



Quantifying the volatility spillover dynamics between financial stress and US financial sectors: Evidence from QVAR connectedness

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ABSTRACT

This study uses quantile vector-autoregressive to examine volatility connectedness among a global financial stress index (including five categories: credit, equity valuation, funding, safe assets, and volatility) and US financial sectors under low, moderate, and extreme volatility conditions. The dataset includes the special periods covering the global financial crisis, China crisis, COVID-19 pandemic, Russian–Ukrainian war, Silicon Valley Bank failure, and Credit Suisse bank crisis. The findings imply that spillover effects among the series are higher during extreme volatility than during low and moderate volatility periods. During periods of low volatility, the credit category of the financial stress index and the US financial sector indices are net shock transmitters, but during extreme volatility periods, the US financial sectors become net shock receivers alongside the credit and funding categories of the financial stress indices. US financial sectors also exhibit net shock recipient roles at extreme volatility levels during those special periods.

1. Introduction

Financial stress levels can indicate potential financial disruptions and market volatility, as noted by Sun et al. (2017). Identifying such stress within the financial sector allows proactive measures to be adopted to minimize uncertainties and mitigate potential financial losses in the markets (Hoque & Low, 2022; Balli, Naeem, & Ozer-Balli, 2022). As especially experienced during the global financial crisis (GFC) and most recently during the COVID-19 pandemic, financial stress affects financial markets, and similarly, financial market turbulence contributes to global financial stress. As the world's largest equity market with a 58.4% share of world equity markets and a critical role in the world economy with a GDP accounting for 15.39% of global GDP according to the The World Bank (2023), the US financial market is the biggest contributor to global financial stress. Any turbulence in the US economy or financial markets enhances the risk of contagion, especially during periods of extreme turbulence, which affects financial stability and growth in the overall economy.

Banks, financial services institutions, and insurance companies are

significant contributors to financial stress due to their intermediary roles with financial market stakeholders (Apostolakis & Papadopoulos, 2015; Billio et al., 2012; Calomiris & Mason, 2003). An extensive body of literature has focused on understanding systemic risk and risk spillovers in the aftermath of global financial sector crises including banks, insurance companies, hedge funds (see, e.g., Billio et al., 2012; Chau & Deesomsak, 2014; Choudhry & Jayasekera, 2014; Diebold & Yilmaz, 2014; Yao et al., 2017; Shahzad et al., 2017; Sun et al., 2019; Zhang, Lv, Naeem, Rauf, & Liu, 2024; Zhang, Naeem, Du, & Rauf, 2024). However, the literature related to the connectedness between the financial sector and financial stress indices (FSIs) is still at an early stage.

This study contributes to the literature by addressing three main research questions: (1) is any connectedness present across various financial stress categories and sectors of US financial institutions? (2) Does connectedness change among these indices for different volatility conditions? (3) How does the transmission mechanism change during special periods such as the GFC, China crisis, COVID-19 pandemic, Russian–Ukrainian war, Silicon Valley Bank failure, and Credit Suisse bank crisis?

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To answer these questions, this study employs the novel quantile vector-autoregressive (QVAR) connectedness approach proposed by Ando et al. (2018), which extends the mean-based vector-autoregression (VAR) approach of Diebold and Yilmaz (2012, 2014), to examine volatility transmission among various financial stress categories and US banking, insurance, and other nonbanking financial institution (NBFI) sectors under moderate (50th percentile), and extreme volatility (95th percentile) conditions to address normal as well as extreme market conditions. The quantile spillover index method is a comprehensive approach that goes beyond relying solely on the middle quantile to measure spillover effects (Ando et al., 2018; Billah et al., 2024; Chen, Wang, & Ren, 2023; Chen, Wang, Zhu, et al., 2023; Khalfaoui et al., 2023; Khan, Rehman, Shahzad, Khan, & Abdul Razak, 2023; Yousaf et al., 2023). This method offers a versatile framework that captures the diverse effects of tail events and tail dependence among variables, enabling the analysis of extreme risk spillovers across markets under various market conditions. As a result, the quantile spillover index method provides a robust tool for experts to examine the intricate relationships among different markets.

We use daily data from the Office of Financial Research (OFR) Financial Stress Index—including five categories: credit (CRD), equity valuation (EQV), funding (FUND), safe assets (SFA), and volatility (VOL)—and the US banking and financial institutions proxied by the NASDAQ Banks (NQ-Bank), NASDAQ Financials (NQ-FIN), NASDAQ Insurance (NQ-INS), and NASDAQ Other FIN SVS (NQ-OFS) indices from January 3, 2000, to July 24, 2023. The study period includes special subperiods—i.e., the GFC, Chinese crisis, COVID-19 pandemic, Russian–Ukrainian war, Silicon Valley Bank failure, and Credit Suisse bank crisis—to identify changes in the transmission mechanism during abnormal periods. This approach can assess the magnitude and direction of connectedness across US financial institutions and global financial stress over time and observe the contagion effect during extreme market conditions.

This study offers tremendous worth and distinctiveness relative to other current literature concerning the correlation between financial stress indicators and US banking and financial institutions. It adds depth to the connectedness literature in two ways. First, it examines the connectedness of financial stress and the US banking, insurance, and NBFI sectors. This empirical evidence will help policymakers develop policy responses that can effectively mitigate the spread of financial stress. Second, the study employs the most recent statistical and econometric techniques, particularly quantile-level connectedness, to examine shock propagation under normal and extreme market conditions. This insightful analysis will undoubtedly help policymakers prepare for worst-case scenarios and develop appropriate policies. Moreover, we concentrate on volatility spillover representing the long-term consequences of the risk transmission mechanism. Third, we use a lengthy dataset (23 years) that considers many special periods, mainly focusing on subsample analysis of the GFC, Chinese crisis, COVID-19 pandemic, Russian–Ukrainian war, Silicon Valley Bank failure, and Credit Suisse bank crisis periods, to further improve our understanding of connectedness during periods that triggered extreme uncertainty in financial markets and led to panic trading and severe economic losses. Finally, we suggest a range of practical steps for policymakers, financial market players, and investors to consider for boosting portfolio diversification and maintaining financial stability.

The study findings suggest several interesting results. First, our full-sample results suggest a moderate level of interdependence and connectedness during low and moderate volatility and a high level of interdependence and connectedness during extreme volatility. Second, during low volatility, US banks and financial institutions are net shock transmitters, whereas categorical global financial stresses are net shock

receivers. However, under extreme volatility, except for the credit category, categorical global financial stresses become net shock transmitters, while US banks and financial institutions become net shock receivers. These findings highlight the importance of using quantile-based estimators to measure the spillovers associated with extreme market movements. Third, a subsample analysis of the GFC, OSR, COVID-19, Russian–Ukrainian war, Silicon Valley Bank failure, and Credit Suisse bank crisis reveals that all US financial sector indices exhibit net shock recipient roles at extreme levels of volatility.

The following section provides a brief literature review on financial spillovers among our variables of interest. The third section presents the methodology and underlying data, and the fourth section provides empirical findings and related discussion. The final section concludes the study and discusses research implications.

2. Literature review

The existing scholarly work on financial stress and spillover mainly focuses on two areas. The first centers on developing and estimating an FSI to track and evaluate financial system stress. This index serves as an essential tool in monitoring financial system stability and identifying vulnerabilities that could trigger systemic risks. Illing and Liu (2003) proposed an FSI to measure the financial stress level in Canada. Following this, many FSIs have been constructed for one country (Bianco et al., 2011; Illing & Liu, 2006; Oet et al., 2015), several countries (Cardarelli et al., 2011; Cevik et al., 2013; Christensen & Li, 2014; Duprey et al., 2017; Melvin & Taylor, 2009; Park & Mercado, 2014), or economic sectors (Ishraque et al., 2020). Variable selection and index synthesis methods differ when constructing FSIs. Similar to Jana et al. (2022), we use the OFR's FSI in our study. The OFR's FSI is a reliable and systematic measure of stress in global financial markets. Using five FSI subcategories (CRD, EQV, FUND, SFA, and VOL), we capture various aspects of financial stress in the global financial markets; furthermore, our comprehensive FSI proxies for broad financial stress.

The second branch of study focuses on the return or volatility spillover effects of FSI components on the economy, financial assets, and real assets. Cardarelli et al. (2009) and Cardarelli et al. (2011) use an FSI to examine why certain financial stress episodes, especially banking distress in the latter case, lead to economic downturns. With a similar scope, Dovern and Roye (2014) use an FSI to study how financial stress, defined as periods of impaired financial intermediation, is transmitted from advanced to emerging economies. Furthermore, Jana et al. (2022), Farid, Naeem, Paltrinieri, & Nepal (2022), Iqbal, Naeem, & Suleman (2022), Mbarki, Omri, & Naeem (2022), Mirza, Naeem, Nguyen, Arfaoui, & Oliyide (2023), Naeem, Adekoya, & Oliyide (2021), Naeem & Arfaoui (2023), Naeem, Conlon, & Cotter (2022), Naeem, Senthilkumar, Arfaoui, & Mohnot (2024), Naeem, Nguyen, Nepal, Ngo, & Taghizadeh-Hesary (2021), and Rahman, Naeem, Yarovaya, & Mohapatra (2024) primarily focus on the international transmission of financial stress during special periods, namely, the COVID-19 pandemic and GFC. In addition, some studies focus on specific regions. Magkonis and Tsopanakis (2020), Cipollini and Mikaliunaitė (2020), and MacDonald et al. (2018) focus on the Eurozone; Chiang et al. (2007) and Apostolakis (2016) concentrate on Asian markets; and Apostolakis and Papadopoulos (2014) and Mensi, Naeem, Vo, & Kang (2022) address G7 advanced economies. Baxa et al. (2013) sought to shed light on the connection between financial instability and monetary policy. In a similar vein, Melvin and Taylor (2009) used an FSI to investigate the impact of the GFC on the foreign exchange market. Apostolakis and Papadopoulos (2015) examined the effects of financial stability (i.e., the FSI), categorized as banking, securities, and foreign exchange markets, on monetary stability (the consumer price index) and the

macroeconomy (GDP growth). It is noteworthy that existing studies on financial stress have some limitations. These studies mostly focus on spillover effects and the transmission of financial stress across countries or markets, but they are mostly conducted under normal market conditions. Unfortunately, empirical research on the spillover effects of financial stress under extreme market conditions is quite limited.

Moreover, some studies focus on financial stress co-movements and spillovers among countries or asset classes. Apostolakis and Papadopoulos (2014) concentrate on spillover among the FSI of G7 economies; Wu et al. (2023) focus on spillover among different asset classes in China and spillover from China to European countries; Magkonis and Tsopanakis (2020) examine the financial stress interconnectedness among the economies of Greece, Ireland, Italy, Portugal, and Spain and Germany; and Elsayed and Yarovaya (2019) address spillover in the MENA region. Chen et al. (2022) investigate extended joint connectedness among the FSI, US stock market, US bank and insurance sectors, oil and gold markets, and broad market volatility. The research suggests that the US government's monetary efforts have played a significant role in connecting financial stress to related factors. They suggest a new era of altered joint connectedness between the banking industry and US financial stress after the COVID-19 pandemic.

