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Soheil Roudari[a], Farzaneh Ahmadian-Yazdi[b], Masoud Homayounifar[c], Walid Mensi[d,e], Khamis Hamed AlYahyaee[f]

[a]Department of Economics, Ferdowsi University of Mashhad, Mashhad, Iran,
Email: soheil.roudari@gmail.com
[b]Department of Economics, Ferdowsi University of Mashhad, Mashhad, Iran
Email: f.ahmadian@um.ac.ir
[c]Department of Economics, Ferdowsi University of Mashhad, Mashhad, Iran,
Email: homayounifar@um.ac.ir
[d]Department of Economics and Finance, College of Economics and Political Science, Sultan Qaboos University, Muscat, Oman
[e]Department of Finance and Accounting, University of Tunis El Manar and IFGT, Tunisia

Email: walidmensi1@gmail.com

[f]Muscat University, Al Ghubrah North, Muscat, Oman

Email: kalyahyaee@muscatuniversity.edu.om

Abstract Purpose – This study examines the predictability of comparable bivariate sectors in the U.S. and Chinese stock markets, including industries such as healthcare, utilities, telecom, energy, and real estate, during periods of high market turbulence. Additionally, it analyzes the spillover effects between U.S. and Chinese sectors across varying investment time horizons, ranging from short-term to long-term. To provide deeper insights, the study also investigates the dependence structure between the two countries' sectoral stock markets.

Design/methodology/approach– This study employs two methodologies to examine both static and dynamic connectedness across short-, medium-, and long-term financial cycles. These methods are the time-varying parameter vector autoregressive frequency connectedness (TVP-VAR-BK) approach proposed by Baruník and Křehlík (2018) and the Cross Quantilogram (CQ) technique.

Findings – The results show that the interrelationship among stock sector returns is sensitive to major events, particularly in the short term. Moreover, China’s energy sector is the main contributor to volatility in US industry returns across all time horizons. The US industry sector consistently acts as a net transmitter of shocks to the network regardless of the investment horizon. Interestingly, US sector returns tend to transmit volatilities, while Chinese sector returns are mostly net recipients of shocks in the long term. Finally, according to the cross-quantilogram results, the optimal opportunity for portfolio diversification arises when an investor selects a similar sector from both US and Chinese markets, and the two markets are in opposite return phases (i.e., one bullish, the other bearish).

Practical implications – Our findings provide valuable insights for speculators, institutional investors, and policymakers. For equity investors, the results offer practical guidance on portfolio diversification and effective hedging strategies across different market horizons. Additionally, they help investors identify the dependence structure during bearish and bullish market conditions, enabling the classification of assets as diversifiers, hedgers, or safe havens. For policymakers, the findings shed light on the sources of asset contagion, offering critical information to design strategies and reforms aimed at reducing the vulnerability of assets that serve as net shock receivers.

Originality/value –Using the methodology developed by Baruník and Křehlík (2018), we examine the size and direction of connectedness across different time horizons (short, medium, and long terms). For robustness, we employ the Cross Quantilogram technique to evaluate the upper and lower dependence between US and Chinese sectors, considering various market conditions (bearish, bullish, and normal scenarios) by analyzing different quantiles.

Keywords– China and US, stock sectoral index, TVP-VAR-BK model, cross-quantilogram approach.

JEL Classification: C58, G14

1. Introduction

Global financial market integration, geopolitical conflicts, and successive global financial crises have led investors and risk managers to pay close attention to the relationships among global financial markets. Therefore, it is important to examine the relationships between different financial market returns to provide leading indicators and frameworks for policymakers and investors to predict the future conditions of global economies and financial management of markets (Maneejuk and Yamaka, 2019; McMillan, 2019; Rahman et al., 2022; Bilio et al., 2021; Maneejuk et al., 2022). Some of the main concerns of investors are how the financial markets and industry sectors of global stock markets are connected and how risks are transferred between them. Several studies provide evidence that international stock markets and their sectors are interdependent on spillover effects (Zhang and Broadstock, 2020). Significant financial integration brings financial markets closer together and increases the need to analyze intermarket interactions for a better investment decision-making process. Policymakers are concerned with preventing the transmission of harmful shocks and promoting financial stability across markets. Thus, global stock markets and their sectors are inevitably interdependent and subject to spillover factors (Arfaoui et al., 2022; Maghyereh et al., 2022; Zehri, 2021; Zorgati and Garfatta, 2021).

