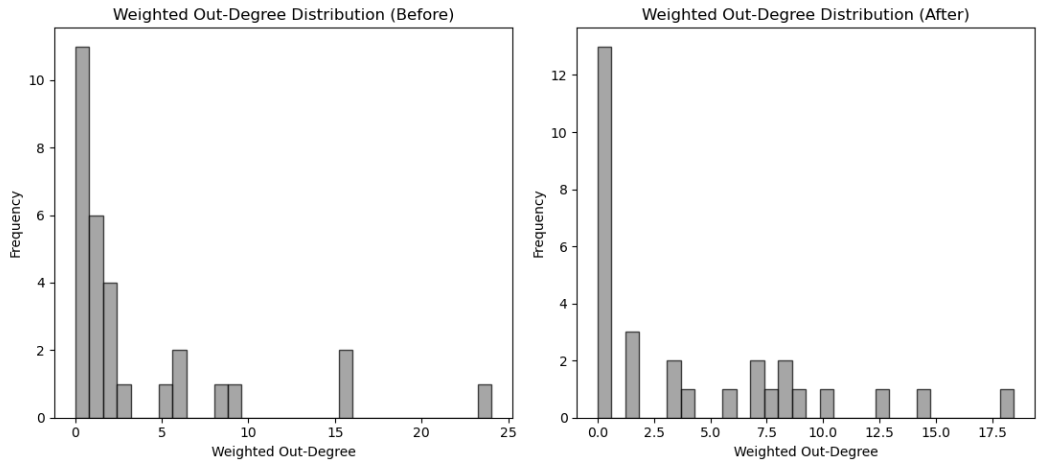

Figure 5. Weighted out-degree distribution before and after SVB's collapse.

4.3.2. Impact of the SVB Collapse on Community Structures

To have a deeper understanding of the network structure, community detection for the directed graph is used to identify groups of nodes within the network that are more densely connected to each other than other nodes in the network. Specifically, the directed Louvain's algorithm (see Section 2.2.2) is applied to maximise modularity to partition the network. There are four communities detected before and after SVB's collapse; the detailed components of one community are shown in Table 6.

It is noteworthy that Visa, Mastercard, Paypal holdings, S&P global, Fiserv, and Fidelity National Information, categorised as financial services companies by the GICS, are detected within a community after the SVB collapse. This shows that the financial services companies have stronger connections with each other than with companies categorised in different subcategories. There is more risk spillover within the financial service companies themselves than in other tech companies, suggesting that the financial institutions are affected by similar financial pressures, such as regulatory changes, as previously addressed. This clustering of the financial services companies demonstrates that the bank failure was attributed to the swift contagion risk that extended from SVB to Signature and Silvergate, as well as affecting the broader banking sector. Additionally, it supports the literature that the financial institutions are largely affected by the failure of SVB's collapse (Akhtaruzzaman et al. 2023; Banerjee et al. 2024).

Table 6. Communities before and after collapse.

Before	
Community 1:	AAPL (TH), MSFT(SW), ADBE(SW), INTU(SW), AMD(SC),QCOM(SC), MU(SC), FI(FS), FIS(FS), ACN(IT), ADP(CE)
Community 2:	ORCL(SW), NVDA(SC), INTC(SC), TXN(SC), AMAT(SC), ADI(SC), MCHP(SC), PYPL(FS), SQ(FS), SPGI(CM), MCO(CM)
Community 3:	LRCX(SC), V(FS), MA(FS), IBM(IT, CSCO(CE)
Community 4:	CRM(SW), NOW(SW), AVGO(SC)
After	
Community 1:	AAPL (TH), AVGO(SC), QCOM(SC), MCHP(SC), SQ(FS), MCO(CM), ACN(IT), IBM(IT)
Community 2:	MSFT(SW), ORCL(SW), NVDA(SC), TXN(SC), AMAT(SC), ADI(SC), LRCX(SC), MU(SC), CSCO(CE)
Community 3:	V(FS), MA(FS), PYPL(FS), FI(FS), FIS(FS), SPGI(CM), ADP(PS)
Community 4:	ADBE(SW), CRM(SW), INTU(SW), NOW(SW), INTC(SC), AMD(SC)

Notes: This table displays the companies grouped into different communities before and after the collapse of SVB. The abbreviations in brackets represent the subcategories classified according the GICS classification.