Therefore, this study represents our attempt to fill this literature gap. We use a QVAR connectedness approach to examine volatility transmission across various financial stress categories and the US banking, insurance, and NBFIs sectors under three distinct volatility conditions, namely low, moderate, and extreme.

3. Methodology and data

This research examines how closely connected volatility levels are between different subindices of financial stress and the banking and financial institutions sectors.

3.1. Volatility estimation

We can use the following equation to estimate the mean equation using a vector of return series, $r_t = [r_{1,t}, \dots, r_{n,t}]$.

$$r_t = \mu_t + \gamma r_{t-1} + \varepsilon_t. \quad (1)$$

Here, μ denotes the vector of the constant term, and $\varepsilon_t = [\varepsilon_{1,t}, \dots, \varepsilon_{n,t}]$ represents a vector of error terms.

Similarly, the estimated conditional volatilities $h_{i,t}^2$ can be obtained from the univariate GARCH (1,1) process using the following equation.

$$h_{i,t}^2 = \omega + \alpha \varepsilon_{i,t-1}^2 + \beta h_{i,t-1}^2. \quad (2)$$

In this equation, $\omega > 0, \alpha \geq 0$, and $\beta \geq 0$. It is noteworthy that $\alpha + \beta < 1$, which is an important condition for ensuring the stability of the process.

3.2. Quantile connectedness

Ando et al. (2018) have suggested a method to estimate the dependency of y_t on x_t in each quantile τ ($\tau \in (0, 1)$) of the conditional distribution of y_t/x_t (Koenker & Bassett, 1978). The approach involves estimating a VAR process with n -variable p th quantiles. The following equation depicts the process.

$$y_t = c(\tau) + \sum_{i=1}^p B_i(\tau) y_{t-i} + e_t(\tau), t = 1, \dots, T \quad (3)$$

Here, y_t represents the n -vector of the dependent variable at time t ; $c(\tau)$ and $e_t(\tau)$ are n -vectors of the intercept or residual on the quantile τ ; and $B_i(\tau)$ is the lagging coefficient matrix on the quantile τ , where $i = 1, \dots, p$. By assuming that the remainder exceeds the population quantile limit $Q_\tau(e_t(\tau) | y_{t-1}, \dots, y_{t-p}) = 0$, we can estimate $\hat{B}_i(\tau)$ and $\hat{c}(\tau)$.

The τ th conditional quantile of the answer population y can be expressed as follows:

$$Q_\tau(e_t(\tau) | y_{t-1}, \dots, y_{t-p}) = c(\tau) + \sum_{i=1}^p \hat{B}_i(\tau) y_{t-i} \quad (4)$$

This estimation method allows us to better comprehend the relationship between y_t and x_t . It is a valuable tool for examining different aspects of the data and reaching insightful conclusions.

At first glance, it seems that the equations in (4) contain the same variables. This means that the regression structure of the estimation problem is independent. The equations estimate the above model using quantile regression equations, which means they estimate at each quantile (Cecchetti & Li, 2008).

3.3. Spillover indices based on Diebold–Yilmaz

Diebold and Yilmaz (2012, 2014) proposed a framework that can determine the spillover index in each quantile by outlining the quantile variation. Eq. (4) can be rewritten in terms of the moving average process of an infinite-order vector as follows:

$$y_t = \mu(\tau) + \sum_{s=0}^{\infty} A_s(\tau) e_{t-s}(\tau), t = 1, \dots, T \quad (5)$$

with

$$\mu(\tau) = (I_n - B_1(\tau) - \dots - B_p(\tau))^{-1} c(\tau), A_s(\tau) = \begin{cases} 0, s < 0 \\ I_n, s = 0 \\ B_1(\tau)A_{s-1}(\tau) + \dots + B_p(\tau)A_{s-p}(\tau), s > 0. \end{cases}$$

The value of y_t can be determined by summing the remaining e_t in each quantile τ .

For Cholesky-factor ordering, the approaches of Koop et al. (1996) and Pesaran and Shin (1998) are invariant concerning the order of variables. This is because the shocks for each variable are not orthogonal, and the total contribution of the variance to the forecast error does not always equal 1. Using the following equation, we calculate the generalized forecast error variance decomposition of a variable due to shocks from various variables for the forecasting horizon H :

$$\theta_{ij}^g(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e'_i h_h \Sigma e_j)^2}{\sum_{h=0}^{H-1} (e'_i h_h \Sigma e_i)} \quad (6)$$

The contribution of the j th variable to the variance of the forecast error of the i -th variable on the H horizon is represented by $\theta_{ij}^g(H)$, where Σ refers to the variation matrix of the error vector, σ_{jj} is the j th diagonal element of the Σ matrix, and e_i is a vector with a value of 1 for the i -th element and 0 otherwise.

Finally, to normalize every entry in the variance decomposition matrix, we use the following formula.

$$\tilde{\theta}_{ij}^g(H) = \frac{\theta_{ij}^g(H)}{\sum_{j=1}^N \theta_{ij}^g(H)} \quad (7)$$

This normalization technique ensures that every entry is standardized and can be compared with other entries in the matrix.

A useful approach for determining connectivity measures in the τ th conditional quantile is presented by Diebold and Yilmaz (2012, 2014). The approach is based on a generalized decomposition of the error variance in the quantile forecast. Specifically, the total connectivity index for quantiles τ can be expressed as follows:

$$TCI(\tau) = \frac{\sum_{i=1}^N \sum_{j=1, i \neq j}^N \omega_{ij}^h(\tau)}{\sum_{i=1}^N \sum_{j=1}^N \omega_{ij}^h(\tau)} \times 100 \quad (8)$$

Furthermore, the directional spillover index for all indices to index i , denoted “TO,” is expressed as Eq. (9) for quantiles τ .

$$S_{i\bullet}(\tau) = \frac{\sum_{j=1, i \neq j}^N \omega_{ij}^h(\tau)}{\sum_{j=1}^N \omega_{ij}^h(\tau)} \times 100 \quad (9)$$

However, the directional spillover index from index i to all other indices, identified as “FROM,” with regard to quantile τ can be written as Eq. (10).

$$S_{\bullet i}(\tau) = \frac{\sum_{j=1, i \neq j}^N \omega_{ji}^h(\tau)}{\sum_{j=1}^N \omega_{ji}^h(\tau)} \times 100 \quad (10)$$

Eqs. (10) and (11) can be used to calculate the net spillover index (NS) for various levels of quantiles (τ). To do this, we use Eq. (11).

$$NSi(\tau) = S_{\bullet i}(\tau) - S_{i\bullet}(\tau) \quad (11)$$

Similarly, we can calculate the pairwise spillover index for different quantiles τ using Eq. (12).

$$S_{ij} = \omega_{ji}^h(\tau) - \omega_{ij}^h(\tau) \quad (12)$$

To assess connectedness, we used a VAR lag of 1, chosen based on Bayesian information criteria. Furthermore, we used the forecast error variance of the forward decomposition in 10 steps. To reflect variations in spillover measures, we applied a rolling-window approach, as described by Diebold and Yilmaz (2014) and Shahzad et al. (2018).

3.4. Dataset and descriptive statistics

The OFR FSI is a tool that provides a daily snapshot of stress levels within global financial markets. It is used by policymakers, industry professionals, and the public to monitor systemic financial stress. The OFR FSI measures five categories of financial stress, namely, CRD, EQV, FUND, SFA, and VOL. The OFR FSI is a useful resource for those concerned with the stability of financial markets. Thus, we have considered a broad FSI with five categorical FSIs. Data related to OFR FSIs are obtained from the OFR website, <https://www.financialresearch.gov/financial-stress-index/>. To proxy US banking and financial institutions, we considered four broad US financial sectors: NQ-Bank, NQ-FIN, NQ-INS, and NQ-OFS. Price data related to the US banking and financial institutions were extracted from Refinitiv® Eikon. We employed daily US financial sector price data and FSI data points for the period from January 3, 2000, to July 24, 2023.

Table 1 displays the descriptive statistics and unit-root test results. The volatility series of categorical financial stresses in our study showed mean values from 0.058 to 0.153 during the sample period. Among these, EQV-related financial stress displayed higher average shocks than VOL- and SFA-related financial stress. Similarly, the volatility series of the US banking and financial institutions exhibited mean values ranging from 0.016 to 0.027, with NQ-Bank and NQ-OFS showing higher volatility than NQ-FIN and NQ-INS. The standard deviation data demonstrate that EQV, VOL, and funding-related financial stress have higher fluctuation. The skewness, kurtosis, and Jarque–Bera test present compelling evidence that challenges the assumption of a normal distribution for categorical financial stress. As shown by the skewness and kurtosis of the index, categorical financial stress exhibited an upward

swing in volatility, and thus stress typically remains in the financial markets, but it depends on the level. The distributional properties of categorical financial stress volatility exhibit uniformity and communicate a coherent storyline. The data has characteristics of skewness, kurtosis, and deviation from normalcy.

In addition, the standard deviation of volatility data for the US banking and financial institutions has values close to zero, suggesting less fluctuation as well as that some volatility is always present within the sector. This finding shows that the industry is steady and not prone to substantial fluctuations in volatility. Despite the low standard deviation of the volatility data, instances of volatility remain within the industry, and investors should be cognizant of the risks associated with investing in this industry. Conversely, the positive skewness and leptokurtosis of the volatility data from the US banking and financial institutions indicate the existence of high volatility. Regarding distribution properties, the kurtosis of volatility of the US banking and financial institutions indicates a flat tail distribution. Additionally, the Jarque–Bera values highlight that volatility series returns are not normally distributed.

Moreover, the values of the ADF unit-root test indicate stationary series. Therefore, these descriptive statistics and unit-root test results support using the QVAR connectedness approach to examine volatility spillover across categorical financial stresses and the US banking and financial institutions.

4. Empirical findings

4.1. Quantile connectedness of volatility spillovers

Tables 2–4 present empirical evidence regarding volatility transmission across various financial stress categories and US financial sectors, specifically focusing on banking and financial institutions.¹ The analysis examines three distinct market conditions: low (5% quantile), moderate (50% quantile), and extreme (95% quantile) volatilities. These tables provide insights into the static nature of volatility spillovers within the specified contexts. The diagonal elements of the matrix in Tables 2–4 indicate the proportion of variance attributed to each variable, while the off-diagonal elements show the proportion of variance shared across variables. The “FROM” values highlight the impact of variable j (column) on variable i (row), while the “TO” measurements indicate the influence of variable i (row) on variable j (column). The disparity between the “TO” and “FROM” measurements produces net spillovers, wherein a positive (negative) value signifies that variable i functions as a net transmitter (receiver) of shocks. The total connectedness index (TCI) quantifies the level of network interconnectivity by calculating the average values of “TO” or “FROM,” resulting in a range from zero to one.