Theoretically, economic crises, geopolitical conflicts, military interventions, and pandemics profoundly influence global financial market dynamics by altering investor sentiment, capital flows, and risk perceptions (Messaoud et al., 2023; Fu et al., 2020). These shocks often lead to heightened market uncertainty and volatility, which can amplify or disrupt the transmission of information and risk across international markets. In particular, the interconnectedness between major economies like the U.S. and China may intensify during such periods due to stronger cross-border financial linkages and synchronized policy responses (Bissoondoyal-Bheenick et al., 2022). For instance, during the COVID-19 pandemic and the

U.S.-China trade war, sectoral comovements and spillover effects between their stock markets became more pronounced (Zhang et al., 2020; Lu et al., 2020). Therefore, understanding the theoretical underpinnings of these global shocks is crucial for interpreting fluctuations in market interconnectedness across different sectors and time horizons.

This study examines the static and dynamic connectedness between the sectoral stock market returns of the two largest economies in the world (the US and China) in short-, medium-, and long-term periods. We focused on the pivotal sectors of the deepest stock markets in the world, which have attracted many institutional and retail domestic and international investors. These sectors include industry, healthcare, telecom, energy, real estate, and utilities, which play a dominant role in diversifying and portfolio management by investors and traders. Moreover, this study considers the response of the Chinese stock market returns of each sector to variations in their counterparts in the US stock market in different quantiles of both markets using heat map plots.

The economic crisis, geopolitical conflicts, military interventions, and infectious diseases represent the key drivers of dynamic connectedness among international markets (Shaik et al., 2024; Adeleke et al., 2022; Zhang and Broadstock, 2020). Recent years have marked a trading tension between the two largest economies in the world, the US and China. More interestingly, since 2017, China has been condemned by the US Trade Representative Office for conducting unfair trade activities due to the violation of property rights. Tensions between the two countries escalated when the US signed a statement against China at the World Trade Organization (WTO) on March 22, 2018. Consequently, restrictions were imposed on China's investments in key technology sectors. Tariffs have also been imposed on Chinese goods. On July 6, 2018, the first tariff on Chinese imported goods was imposed by the US Customs Department, and thus, a trade war between the two countries began (Moosa et al., 2020). Regarding military factors, the tension between Ukraine and Russia has affected communication between different parts of the US and Chinese stock markets.[1] The spread of coronavirus disease (COVID-19) has adversely affected both the supply and demand sides of the global economy, thereby creating conditions of uncertainty in investors' decisions and different parts of the stock markets. Based on this, investigating how the relationship between financial markets in leading countries such as the US and China has been affected is necessary. Therefore, there is a requisite need to investigate the magnitude and direction of the dynamic connectedness between different global industries, determine the predictability and movement between these international industries, and determine which industries and countries are leaders and which are followers. Subsequently, it is crucial to examine which industries, in which countries, and in which periods are front and center, have the highest degree of output, and can transfer more risk to other industries, which can be important for investors and risk managers (Diebold and Yilmaz, 2009, 2015; Demirer et al., 2018; Vidal-Liana et al., 2023; Shi et al., 2021). Knowing the communication, co-movement, and predictability of similar industries in the US and China, as the major global economies, can be helpful during political and economic events and even health-related issues in the future.

This study is innovative and contributes to the literature in the following ways: First, it investigates the static and dynamic risk propagation among similar sectors in the US and Chinese stock markets to determine the net receivers and net transmitters in different investment horizons between December 12, 2014 and February 29, 2023. To that aim, the TVP-VAR-BK technique, introduced by Baruník and Křehlík (2018) has been applied; it provides a time-varying spillover effect between network indices in short-, medium- and long-term periods. This technique estimates the total and directional spillover effects and, in its framework, the forecast error variance decompositions are invariant based on the order of the variables. With regard to the different investment appetites of investors and by considering the fact that the

[1] Russia and Ukraine play an important role in the field of agricultural products and commodities.