In addition, we also observe evident clustering communities within other subcategories of companies. For instance, semiconductor companies, NVIDIA, Texas Instruments, and Applied Materials are grouped in Community 2. These companies play a crucial role in the global tech landscape, leading frontier technologies like AI and cloud computing. Similarly, we notice that a few software companies, including Adobe and Salesforce, are part of Community 4. Although Intel and Advanced Micro Devices are semiconductor companies, their products are essential for software applications, which explains their common reactions to market shocks. This suggests that following the SVB failure and the government's intervention, the market not only cut off the link between financial service companies and other tech companies but also signalled that investors view semiconductors and software companies as resilient and essential parts of the tech ecosystem.

Furthermore, we discovered there is a change in the number of companies within each community. Before SVB's collapse, the companies were more centralised with more companies grouped in community 1 and community 2. We observe a more even distribution across the communities for post-collapse. The change in the number of companies within the communities suggests a diversification and dispersion among those tech companies, which explains their similar reaction to the challenges.

To conclude, we observe a clear drop in network connectedness immediately following the event, as indicated by a rolling window analysis. Hence, we believe the network structure must be affected by the failure of SVB. By further comparing different network properties using methods such as community detection before and after the failure of SVB, we observe that several companies belonging to specific sub-categories, such as financial services companies, are classified into one community after the SVB collapse. These results provide valuable insights for the investors and regulators, helping guide market regulation in the event of such failures. They also suggest that future regulatory frameworks should focus on isolating risk in troubled sectors to mitigate the domino effect.

5. Conclusions

In previous studies, Akhtaruzzaman et al. (2023) found that banks played a dominant role in transmitting risk, with contagion primarily being limited to the banking sector and having little effect on other industries. Similarly, Ali et al. (2024) discovered that the banking sector has a substantial negative return, while tech companies were mostly unaffected on the day of SVB collapse. However, our study extends these findings by exploring the changes in the volatility risk contagion among the top 30 large-cap technology companies in the US following the collapse of SVB failure by using Diebold–Yilmaz connectedness approach and several network analyses. We observe a decreased total connectedness index among these companies after the SVB collapse, indicating a decrease in risk contagion in the tech companies. This suggests that the government's rapid intervention to protect tech companies deposits was partially effective in preventing the risk spillover from the banking crisis to the broader market. The visualisations of the net shock contagion paths, along with the in-/out-degree distribution, highlight the key players in the network, providing valuable information to the stakeholders.

These observations, as noted by previous studies, suggest that although the contagion effect is mainly in the banking sector, the tech companies show a more interesting market reaction. In particular, we find that financial service companies among these tech companies are detected in one community after the SVB bank collapse, which shows how closely interconnected these institutions became following the failure of SVB and how risk contagion separate these financial services companies from other tech companies. Similarly, we observe that several software companies are grouped into one community, as are semiconductor companies. This highlights a noteworthy market reaction to the failure of SVB.

Despite these findings, we acknowledge several limitations in our current study. First, we selected solid companies which may have stronger risk management strategies, limiting the ripple effect originating from the failure of SVB. Additionally, we notice that these companies started to diversify risk, as evidenced by the community detection result. Therefore, future studies can look into high-growth tech, mid-cap tech, and small-cap tech companies, where the risk contagion may appear sharply. Furthermore, it will be valuable to explore and compare the contagion effect among FinTech companies and different subcategories companies. Moreover, it is also worthwhile to conduct a broader comparison study on different financial shocks, such as the global financial crisis and COVID-19, which would provide comprehensive insights into how contagion spreads across sectors under distinct economic conditions.

Lastly, our analysis relied on daily data, which may not pick up the short-term rapid responses. Future research could use high-frequency data to capture additional short-term information.

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Data Availability Statement: Data are available on Yahoo! finance.

Conflicts of Interest: The authors declare no conflicts of interest.

Notes

1. https://www.cbsnews.com/news/first-republic-bank-fdic-jpmorgan-chase-control/ (accessed on 5 September 2023).
2. SVB's review at https://www.federalreserve.gov/publications/files/svb-review-20230428.pdf (accessed on 5 September 2023).
3. The Federal Reserve System of the United States has taken actions to increase the interest rate from 0–0.25% to 4.5–4.75% between 2020 and 2023, which has heavily exposed the tech sector and firms to interest rate risk.
4. Reuters-global-firms-with-exposure-collapsed-svb (accessed on 5 September 2023).
5. We apply a multiplier of $\times 100$ to all connectedness measures for the presentation of results.
6. Within a week after SVB collapse, the regulator stepped in to stabilise market confidence. Thus, we chose a 5-day forecast horizon. Moreover, when deciding on the rolling window size, we tested a 360-day rolling window. The TCI shows a consistent but smoother trend compared with a 120-day rolling window. Considering that the model estimation requires estimating 930 parameters, we decided not to further reduce the window size to maintain model efficiency.
7. Economics Times News (accessed on 5 September 2023).

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