The analysis examines three distinct market conditions: moderate (50% quantile), and extreme (95% quantile) volatilities. These tables provide insights into the static nature of volatility spillovers within the specified contexts. The diagonal elements of the matrix in Tables 2–4 indicate the proportion of variance attributed to each variable, while the off-diagonal elements show the proportion of variance shared across variables. The “FROM” values highlight the impact of variable j (column) on variable i (row), while the “TO” measurements indicate the influence of variable i (row) on variable j (column). The disparity between the “TO” and “FROM” measurements produces net spillovers, wherein a positive (negative) value signifies that variable i functions as a

¹ Market responses to each source of stress is interconnected with the others through market mechanisms and investors. Thus, it requires considering them comprehensively to capture the true degrees of connectedness within the financial system. So, one could argue that studying sources independently undermines the connectedness of the financial network. Similarly, financial institutions are also exposed to all categories of financial stress.

Table 1
Descriptive statistics and unit-root test.

		Mean	Max	Min	SD	Skew	Kurt	JB	ADF
Financial stress & sub-indices	OFR Financial Stress Index (FSI)	0.193	29.320	−5.334	4.321	2.302	11.615	7842610***	−64.032***
	Credit (CRD)	0.257	8.620	−2.417	1.543	1.673	7.706	9557727***	−59.787***
	Equity valuation (EQV)	−0.005	3.281	−1.389	0.550	1.298	6.456	3004143***	−61.628***
	Safe assets (SFA)	0.065	2.177	−0.668	0.374	1.791	7.929	152,341.40***	−62.100***
	Funding (FUND)	0.139	9.582	−1.512	1.089	3.247	18.552	19864230***	−48.035***
	Volatility (VOL)	−0.264	9.787	−2.597	1.480	1.952	10.350	25573145***	−65.364***
Banking and Financial Institutional Sectors	NASDAQ Banks (NQ-Bank)	0.026	0.491	0.004	0.000	4.764	32.914	243,862.70***	−62.616***
	NASDAQ Financial (NQ-FIN)	0.024	0.562	0.003	0.000	5.712	43.246	433,045.20***	−65.314***
	NASDAQ Insurance (NQ-INS)	0.016	0.538	0.003	0.000	8.177	91.659	2010953***	−65.915***
	NASDAQ other FIN SVS (NQ-OFS)	0.027	0.623	0.002	0.001	5.785	42.005	409537***	−67.219***

Note: This table provides descriptive statistics for the volatility of financial stress sub-indices, banking and financial intuitional sectors under study. Max, Min, SD, Skew, Kurt, JB, and ADF represents Abbreviation, Maximum, Minimum, Standard Deviation, Skewness, Kurtosis, Jarque-Bera, and Augmented Dicky-Fuller test, respectively. *** Indicates significance at 1%.

Table 2
5th Quantile Volatility Spillovers between financial stress sub-indices, banking and financial intuitional sectors.

	FSI	CRD	EQV	SFA	FUND	VOL	NQ-Bank	NQ-FIN	NQ-INS	NQ-OFS	From
FSI	64.80	8.20	3.68	2.22	4.41	11.43	1.36	1.27	1.29	1.34	35.20
CRD	9.40	74.75	1.97	2.23	2.42	2.90	1.45	1.50	1.48	1.90	25.25
EQV	4.44	2.02	80.25	1.97	1.32	2.12	1.99	1.96	1.95	1.99	19.75
SFA	2.67	2.58	2.06	82.85	1.58	1.07	1.84	1.85	1.62	1.89	17.15
FUND	5.52	2.76	1.32	1.57	77.41	2.38	2.11	2.26	2.52	2.13	22.59
VOL	12.59	2.75	1.97	0.93	2.23	74.36	1.25	1.24	1.22	1.47	25.64
NQ-Bank	0.79	0.77	0.96	0.81	1.03	0.65	32.14	26.94	18.40	17.50	67.86
NQ-FIN	0.68	0.72	0.82	0.74	1.05	0.57	24.54	30.27	19.25	21.35	69.73
NQ-INS	0.80	0.84	0.98	0.76	1.32	0.68	19.41	22.34	34.63	18.23	65.37
NQ-OFS	0.85	0.98	0.99	0.89	1.19	0.76	18.18	24.41	18.00	33.77	66.23
TO	37.75	21.62	14.75	12.12	16.54	22.58	72.13	83.75	65.73	67.82	TCI
NET	2.55	−3.63	−5	−5.04	−6.05	−3.06	4.27	14.02	0.35	1.58	41.48

Note: Quantile Spillover indices are calculated from variance decomposition based on 10-step-ahead forecasts. The underlying forecast error variance decomposition (FEVD) is based on upon a ten-dimension FIVAR of order 1, which is indicated by the AIC.

Table 3
50th Quantile Volatility Spillovers between financial stress sub-indices, banking and financial intuitional sectors.

	FSI	CRD	EQV	SFA	FUND	VOL	NQ-Bank	NQ-FIN	NQ-INS	NQ-OFS	From
FSI	68.43	8.28	3.42	2.06	4.12	11.44	0.63	0.53	0.50	0.59	31.57
CRD	10.23	77.42	2.02	2.69	1.90	2.66	0.64	0.73	0.59	1.12	22.58
EQV	4.40	1.73	85.00	1.70	1.00	1.89	1.06	1.08	1.03	1.11	15.00
SFA	2.49	2.29	2.00	87.73	1.46	0.88	0.87	0.85	0.64	0.79	12.27
FUND	6.47	2.77	1.57	1.47	79.89	3.00	1.04	1.21	1.48	1.10	20.11
VOL	13.15	2.34	1.85	1.25	1.85	77.23	0.53	0.56	0.50	0.73	22.77
NQ-Bank	0.81	0.87	0.97	1.02	1.37	0.74	33.45	27.66	17.30	15.81	66.55
NQ-FIN	0.76	0.89	0.86	0.80	1.74	0.74	24.47	31.31	18.57	19.88	68.69
NQ-INS	0.73	0.89	0.90	0.94	1.77	0.81	18.42	22.46	36.38	16.70	63.62
NQ-OFS	0.75	1.07	1.08	0.88	1.81	0.96	17.05	24.49	17.37	34.56	65.44
TO	39.80	21.13	14.66	12.80	17.03	23.11	64.70	79.58	57.97	57.84	TCI
NET	8.23	−1.44	−0.34	0.53	−3.08	0.34	−1.86	10.88	−5.65	−7.6	38.86

Note: Quantile Spillover indices are calculated from variance decomposition based on 10-step-ahead forecasts. The underlying forecast error variance decomposition (FEVD) is based on upon a ten-dimension FIVAR of order 1, which is indicated by the AIC.

Table 4

95th Quantile Volatility Spillovers between financial stress sub-indices, banking and financial intuitional sectors.

	FSI	CRD	EQV	SFA	FUND	VOL	NQ-Bank	NQ-FIN	NQ-INS	NQ-OFS	From
FSI	11.99	9.56	17.63	12.42	9.30	14.91	5.82	6.42	6.17	5.79	88.01
CRD	11.30	11.25	17.65	12.32	9.00	14.24	5.80	6.42	6.21	5.81	88.75
EQV	11.05	9.29	20.06	12.04	9.48	13.46	5.88	6.47	6.36	5.90	79.94
SFA	11.48	9.30	17.29	14.45	9.20	14.22	5.76	6.28	6.22	5.80	85.55
FUND	11.55	9.13	17.47	11.95	10.37	14.70	5.88	6.48	6.42	6.05	89.63
VOL	11.75	8.41	17.23	12.28	9.42	16.56	5.91	6.32	6.26	5.87	83.44
NQ-Bank	11.61	8.98	17.56	12.17	9.27	15.02	6.05	6.63	6.57	6.12	93.95
NQ-FIN	11.76	9.00	17.28	11.76	9.42	15.10	6.13	6.77	6.61	6.15	93.23
NQ-INS	11.78	9.21	17.88	11.86	9.03	15.05	5.97	6.64	6.53	6.05	93.47
NQ-OFS	11.64	8.78	17.48	11.88	9.31	15.35	6.12	6.65	6.56	6.24	93.76
TO	103.93	81.66	157.47	108.68	83.43	132.06	53.26	58.31	57.38	53.55	TCI
NET	15.92	-7.09	77.53	23.13	-6.20	48.62	-40.68	-34.92	-36.09	-40.21	88.97

Note: Quantile Spillover indices are calculated from variance decomposition based on 10-step-ahead forecasts. The underlying forecast error variance decomposition (FEVD) is based on upon a ten-dimension FIVAR of order 1, which is indicated by the AIC.