behavior of speculators is different from that of long-term investors, the results of this technique help in sectoral diversification, which is of importance for scholars, investors, and policy makers. Moreover, focusing on the main sectors in the two largest global stock markets can provide a full picture of the entire market and help investors manage their portfolios. Second, we use a cross-quantilogram methodology to determine the impact of US stock market returns on Chinese financial market returns in similar sectors in different quantiles. To the best of our knowledge, this is the first study to apply this technique to high-frequency data in different market modes (bear, mean, and bull). The cross-quantilogram approach was applied to explore the directional predictability of US market returns on similar sector returns in the Chinese financial market to evaluate how Chinese sectoral returns respond to an increase in US stock market returns in different quantiles in each market. Compared to the linear quantile regression, this technique provides a better picture of the quantile-based link between the Chinese financial market and its predictors, which cannot be scrutinized by applying other techniques.

The results show that in the short, medium, and long terms, the US industry sector is the main transmitter of volatility to the network. Moreover, a strong interconnectedness exists between energy and industry returns in both the US and Chinese stock markets in the short, medium, and long term. Furthermore, the Chinese energy index is the main volatility contributor to US industry returns for all time horizons, and the total connectedness index (TCI) in all three timeframes illustrates a high percentage of connectedness among US and Chinese stock market returns in the short term. Therefore, portfolio management is required to reduce investment risk. However, the TCI index in the network decreases considerably in the long term, implying an opportunity for portfolio diversification in the long run. Moreover, based on the results of the cross-quantilogram technique, a negative relationship exists between US and Chinese stock market returns, especially when they in the higher (bullish mode) and lower quantiles (bearish mode). Therefore, the Chinese stock market returns offer good diversification for investing in the US stock market when these two indices are contradictory. Thus, our findings confirm that investors should attend to the levels of US and Chinese stock market return volatilities to reduce their portfolio risk. If an investor considers the status of these two stock market indices (bull, mean, and bear), the Chinese stock market indices will be highly diversified for investors in the US stock market sectors.

The remainder of this paper is organized as follows. Section 2 reviews the relevant literature. Section 3 discusses the methodology used in the study. Section 4 presents the empirical findings, and Section 5 provides conclusions and policy implications.

2. Literature Review

Various studies have examined the interrelationships between the US and China stock markets. Chen et al. (2025) highlighted dynamic volatility spillovers among the U.S., China, and Hong Kong stock markets, with the U.S. as the main source and Hong Kong as both key recipient and intermediary. Hong Kong plays a central role in transmitting U.S. monetary shocks to China, especially during periods of global stress like the trade war and COVID-19. Spillover patterns are time-varying and underscore Hong Kong's strategic position in regional financial transmission. Wu et al. (2025) found significant spillovers of extreme downside and upside risks from the U.S. and China to their major trading partners' equity markets, intensified during the U.S.–China trade war. Downside risk spillovers dominate upside ones, with developed countries more exposed to U.S. risks and emerging markets more to China's. The trade war notably altered spillover magnitudes, especially in South Korea, Brazil, Taiwan, and India.

Zhang et al. (2025) investigated how volatility spread from the U.S. to BRICS stock markets during COVID-19 and the Russia–Ukraine war, using regime-switching and dynamic correlation models. It finds that U.S. volatility had a stronger and more lasting impact on BRICS markets during the pandemic, while the Ukraine conflict triggered only brief, inconsistent reactions. The structure of volatility linkages varied widely across markets and lacked a unified pattern during the war. Yan & Işık (2025) analyzed risk spillovers between China's carbon market, its domestic energy market, and the U.S. energy market from 2018 to 2022 using advanced CoVaR modeling. They found that risk transmission between China and the U.S. energy markets is bidirectional and time-varying, with China's energy market increasingly influencing its carbon market. Additionally, China's carbon market showed higher volatility and reacted more sharply to shocks compared to energy markets.

Chen & Zhou (2024) investigated the dynamic interdependence and risk spillover between the Chinese and U.S. stock markets. They found that sectors like Energy, Materials, and Financials play dominant roles in transmitting risk across the two markets. The degree of risk spillover increases with market volatility, highlighting how sectoral shocks in one market can affect the other. Sahoo & Kumar (2024) analyzed sectoral volatility spillovers across emerging (India, China) and developed (U.K., U.S.) markets. It shows the U.S. IT sector exerts dominant spillover effects on counterpart sectors in emerging markets, including China. The results emphasize that cross-market hedging is most effective when combining emerging and developed sectors, significantly influenced by U.S. sectoral volatility.

Ouyang et al. (2024) built a multilayer network to analyze how tail risk—extreme market moves—transfers between the Chinese and U.S. stock markets over periods of political tension and reconciliation. They showed that overall interconnectedness surges during tensions and drops during easing, while inter-market spillovers are driven by abrupt shocks in specific distressed sectors rather than steady flows. Furthermore, certain sectors acted as key transmitters (high out-strength), indicating asymmetric roles in driving cross-border tail risk. Mao et al. (2024) examined how crude oil volatility affected stock market returns in China, the

U.S., and India during and after the COVID-19 pandemic. It finds that volatility spillovers were stronger during the pandemic, especially from oil to equity markets. The impact varied by country and period, highlighting changing interlinkages between energy and financial markets across crises.

Wang and Xiao (2023) analyzed cross-country risk spillovers through a C-vine copula quantile regression and found that both the US and Chinese markets can emit significant risk spillovers to East Asian markets through an intermediary market, with the US having a stronger spillover magnitude than China. Similarly, Aloui et al. (2022) analyzed the transmission of financial risks from China to the G7 countries before and during the COVID-19 pandemic. The results showed that before the pandemic, the systemic risk was comparable among all countries. However, during the pandemic, interdependence among the G7 countries increased, and the spillover effects were more significant, except for in Japan. Pan et al. (2022) investigated the dynamic conditional correlations with leverage effect and spillover effect between the Chinese and US stock markets. Their findings showed a symmetric and highly persistent shock transfer to the dynamic conditional correlation between the two stock market indices. Cao (2022) demonstrated significant bidirectional extreme risk spillovers between the US and other markets, with contributions varying across crises. The COVID-19 pandemic and the 2007–2008 global financial crisis contributed more to extreme risk spillovers, with the former being more dependent on non-financial channels, leading to larger losses.

Shi et al. (2021) examined the impact of the US–China trade war on co-movements between the US and Chinese stock markets at the market and sector levels. Using an event study analysis, the authors found that co-movements among the three markets were positively affected by news releases, with a more significant enhancement found after the official start of the trade war on July 6, 2018. Hanif & Mensi (2021) studied how COVID-19 affected risk spillovers between U.S. and Chinese equity sectors using Copula and CoVaR methods. They found asymmetric tail dependence in most sectors and time-varying, bidirectional risk spillovers. Notably, risk flowed more from the U.S. to China pre-COVID, but reversed during the outbreak, with peak spillovers from China to the U.S. between March and April 2020.

Other studies have investigated the connectedness between different financial market sectors in the US or China. For instance, Tian et al. (2022) use a GARCH copula quantile regression model to analyze systemic risk spillovers from the banking, securities, and insurance sectors to the entire financial system in China. The results show that the insurance sector has the largest risk spillover effect on the financial system, followed by the banking and securities sectors. Risk spillovers were much larger during the global financial crisis than during other crises. Mensi et al. (2021) and Laborda and Olmo (2021) also found time-varying spillovers among the US stock sectors that intensified during economic, energy, and geopolitical events. The connectedness network among sectors exhibits asymmetric behavior, with some sectors being net receivers of spillovers under good volatility, whereas others become net contributors of spillovers under bad volatility. For more information, see Mensi et al. (2024); Chen et al. (2023), and Costa et al. (2022).

Previous approaches have generally been unable to capture the interconnectedness of assets across different investment horizons. In contrast, the methodology employed in this study (TVP-VAR-BK) allows for the examination of how asset linkages can vary in the short, medium, and long term (Baruník & Křehlík, 2018). Since the objective of this research is not only to assess the overall connectedness between U.S. and Chinese sectoral markets, but also to investigate the net pairwise connectedness across comparable sectors at different quantiles, this approach proves particularly suitable. Unlike traditional methods, it enables the analysis of dependence structures at various points in the return distribution (Han et la., 2016).