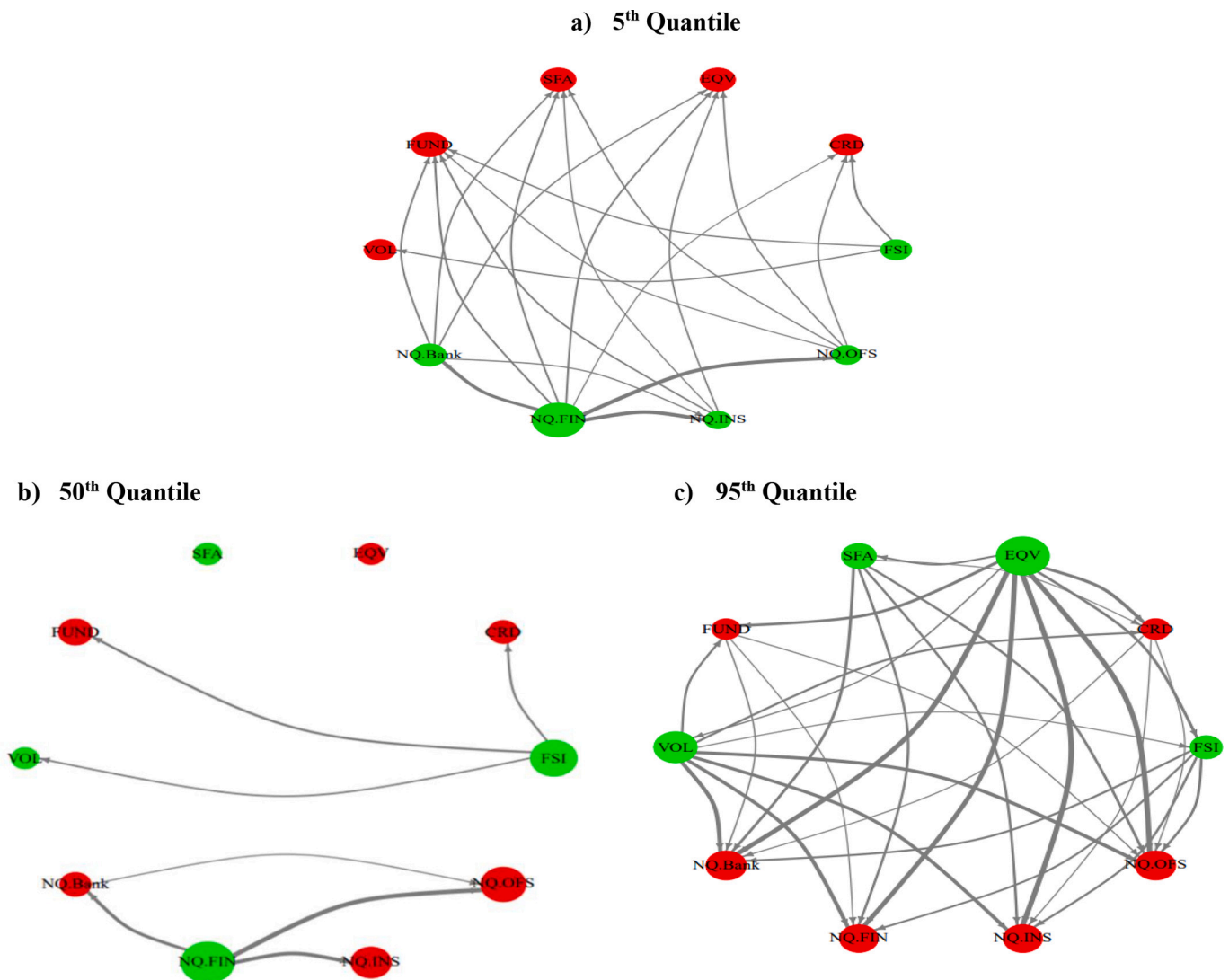


Fig. 1. Full-sample volatility connectedness networks between financial stress subindices, banking, and financial intuitional sectors. Lags = 1 based on SIC. Forecast horizon of 10 days.

Note: Total connectedness is measured using the Diebold–Yilmaz framework. The size of the node shows the magnitude of the contribution of each variable to system connectedness, while the color indicates the origin of connectedness. Node size signifies the extent of spillover effect and color specifies whether a market is a net transmitter (green) or recipient (pink) of spillovers. The forced-directed layout algorithm sets a node location where the sum of the vectors sets the node route. Arrow width signifies the strength of the pairwise spillovers and color specifies strongest (red) to weakest (black) directions of spillovers.

net transmitter (receiver) of shocks. The total connectedness index (TCI) quantifies the level of network interconnectivity by calculating the average values of “TO” or “FROM,” resulting in a range from zero to one.

When looking at total spillover under the three distinct market conditions, we noted TCI values of 41.48%, 38.86%, and 88.97% under low (5% quantile), moderate (50% quantile), and extreme volatilities (95% quantile), respectively. These values suggest a moderate level of interdependence and connectedness under low to moderate volatility conditions and a higher level of interdependence and connectedness under extreme volatility conditions. This implies that during periods of financial strain, the likelihood of shocks spreading among sectors is greatly heightened. With regard to financial stress, the prevalence of contagious threats has increased. In addition, the increased volatility spillover poses a risk to US financial institutions, markets, and the overall economy. Therefore, any unexpected disruption in the financial system may lead to a swift response to such shocks. In the end, this will lead to more disruptions in the financial market and economic activity. The US financial market holds a dominant position in the global financial landscape. As a result, any disruptions in the US market can have far-reaching consequences on other countries' financial markets. These effects are transmitted through various financial stress factors, causing significant impacts worldwide. Moreover, a study conducted by Apostolakis and Papadopoulos in 2015 reinforces our findings on volatility transmission across sectors and categories within the United States. Financial stress was determined to have spillover effects on various markets, such as banking, securities, and foreign currency. [Chen et al. \(2022\)](#) identified a noteworthy correlation and transmission of financial stress within the United States, specifically among the banking sector, insurance sector, and overall interconnectedness. [Hoque et al. \(2023\)](#) found increased time-varying interconnectedness between gold and bitcoin, as evidenced by their correlation with categorical and regional FSIs. Previous studies have primarily focused on the return spillover, while Our focus is on volatility spillover with the extreme risk transmission mechanism. Moreover, the presence of volatility-induced spillover within financial networks aligns with prior studies ([Dai & Zhu, 2023](#); [Gong et al., 2023](#); [Xie, 2021](#)). [Chen, Wang, and Ren \(2023\)](#) and [Long and Li \(2023\)](#) found a quantile-dependent spillover effect on financial markets from financial stress.

In terms of spillover effects under different volatility conditions, we noted that banking and financial institutions sectors have some spillover among themselves under low (5% quantile) and moderate (50% quantile) volatility conditions and modest levels on categorical global FSIs. Similarly, categorical global FSIs mostly have spillover within them, with no spillover evident within the US banking and financial institutions. The prevalence of intersectoral spillovers, especially during periods of low volatility, emphasizes the banking and financial institutions' underlying interconnectedness. Continuous surveillance of cross-sectoral risks is thus required. However, under extreme volatility (95% quantile) conditions, significant spillover occurs among global FSIs on the US banking and financial institutions, and vice versa. The heightened spillover observed during extreme events reflects cyclical increases in interconnectedness within the system. As a results, this procyclicality may further spread and magnify shocks, particularly during a crisis. Hence, this further strengthens the argument for implementing countercyclical hedges or instruments to limit interconnections across sectors when financial stability worsens. Moreover, during periods of high turbulence or volatility, the flow of feedback between global categorical financial stress and US banking and financial institutions increases, emphasizing the significance of international coordination. Furthermore, the effect of volatility state

dependency emphasizes the significance of financial institutions improving their risk management practices.

The net positions of each market under low to high volatility conditions are presented in the last row of [Tables 2–4](#) and [Fig. 1](#). During periods of low volatility (5% quantile), we can observe that FSI (2.55%), NQ-Bank (4.27%), NQ-FIN (14.02%), NQ-INS (0.35%), and NQ-OFS (1.58%) act as net shock transmitters with regard to connectedness between financial stress categories and sectors of US financial institutions. Under the same market conditions, CRD (−3.63%), EQV (−5%), SFA (−5.04%), FUND (−6.05%), and VOL (−3.06%) are net shock receivers. Hence, at low volatility levels, US financial sectors (NQ-Bank, NQ-FIN, NQ-INS, NQ-OFS) dominate in terms of shock transmission, whereas overseas components (CRD, EQV, SFA, FUND, VOL) predominantly experience spillover impacts. This is compatible with the underlying degree of interconnection. These findings are consistent with those of [Apostolakis and Papadopoulos \(2015\)](#), who state that financial markets are shock transmitters of financial stress.

Furthermore, under moderate volatility (50% quantile) conditions, we observe that FSI (8.23%), SFA (0.53%), VOL (0.34%), and NQ-FIN (10.88%) are net shock transmitters within the connectedness of financial stress categories and US financial institutions sectors. Under the same market conditions, CRD (−1.44%), EQV (−0.34%), FUND (−3.08%), NQ-Bank (−1.86%), NQ-INS (−5.65%), and NQ-OFS (−7.6%) are net shock receivers. During periods of moderate volatility, the transmission roles become less distinct due to the influence of global factors such as the FSI and its SFA and VOL subindices, which also serve as transmitters. However, when looking at transmission mechanisms and interactions, US financial sectors are not interdependent on global categorical financial stresses. The US financial sector can be considered a hedge on categorical financial stress for other sectors of the US stock market and other countries' financial markets.

Moreover, under extreme volatility (95% quantile) conditions, we observe that FSI (15.92%), EQV (77.53%), SFA (22.31%), and VOL (48.62%) are net shock transmitters within the connectedness of financial stress categories and US financial institution sectors. Under the same market conditions, CRD (−7.09%), FUND (−6.20%), NQ-Bank (−40.68%), NQ-FIN (−34.92%), NQ-INS (−36.92%), and NQ-OFS (−40.21%) are net shock receivers. Significantly, the presence of severe volatility causes a trend reversal: categorical FSIs such as EQV, SFA, and VOL rise significantly, becoming the key drivers of contagion. This demonstrates a noteworthy shift toward global shocks with a significant influence on US financial market volatility. Simultaneously, all the US financial sectors changed from net transmitters to net receivers. Hence, our research findings indicate the existence of a financial system with increasing interconnectedness that follows a procyclical pattern. As turbulence increases, stress transmission within the network tends to shift toward pathways with substantial international influence. This shift increases exposure to external risks and reduces the US financial system's potential to handle disruptions independently. Thus, addressing systemic crises necessitates a well-coordinated policy.

4.2. Time-varying volatility spillovers and net direction

[Figs. 2a–2c](#) present time-varying spillovers under low (5% quantile), moderate (50% quantile), and extreme volatilities (95% quantile), respectively. Under low and moderate volatility conditions, we observe moderate-level time-varying spillover among categorical global FSIs and US financial sectors. Furthermore, during periods of extreme volatility, we observe higher-level time-varying spillover among categorical global FSIs and US financial sectors. The aforementioned results elucidate the