This feature is especially important in financial market studies, where it is crucial to understand how asset interdependencies behave under different market conditions—such as extreme downturns or upswings. By uncovering quantile-specific and horizon-specific connectedness, this framework provides valuable, tailored insights for investors with varying risk appetites and investment horizons, as well as for portfolio risk managers and policymakers aiming to better understand systemic risk transmission.

3. Data and models

3.1. Data

This study uses daily data for six sectors[2] of the US and China's stock market indices from December 12, 2014, to February 28, 2023. The use of daily data enables the analysis of short-term market dynamics and co-movements that might be obscured when employing lower-frequency data, such as monthly or quarterly observations. This frequency is particularly suitable for capturing the immediate transmission of shocks resulting from events such as political turmoil, earnings announcements, or macroeconomic releases. Furthermore, daily returns offer a more refined and granular understanding of financial market interdependence, thereby improving the accuracy of connectedness estimations (Selmi et al., 2018). Therefore, our sample data cover major economic and political events, including the trade war between the US and China, the US presidential election, the COVID-19 crisis, and the Russia–Ukraine war. Data were compiled from https://www.investing.com/indices/ and https://www.spglobal.com/spdji/en/index-family/equity/us-equity/sp-sectors/#overview. Figure A-1 shows the return dynamics of the main sectors of the US and Chinese stock markets. As this figure shows, all returns in both the Chinese and US stock markets experienced significant fluctuations during the sample period. More precisely, the return volatility domain increased significantly, particularly during the trade war between China and the US as well as during the COVID-19 pandemic. As shown in this figure, the intensity of the fluctuations increased again

[2] These sectors include: industry, healthcare, energy, real estate, utilities, and telecommunications.

with the start of the Russia– Ukraine tensions. Therefore, economic, political, and health crises have significantly affected asset returns in the six major sectors of the Chinese and US stock markets. From an investor's perspectives, this issue indicates a higher risk in these markets during the sample period. In addition, the higher the range of fluctuations in the returns of these indices, the higher the range of fluctuations in the returns.

Table 1 presents the descriptive statistics and unit root tests for all return series. As we can see, all return series (except CN real estate) have positive mean returns. CN telecom is the most volatile variable, whereas US real estate has the lowest unconditional volatility. The skewness values provide evidence of asymmetry. With regard to the skewness values in the US and Chinese stock market sector returns, the Chinese sectors are riskier than the US stock market servers. The kurtosis values indicate that all returns follow a leptokurtic distribution with fat tails. The Jarque-Bera (JB) test also reveals that all return series exhibit non-normal distributions. The return series exhibits a leptokurtic distribution along with jumps and structural breaks, as shown by the Elliott, Rothenberg, and Stock (ERS) unit root test.[3] Lastly, according to the Fisher and Gallagher (2012) weighted portmanteau test, returns and squared returns show autocorrelation with each other, proving that choosing the TVP-VAR version to model interconnection indices with time-varying variance covariances is valid.

[3] https://www.sciencedirect.com/science/article/pii/S0140988322001372

Table 1. Descriptive statistics of return series

	CN industry	CN healthcare	CN energy	CN real estate	CN utility	CN telecom	US telecom	US real estate	US industry	US healthcare	US energy	US utility
Mean	0.016	0.028	0.003	-0.031	0.001	0.014	0.012	0.019	0.025	0.035	0.000	0.025
Variance	3.122	3.245	3.571	3.446	2.512	4.563	1.722	1.856	1.826	1.33	4.359	1.648
Skewness	-0.538**	-0.648*	-0.563*	-0.475*	-0.677*	-0.705*	-0.528*	-1.535*	-0.636*	-0.461*	-0.659*	-0.315*
Kurtosis	5.476*	3.109*	4.305*	3.379*	6.097*	4.068*	7.497*	23.937*	14.162*	9.483*	15.450*	18.537*
JB	2303.728*	838.813*	1464.613*	911.196*	2884.600*	1370.829*	4238.761*	43075.034*	14953.682*	6713.737*	17781.641*	25444.290*
Prob.	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
ERS	-13.051*	-16.042*	-18.197*	-17.358*	-17.345*	-13.950*	-4.902*	-9.820*	-5.262*	-5.131*	-6.549*	-8.908*
Prob.	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Q.20.	21.178	22.798	7.711	19.905	26.033	19.323	91.853	109.92	109.57	118.76	63.269	143.89
X.5	0.01	0.005	0.755	0.018	0.001	0.023	0.000	0.000	0.000	0.000	0.000	0.000
Q2.20.	1270	1010.8	549.59	475.12	1430.74	1038.65	1329	1268.93	2045.41	2153.56	824.63	2843.16
X.6	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Notes: * denotes significance at 99% and ** denotes significance at 95%. "EX.Kurtosis," "JB," and "ERS" stand for excess kurtosis, Jarque-Bera test for normality, and Elliot, Rothenberg, and Stock for unit root test, respectively. Q.20 and Q2.20 denote returns and squared returns based on the Fisher and Gallagher weighted portmanteau test.

Figure 2 presents the correlation matrix. We show a positive correlation between all return series (except for the utility sector of the US stock market, which is negative and not statistically significant). In addition, in most cases, a high and significant correlation is observed between the returns of different sectors of the Chinese and US stock markets, which confirms the need for optimal portfolio management to reduce investment risk in these sectors.

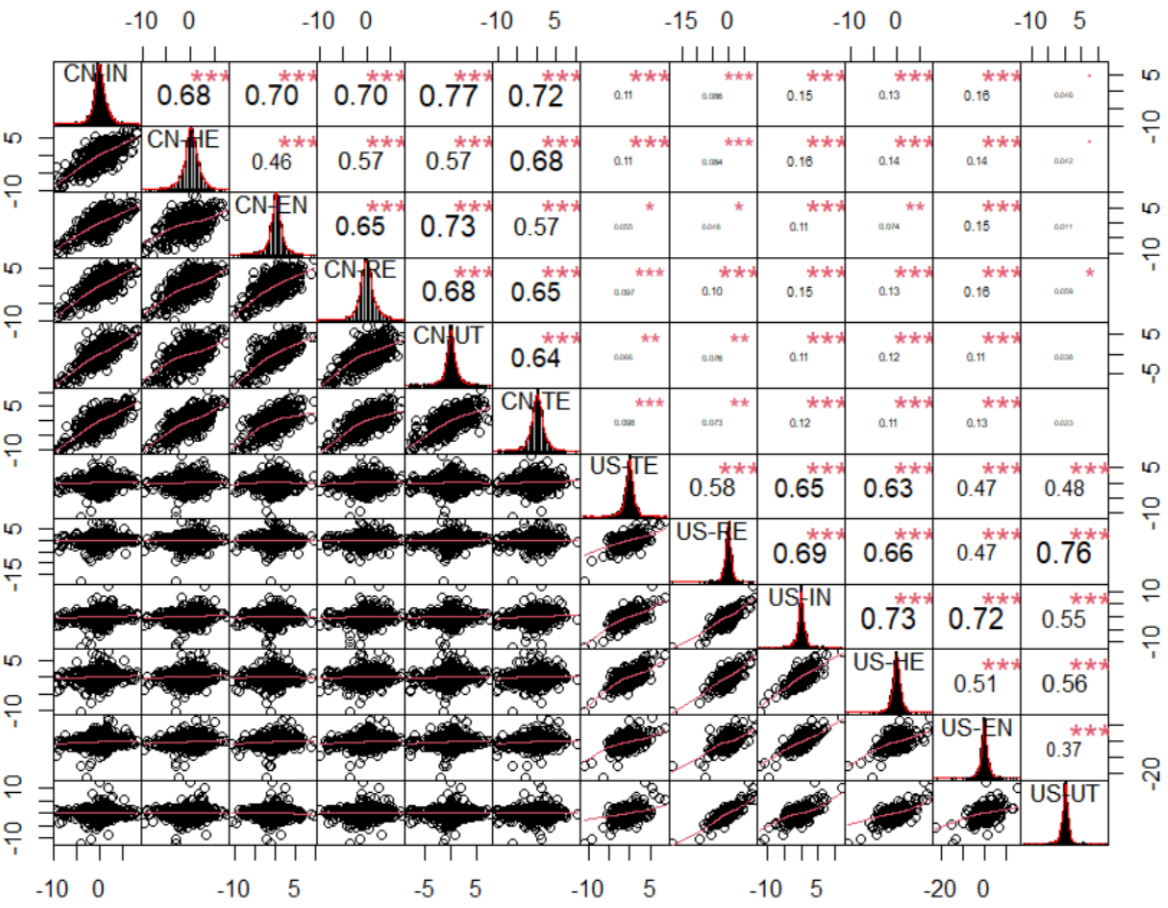


Figure 1. Correlation matrix

Notes: * denotes significance at 99% , ** denotes significance at 95%, and *** denotes significance at 90%.