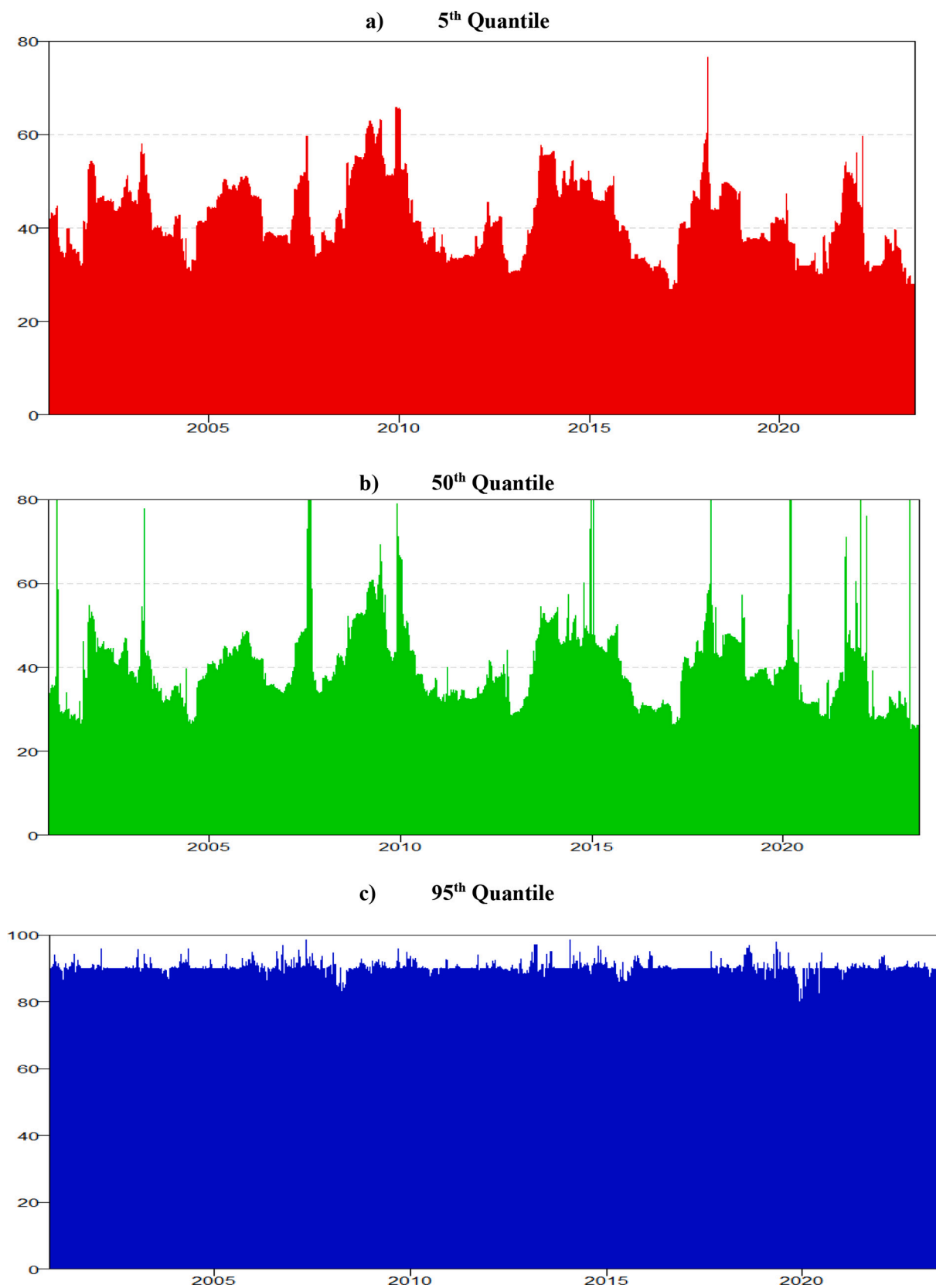


Fig. 2. Dynamic rolling-window connectedness between financial stress subindices, banking, and financial intuitional sector volatilities using 200-day rolling-window lags = 1 based on SIC. Forecast horizon of 10 days. The dashed black line represents the average connectedness.

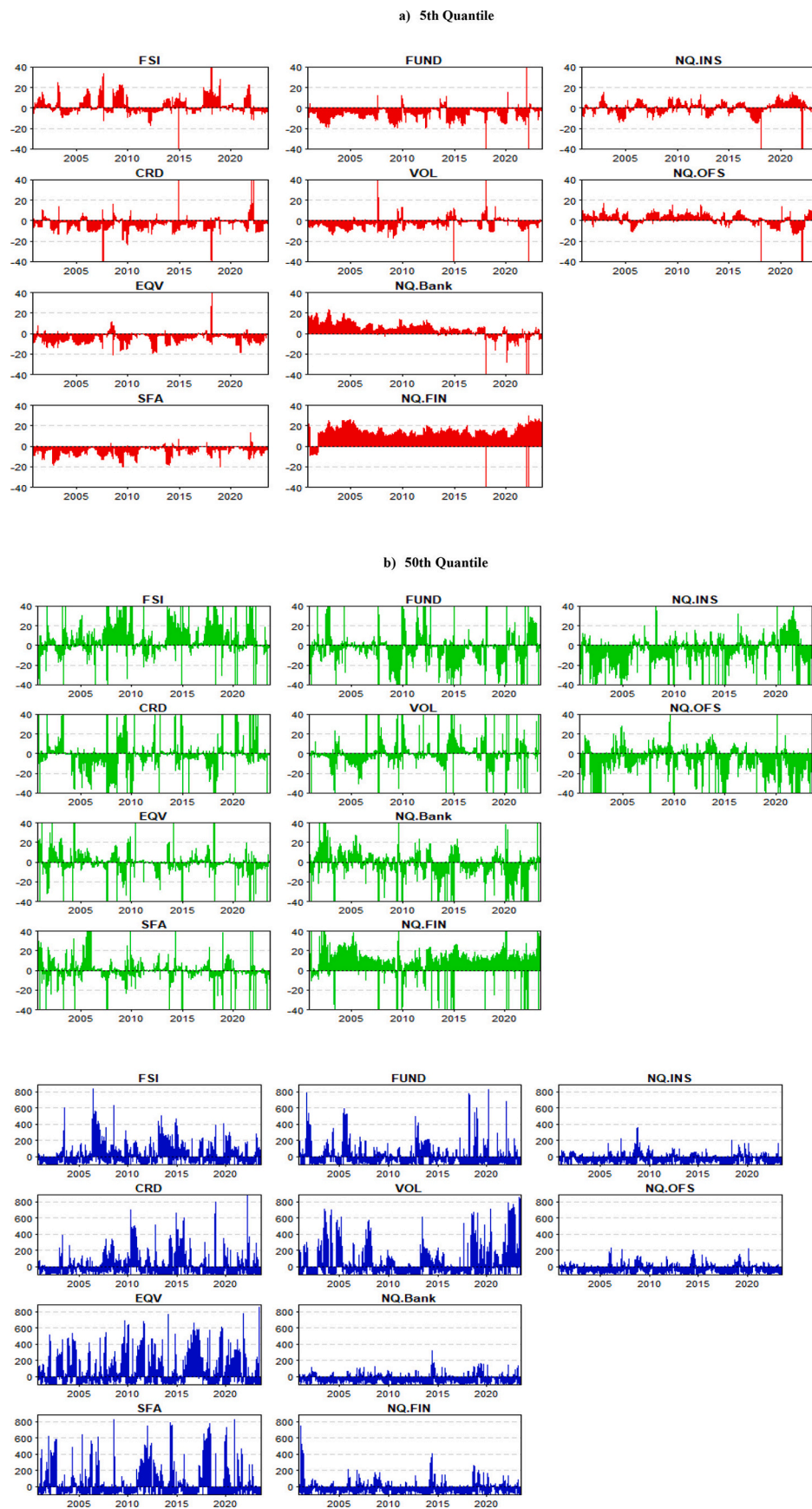


Fig. 3. Dynamic rolling-window NET connectedness between the financial stress subindices, banking and financial intuitional sector volatilities using 200-day rolling-window lags = 1 based on SIC. Forecast horizon of 10 days.

evolving dynamics of spillover effects and their reliance on the degree of volatility within financial markets. This suggests that a more pronounced link exists between global financial stress indicators and US financial sectors during periods of heightened volatility. The careful monitoring and comprehensive understanding of spillover effects, particularly in periods of market crisis, are crucial for identifying possible systemic risks and linkages within the financial system.

The TCI under low and moderate volatility conditions exhibits similar patterns. Under low and moderate volatility conditions, we observe spikes in the TCI line in late 2001 and 2004 triggered by the Argentinean financial crises of 2001–2002, dot-com crash, and US–Iraq War. Notably, the global FSIs exhibited systematic risk spillover. During 2008–2011, connectedness among global financial stress indicators and US financial sectors increased due to the subprime and global financial crises. The European sovereign debt crisis of 2010–2012 also contributed to increases in connectedness and spillover. Furthermore, the 2013 taper tantrum episode, 2014 Russian financial crisis, oil price shocks of 2014–2015, 2015 Greek debt crisis, and China crisis of 2015 caused stress in financial markets and increased integration and spillover levels during that time. The US–China trade war and Brexit negotiations in 2018, followed by the Middle East tension and oil price shocks of 2019, contributed to financial market volatility and thus increased spillover. The COVID-19 pandemic and the 2020 recession further contributed to spillover. The recent 2022 Russian–Ukrainian war has generated financial stress and oil price shocks, contributing to increased connectedness. The failure of Silicon Valley Bank and the Credit Suisse bank crisis caused financial stress in the global market, leading to increased integration during that period. These findings emphasize the vulnerability of the global financial system to significant economic, geopolitical, and systemic shocks and their connectedness across categorical global FSIs and US financial sectors.

However, under high volatility conditions, connectedness among global financial stress indicators and US financial sectors remained elevated. However, we observe some spikes, which implies further increased connectedness levels triggered by the Argentinean financial crises of 2001–2002, dot-com crash, US–Iraq War, European sovereign

debt crisis of 2010–2012, 2013 taper tantrum episode, 2014 Russian financial crisis, oil price shocks of 2014–2015, 2015 Greek debt crisis, China crisis of 2015, COVID-19 pandemic and 2020 recession, and 2022 Russian–Ukrainian war.

Figs. 3a–3c depict time-varying net directional spillovers at different levels of volatility: low (5th percentile), moderate (50th percentile), and extreme (95th percentile), respectively. Under low volatility conditions, our analysis reveals that US banks and NBFIs primarily function as shock transmitters in terms of net time-varying directional spillover. The role of the US insurance sector and other financial services has changed over time due to economic, political, and global events. Global financial stress has been transmitted to subindices and US financial sectors. During periods of global financial crises, such as the European debt crisis, 2014–2015 oil price shocks, and Russian–Ukrainian war, financial stress indicators such as CRD, FUND, EQV, and VOL shift from being primarily affected by shocks to becoming transmission sources themselves. Furthermore, under moderate volatility conditions, system variables showed their dynamic net role in the shock transmission mechanism; their roles have also changed due to economic, political, and global events. Moreover, under extreme volatility conditions, although broad global financial stress and categorical indices demonstrated a net transmitting role, that role changed over time in response to major global events. Furthermore, while US financial sectors were mostly net receivers of shocks, they acted as net transmitters of shocks during periods of global financial crises, such as the GFC European debt crisis, 2014–2015 oil price shocks, COVID-19 pandemic, Russian–Ukrainian war, and bank failures such as Silicon Valley Bank and Credit Suisse.

4.3. Robustness tests

We performed robustness checks of the original QVAR estimation using rolling windows and alternative forecast horizons. Specifically, we re-estimated the model with rolling windows of 150 and 250 days and forecast horizons of 5 and 10 days, respectively. The resulting dynamic spillover index lines from these robustness checks are shown in Fig. A1,

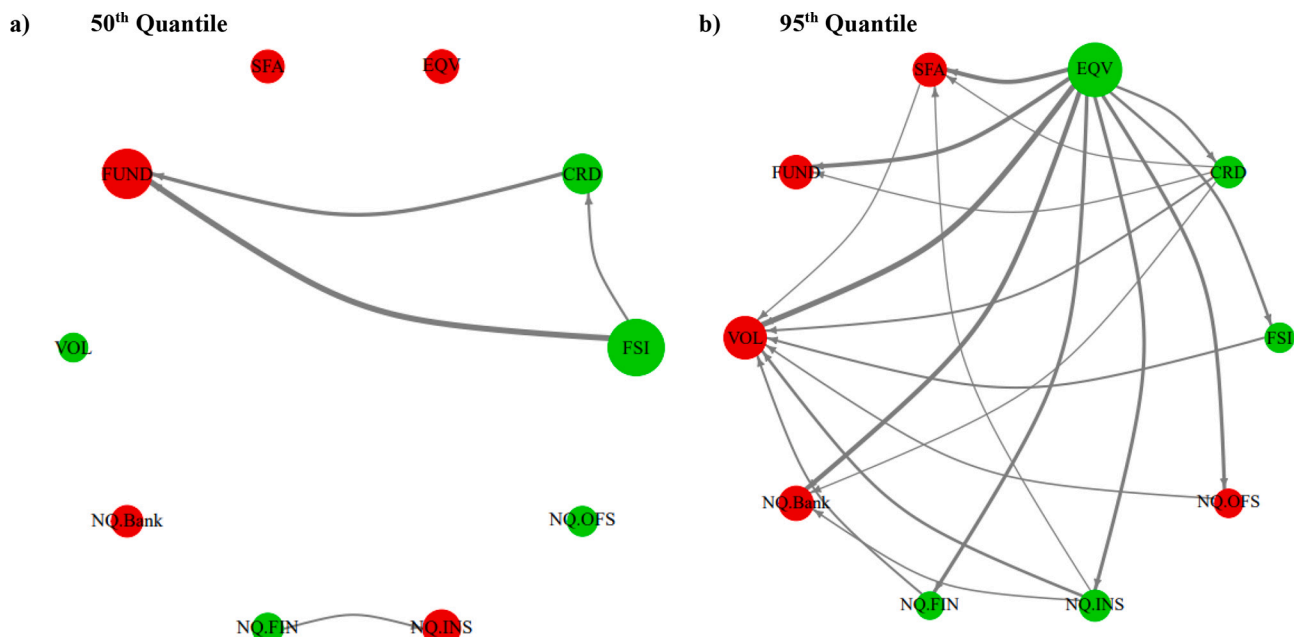


Fig. 4. Volatility connectedness networks during GFC between financial stress subindices, banking, and financial intuitional sectors. Lags = 1 based on SIC. Forecast horizon of 10 days.

Note: See Fig. 2

with the 150-day window/5-day forecast horizon results shown as the green line and the 250-day window/10-day forecast horizon results shown as the red line. This allows us to verify the stability of our findings under varying model specifications. In both lower quantiles, the time-varying conditional index remained at a moderate level, consistent with the results presented in Fig. 2a. Consistent with the estimated results from the QVAR model using a 200-day rolling window, in these two models, we observed that connectedness and spillover effects intensified during the Argentine financial crisis of 2001–2002, dot-com crash, US–Iraq War, European sovereign debt crisis of 2010–2012, 2013 taper tantrum episode, 2014 Russian financial crisis, 2014–2015 oil price shocks, 2015 Greek debt crisis, 2015 China crisis, COVID-19 pandemic and 2020 recession, and 2022 Russian–Ukrainian war. Furthermore, in both upper quantiles, connectedness and spillover effects remained at extreme levels. Across all three cases, it is evident that the index increased substantially during the GFC, European debt crisis, 2014–2015 oil price shocks, COVID-19 pandemic, Russian–Ukrainian war, and bank failures such as Silicon Valley Bank and Credit Suisse. Thus, the findings derived from using two distinct QVAR models and employing alternative rolling-window specifications demonstrate a parallel and analogous trend in terms of dynamic connectivity and spillover effects. These remain consistent across various periods and market conditions. The consistency observed in the findings lends support to the robustness of our main results concerning fluctuations in interconnectedness and spillovers among categorical financial stress and US financial sectors, in particular, their escalation during periods of financial strain and crisis.

To reinforce the relevance of the quantiles chosen, we conducted additional testing using QVAR with 10 quantiles. The results, presented in Fig. A2, consistently show that the connectedness of volatility among the financial stress categories and stocks of the US banking and financial

institutions increases as volatility rises to extreme levels. This additional analysis strengthens the finding that interconnectedness within the system varies significantly depending on the degree of market turbulence.

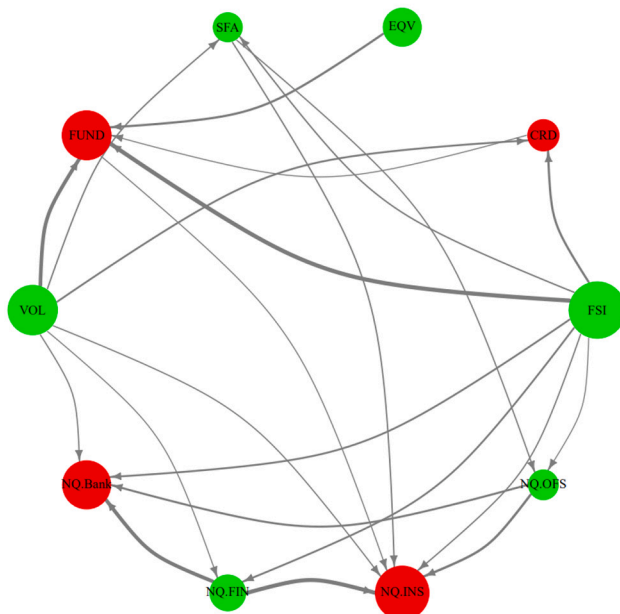
4.4. Impact of the global financial crisis

Fig. 4 displays a transmission network plot of connectedness and spillover among various financial stress categories and US financial institution sectors during the GFC in 2009. When volatility conditions are at the 50th percentile, no discernible association appears to exist between the FSIs and the US financial sectors. There is no evidence of major shock transmission or spillover effects among these variable categories. Moreover, each variable showed significant connectedness within the overall system under conditions of extreme volatility (95th percentile). Specifically, the FSI, EQV, CRD, NQ-FIN, and NQ-OFS variables demonstrated a net transmitting role for shocks. Meanwhile, the SFA, VOL, NQ-Bank, and FUND variables primarily received shocks transmitted from other parts of the system. Thus, comparing the results with Fig. 2 indicates variations in the transmission mechanisms, particularly under conditions of low and extreme volatility. The variables acting as net shock transmitters and receivers vary between low and extreme volatility states. The overall patterns of interconnectedness and spillover within the system differed significantly due to global financial conditions.

4.5. Impact of the Chinese crisis

Fig. 5 displays the connectivity and overflow repercussions prevalent during the Chinese crisis among various financial stress classes and US financial institution sectors through transmission network diagrams.

a) 50th Quantile



b) 95th Quantile

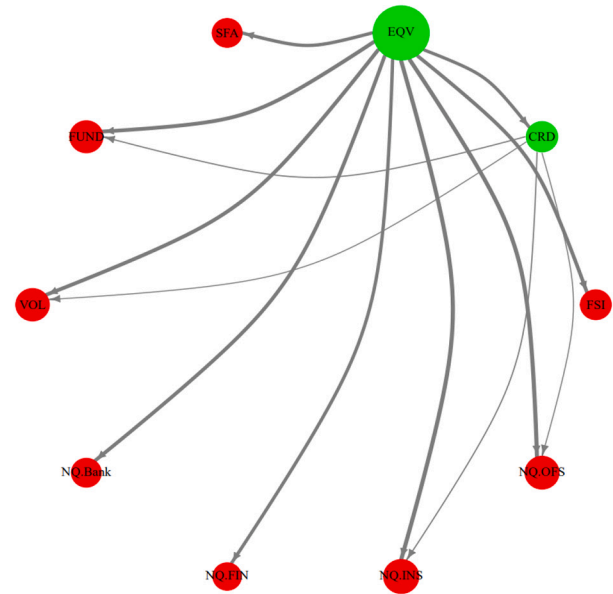


Fig. 5. Volatility connectedness networks during Chinese crisis between financial stress subindices, banking, and financial institutional sectors. Lags = 1 based on SIC. Forecast horizon of 10 days. Note: See Fig. 2.

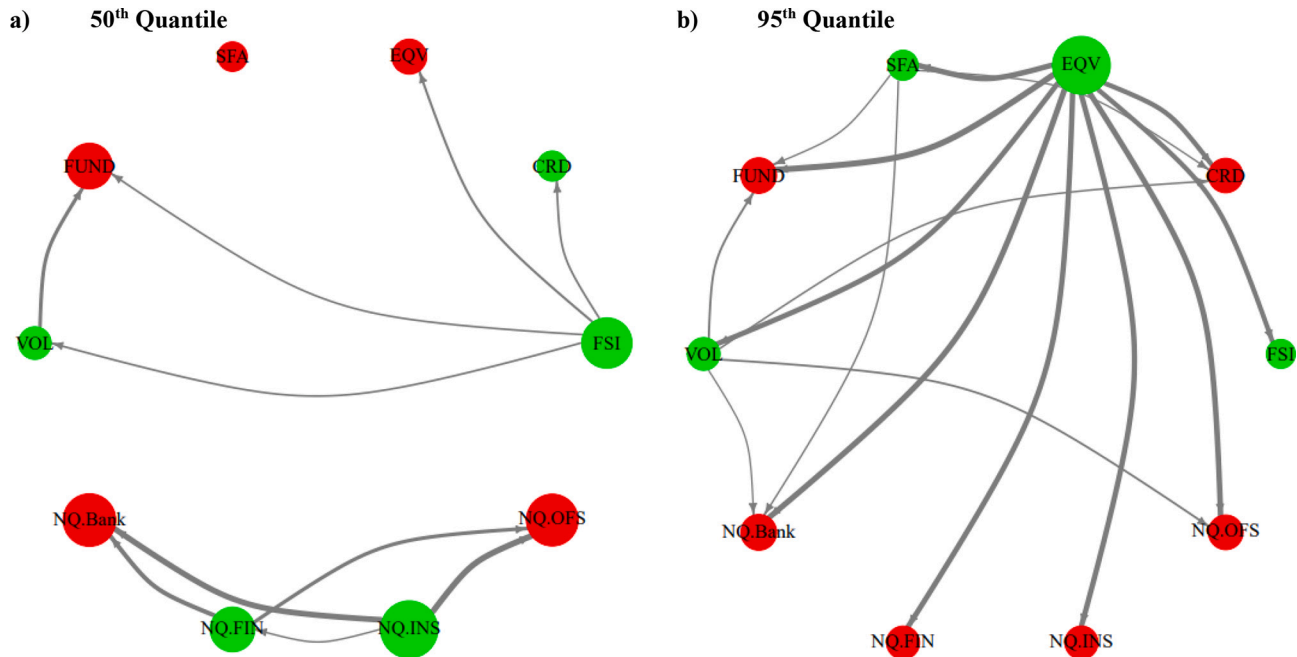


Fig. 6. Volatility connectedness networks during COVID-19 between financial stress subindices, banking, and financial intuitional sectors. Lags = 1 based on SIC. Forecast horizon of 10 days.