3.2. Methodology

This study uses two approaches to explore the static and dynamic spillover effects in different investment horizons and detects the response of each sector's return to its counterpart sector in different quantiles.

3.2.1. TVP-VAR-BK

To investigate the scale–time relationship between return volatilities in the network, we initially used the TVP-VAR-BK approach introduced by Baruník and Křehlík (2018). The TVP-VAR-BK model is utilized to capture spillover effects across varying time horizons (short-, medium-, and long-term). While numerous models exist for measuring inter-market connectedness, its framework offers a novel method based on forecast error variance decomposition (FEVD) derived from a time-varying vector autoregressive model. This dynamic structure is particularly useful in tracking evolving market interactions over time.

The BK approach offers several benefits: it is robust to outliers, avoids the arbitrary selection of rolling windows, accommodates datasets with lower frequency, and handles missing data well. Moreover, it remains unaffected by the ordering of variables and provides a clear picture of directional spillovers between markets over time. This model also allows for a more nuanced analysis across frequency domains. Therefore, this approach enables a deeper understanding of asset behavior and offers insights into optimal asset choices for short-term, medium-term, and long-term investment horizons (Ahmadian-Yazdi et al., 2025; Asadi et al., 2022).

The spectral decomposition was used in this model, and Equation (1) defines the periodic response function as follows:

$$\alpha(\pi^{-xy}) = \sum_{z} \pi^{-xyr} \alpha_r \tag{1}$$

In Equation (1), α is decomposed based on the Fourier Function with $x = \sqrt{-1}$. The generalized autocorrelation spectrum for periodicities is defined as Equation (2) with $\alpha \in$ *(-k, k)*:

$$(f(\alpha))_{j,k} = \frac{\omega_{kk}^{-1} \, |((\alpha(\pi^{-xy}) \sum j,k|^2)}{\alpha(\pi^{-xy}) \sum \alpha'(e^{+xy}) j,j} \tag{2}$$

In Equation (2), $\alpha(\pi^{-xy}) = \sum_m e^{-ixy} \alpha_m$ represents the Fourier transform in the impulse response function α. It should also not be forgotten that $(f(\alpha))_{j,k}$ represents a portion of the spectrum of variable j at periodicity α due to shocks to variable k. We can extract Equation (2) to quantify the periodicity causality based on the spectrum of variable j at periodicity α. To generalize the spectral decomposition, $(f(\alpha))_{j,k}$ is weighted by the periodic variance share of variable j. Equation (3) shows the weighting function:

$$\emptyset_j = \frac{(\pi^{-xy})\sum \alpha'(e^{+xy})i,j}{\frac{1}{2\beta}\int_{-\beta}^{\beta} e^{-i\partial} \sum \alpha'(e^{+i\partial})j,j\, d\partial} \tag{3}$$

In Equation (3), the power of the jth variable is shown in a given period and also acts in the period α, and the total of the periods is a constant value of 2β. Although the Fourier transform of the impulse response function is composed of complex numbers, the extended spectrum of the weighting coefficient is the squared magnitude of the complex number and is therefore a real number. To formulate this, we replace the extended variance decomposition of the prediction error with the period $v = (p, s): p,s \in (-\beta, \beta), s > p$:

$$(\gamma_v)_{j,k} = \frac{1}{2\beta}\int_{v}^{0} \emptyset_j\, (f(\alpha))_{j,k}\, d\alpha \tag{4}$$

Expressing the relationship in a specific cycle through spectral representation and using generalized variance decomposition for predictive error is not challenging. We can express the scaled generalized variance decomposition for predictive error on cycle $v = (p, s): p,s \in (-\beta, \beta), s > p$ as in Equation (5):

$$(\approx \gamma_v)_{j,k} = (\gamma_{v_{j,k}} / \textstyle\sum_k (\gamma_\infty)_{j,k}) \tag{5}$$