Note: See Fig. 2

Under the moderate volatility level (50th percentile), there was substantial spillover and interdependence between system variables. In particular, the FSI, VOL, EQV, SFA, NQ-FIN, and NQ-OFS played a net transmitting role for shocks, whereas the CRD, FUND, and NQ-FIN indices predominantly received shocks transmitted from other variables within the system. Moreover, in instances of highly unstable market conditions (95th percentile), certain levels of interdependence and contagion exist between US financial sectors and FSIs, with EQV and CRD being the primary channels for transmitting shocks. In terms of net roles, US financial sectors are net risk recipients, along with FSI, VOL, SFA, and FUND. Compared with nodes under moderate volatility, the nodes under this market condition come to US banking and financial institutions, implying that when financial stress shocks increase from moderate to extreme, US banking and financial institutions experience contagion from global financial market stress. A comparison of these findings with those in Figs. 2 and 4 reveals differences in transmission mechanisms for different volatility conditions. In particular, the degree of interconnection and spillover within the system varied dramatically between periods of moderate and excessive volatility. These disparities seemed to result from shifting global financial circumstances and oil price shocks over time.

4.6. Impact of the COVID-19 pandemic

Fig. 6 graphically represents interconnections and spillover impacts across various financial stress categories and sectors of US financial institutions during the COVID-19 period. Under the moderate degree of volatility (50th percentile), interaction is clearly lacking among the FSIs and US financial sectors. However, under conditions of extreme volatility (95th percentile), connectedness and spillover exist among FSIs and US financial sectors, with EQV-related stress being the main shock

transmitter, followed by VOL, SFA, and FSI. Moreover, US financial sectors, including CRD and FUND, are net risk receivers. When we compare these findings with those in Figs. 2, 4, and 5, differences are revealed in the transmission mechanisms under low and excessive volatility. The degree of system interconnectedness and spillover, for instance, varies considerably during periods of moderate and high volatility. This difference seems to result from changing global financial conditions, oil price shocks, and the COVID-19 pandemic over time. However, a common factor is that no connectedness is seen among US financial sectors and categorical FSIs. Furthermore, US financial sectors acted as net recipients at times of high volatility.

4.7. Impact of the Russian and Ukrainian war

Fig. 7 visually depicts the connections and spillover effects between various financial stress groups and US financial sectors during the Russian–Ukrainian conflict. Under moderate volatility, it becomes evident that a dearth of interaction exists between FSIs and US financial sectors. Nonetheless, empirical data suggest that significant interdependence and interconnectedness exist across various FSIs, and this pattern is seen within US financial sectors. Furthermore, under extreme volatility conditions, interconnectedness and spillover effects are evident across FSIs and various sectors within the US financial system. The primary transmitter of shocks is VOL, followed by EQV and FSI. Moreover, similar to categorical FSIs, the US financial sectors are net risk receivers. In addition, the transmission channels differ when comparing these findings with the patterns shown in Figs. 2, 4, 5, and 6, indicating the impact of volatility levels and crisis events. However, a prominent trend has emerged from the absence of identifiable linkages between the US financial sectors and categorical FSIs at a moderate level of volatility.

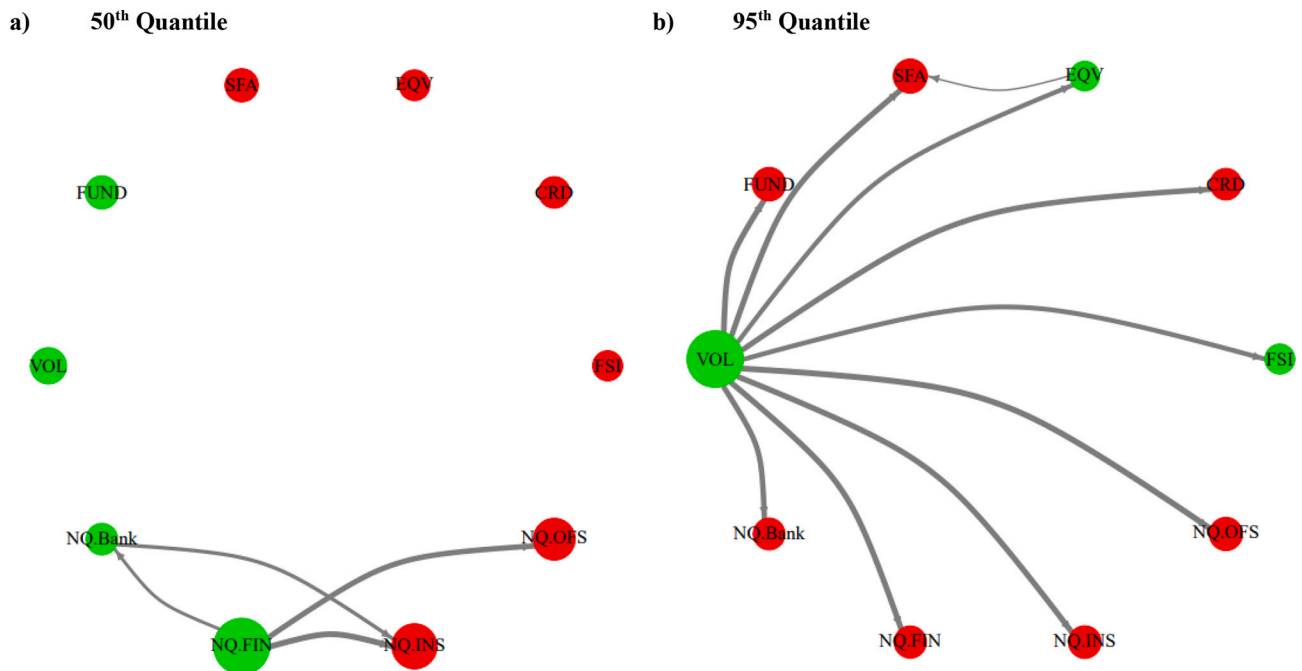


Fig. 7. Volatility connectedness networks during the Russian-Ukrainian war between financial stress subindices, banking, and financial intuitional sectors. Lags = 1 based on SIC. Forecast horizon of 10 days.

Note: See Fig. 2

4.8. Impact of the Silicon Valley Bank failure and credit Suisse bank crisis

Fig. 8 illustrates transmission network plots of the interdependence and impact of shocks propagating from various financial strain categories and the US financial sectors during the Silicon Valley Bank and Credit Suisse bank crises. Moreover, at the 50th percentile of volatility, significant spillover and interdependence are observed among system variables. FSI, CRD, NQ-FIN, and NQ-OFS are net shock propagators,

with the other variables acting as net shock receivers. Viewing the nodes, the board FSI transmits shocks to the US banking and financial institutions, which further transmit shocks to the financial stress categories, with FUND the largest shock recipient. Moreover, in situations of heightened instability, specifically within the top 5%, interconnectivity and transmission of financial pressure are increased among the US financial sectors, as evident in the node clustering. FSI, CRD, EQV, VOL, NQ-FIN, and NQ-INS are net shock propagators, with the other variables

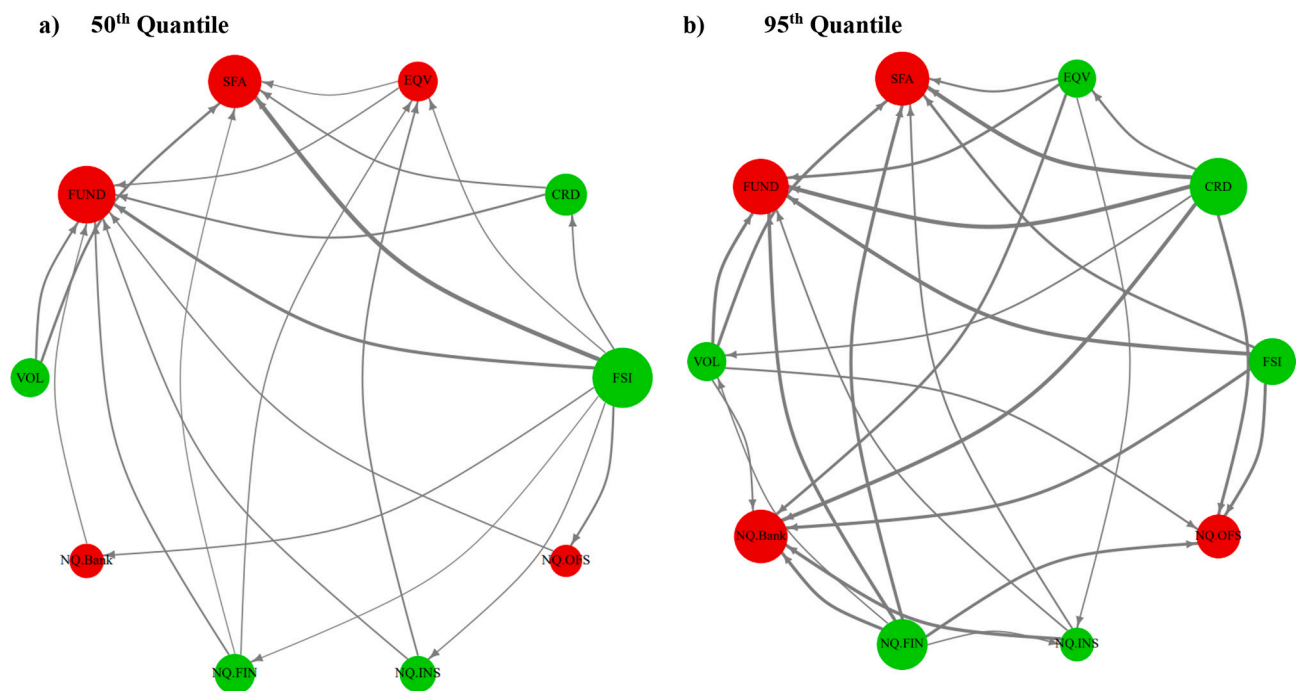


Fig. 8. Volatility connectedness networks during the US Silicon Valley Bank crisis between financial stress subindices, banking, and financial intuitional sectors. Lags = 1 based on SIC. Forecast horizon of 10 days.

Note: See Fig. 2

acting as net shock receivers. When the findings are compared with Figs. 2, 4, 5, 6, and 7, the transmission method varies as volatility increases. The interconnection and spillover of the system are altered dramatically between low and high volatility. These disparities appear to result from a shifting global financial environment.

5. Conclusion and policy implications

The US financial market, being the world's largest, contributes to market turbulence that results in global financial stresses, which in turn further influence US markets. Hence, US banking and financial institutions and global financial stress are interrelated and interdependent. Hence, a correlation and transfer of financial instability exist between the US financial sectors and the global economy. Given this and the research gaps in the field, this study delves into the mechanism of the spread of instability across various financial stress categories and sectors of US banking and financial institutions. This study focuses specifically on three comparative conditions of instability, namely, low (5th percentile), moderate (50th percentile), and extreme (95th percentile) volatilities. In the estimation, this study employs a novel QVAR connectedness approach with a rolling window. The study also focuses on subsamples of the GFC, Chinese crisis, COVID-19 pandemic, Russian–Ukrainian war, and Silicon Valley Bank failure to identify how these events affect the transmission mechanism. The empirical results demonstrate a moderate level of interdependence and connectedness at low and moderate volatility conditions and a higher level of interdependence and connectedness under extreme volatility. The empirical findings indicate spillover effects among banking sectors and financial institutions, particularly during periods of low and moderate volatility. These spillover effects are also observed, to a lesser extent, with global FSIs. Furthermore, categorical global FSIs typically exhibit spillover effects within their specific groups but not on the US banking and financial institutions sectors. During periods of high volatility, notable spillover effects are observed between global FSIs and the US banking and financial institutions, and vice versa. In terms of roles, under low volatility conditions, the FSI, NQ-Bank, NQ-FIN, NQ-INS, and NQ-OFS are net shock transmitters, whereas CRD, EQV, SFA, FUND, and VOL are net shock receivers. Under moderate volatility conditions, the FSI, SFA, VOL, and NQ-FIN are net shock transmitters, while CRD, EQV, FUND, NQ-Bank, NQ-INS, and NQ-OFS are net shock receivers. Moreover, under extreme volatility conditions, the FSI, EQV, SFA, and VOL are net shock transmitters, while CRD, FUND, NQ-Bank, NQ-FIN, NQ-INS, and NQ-OFS are net shock receivers. The subsample analysis of the GFC, OSR, COVID-19, and Russian–Ukrainian war periods indicates that the transmission mechanism and net role of variables change at low and high volatility conditions across subsamples. In the four crisis periods, interaction between FSIs and US financial sectors is lacking at moderate levels of volatility. During the periods of the GFC, OSR, COVID-19, and Russian–Ukrainian war, the four US financial sectors exhibited net shock recipient roles at extreme volatility levels.

Several implications can be gleaned from the empirical results that

will be helpful for policy makers and regulators to manage the systematic risk. First, this study highlights the interconnectedness and transmission of effects between US banking and financial institutions and global financial stress. Policymakers and financial institutions should be aware of these dynamics to effectively manage systemic risks. It is advisable to prioritize the creation of comprehensive risk management frameworks that consider transmission mechanisms and the overall impact of variables for different levels of volatility. Second, analyzing the evolving roles of various factors such as transmitters or receivers of shocks can inform regulatory priorities under different conditions. Third, during periods of low and moderate volatility, it is possible to enhance the resilience of the financial system by implementing measures such as augmented capital buffers. This preparation will enhance the system's ability to effectively manage unexpected surges in volatility. Furthermore, the absence of spillover effects from global stress to US banking and financial institutions stocks, particularly during periods of moderate volatility, indicates that financial risks may be effectively managed and contained at this level. However, regulatory bodies should enhance their monitoring of global stress indicators to detect early signs of potential risks, particularly where the transmission of these indicators to the United States is restricted during periods of moderate volatility. The implementation of this measure is considered crucial due to the potential for rapid and extensive spillover effects. Fourth, the findings of this study suggest a rise in interconnectivity due to financial globalization, particularly during times of heightened volatility. This underscores the importance of implementing coordinated regulatory measures that span multiple countries. Enhanced information-sharing mechanisms and the establishment of cross-national collaboration may be required by regulatory agencies.

This study has many implications for the investors as well. The investors should be cautious during the periods of financial strain as the likelihood of shocks spreading among sectors is greatly heightened. Particularly, under extreme volatility (95% quantile) conditions, significant spillover occurs among global FSIs on the US banking and financial institutions, and vice versa. Investors should implement countercyclical hedges or instruments to limit interconnections across sectors when financial stability worsens to protect their portfolio and overall financial system.

As a future work, it will be worth to examine the effect of the global or regional stress indices on the main advanced economies other than the US and emerging markets. This will allow academics also to compare the effect of the stress indices on advanced and emerging economies. Additionally, distinguishing short-term and long-term spillover will be worthy for market players including regulators. Hence, this study proposes future research involving a quantile frequency connectedness framework to conduct both short-term and long-term analysis within extreme market condition.

Data availability

Data will be made available on request.

Appendix A. Appendix

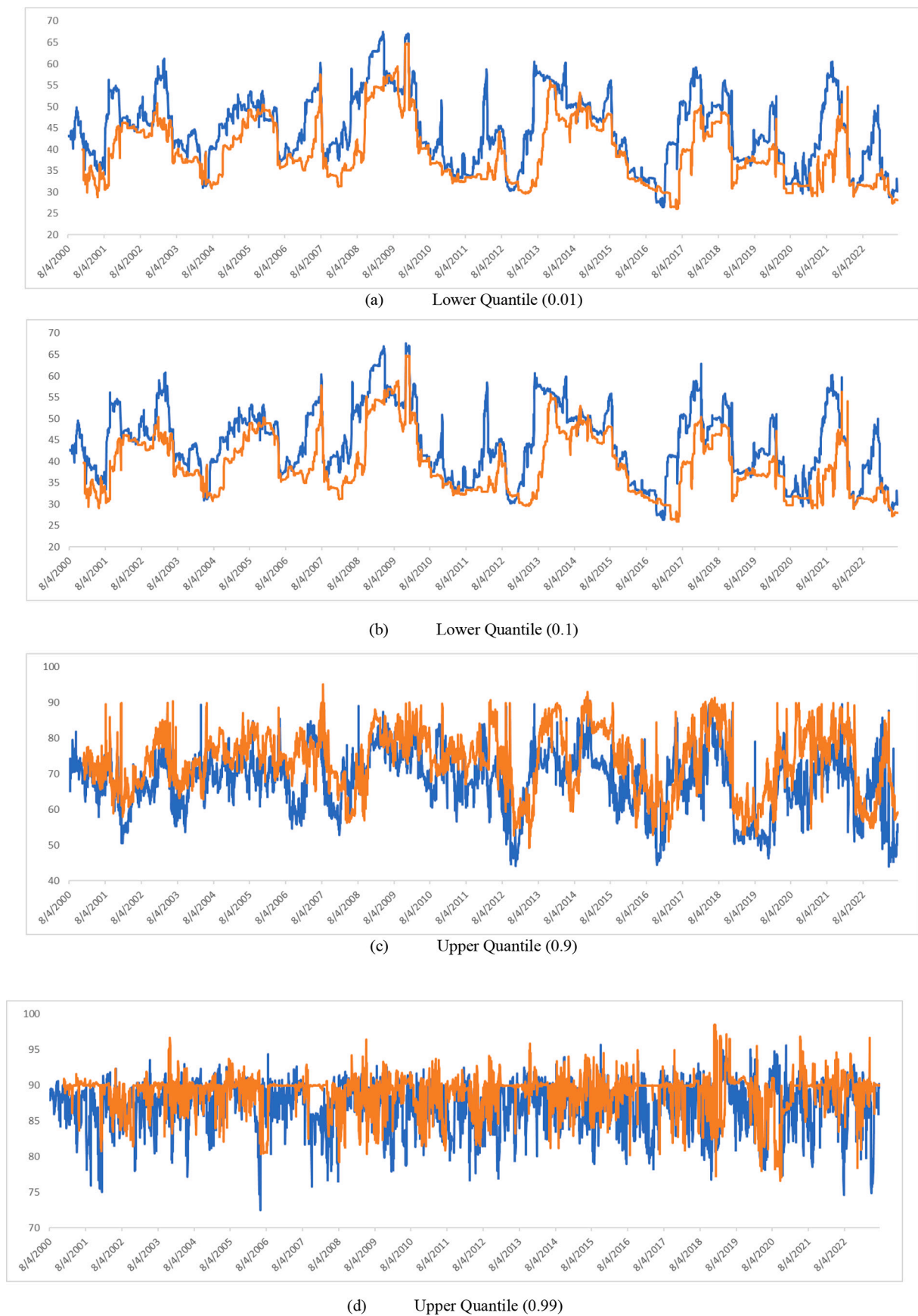


Fig. A1. Robustness between financial stress subindices, banking, and financial intuitional sectors for volatility spillovers to the choice of rolling window and forecast horizon.

Notes: Results for each other combination of $w \in \{150, 250\}$ and $h \in \{5, 10\}$ trading days are shown as green and red lines.

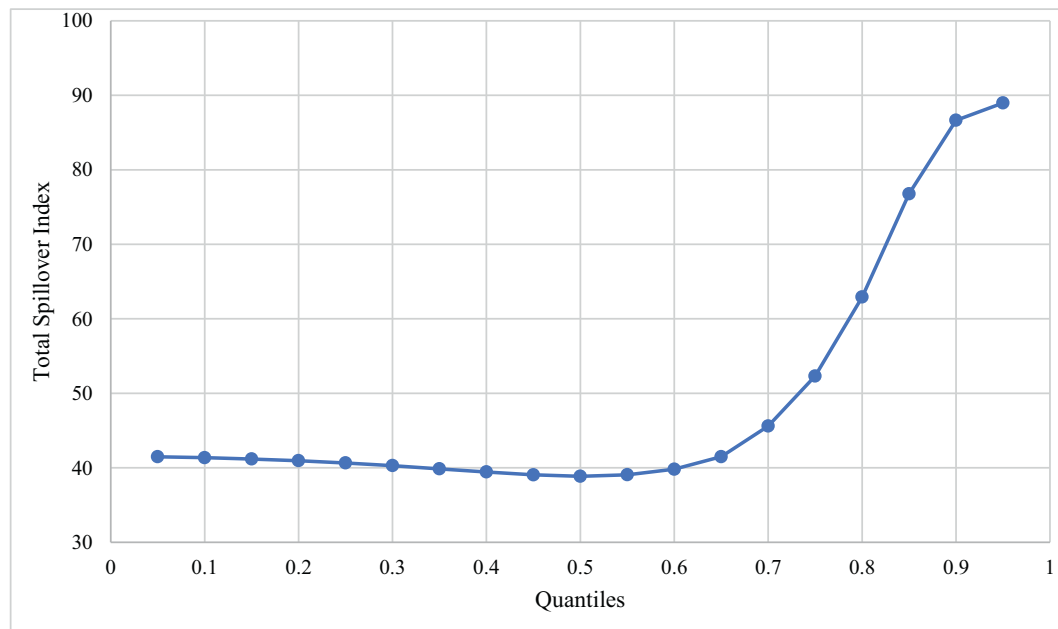


Fig. A2. Total spillover index over quantiles.

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