The spectral overflows will be given by Equation (6):

$$N_v^f = 100\, \left(\frac{\sum_{j\neq k} \approx(\gamma_v)_{j,k}}{\sum_k (\gamma_\infty)_{j,k}} - \frac{Tr\,\{\gamma_v\}}{\sum \approx(\gamma_v)_{j,k}}\right) \tag{6}$$

The formulation of the overflow via periodicity is given by Equation (7) (Asadi et al., 2022):

$$N_v^f = 100\, \left(1 - \frac{Tr\,\{\gamma_v\}}{\sum \approx(\gamma_v)_{j,k}}\right) \tag{7}$$

3.2.2. The Cross Quantilogram

This study applies the cross-quantilogram approach suggested by Han et al. (2016) to analyze the bivariate causal relationships between return series movements in six sectors of the Chinese and US stock markets. The cross-quantilogram technique provides a powerful and flexible framework for analyzing dependence structures between time series across different quantiles. Unlike traditional correlation measures that focus on average relationships, this method captures tail and asymmetric dependencies, offering deeper insights into extreme events and nonlinear dynamics. The advantages of this approach over other approaches are as follows: First, it is suitable for scrutinizing the spillover effect between variables when we have abnormal distributions and extreme observations. Second, using separate quantiles, shock transmissions between the variables have been provided. Third, this technique supports robust statistical inference through the use of stationary bootstrap methods, which ensure consistent confidence intervals even in the presence of nuisance parameters. Forth, the self-normalized version of the test produces an asymptotically pivotal statistic, enhancing the reliability of hypothesis testing without requiring explicit estimation of nuisance components. Fifth, by focusing on different lag lengths, the direction and duration of shocks can be estimated using this technique. These strengths make the cross-quantilogram especially valuable in financial applications, such as detecting predictive relationships between market variables and assessing systemic risk, where understanding dependence beyond the mean is crucial.

The quantile hits between two events $\{y_{1t} \leq q_{1t}(\tau_1)\}$ and $\{y_{2t-k} \leq q_{2t-k}(\tau_2)\}$ are presented in Equation (8). In this equation, k denotes the lag length ($k = \pm1, \pm2$) for an arbitrary pair of (τ_1, τ_2), and $y_{i,t}$ denotes stochastic stationary processes. t is time ($t = 1,2,\ldots, T$), and i is equal to 1, 2, or 3, indicating exchange rates and oil or gas prices. $\psi_a(u) = 1[u < 0] - a$ is the quantile-hit process, and $q_{it}(\tau_i)$ is the corresponding quantile function for $\tau_i \in (0, 1)$.

$$\rho_\tau(k)=\frac{E[\psi_{\tau1}(y_{1t}-q_{1t}(\tau_1))\psi_{\tau2}(y_{2t-k}-q_{2t-k}(\tau_2))]}{\sqrt{E[\psi^2_{\tau1}(y_{1t}-q_{1t}(\tau_1))]}\sqrt{E[\psi^2_{\tau2}(y_{2t-k}-q_{2t-k}(\tau_2))]}} \tag{8}$$

The cross-quantilogram technique considers serial dependence between series and is invariant to monotonic transformations in variables. If ρτ (k) = 0, there is no cross-sectional dependence from event {y2t−k ≤ q2t−k (τ2)} to {y1t ≤ q1t(τ1)}.

To measure the statistical significance of ρτ (k), we employ Box–Ljung test. Equation (9) defines the test statistics:

$$Q^*_\tau(P)=T(T+2)\sum_{k=1}^{p}\hat{\rho}^2_\tau(k)/(T-k) \tag{9}$$

In Equation (2), $\hat{\rho}_\tau(k)$ is the cross-quantilogram derived by Equation (10)

$$\hat{\rho}_\tau(k)=\frac{\sum_{t-k+1}^{T}\psi_{\tau1}(y_{1t}-\hat{q}_{1t}(\tau_1))\psi_{\tau2}(y_{2t-k}-\hat{q}_{2t-k}(\tau_2))}{\sqrt{\sum_{t-k+1}^{T}\psi^2_{\tau1}(y_{1t}-\hat{q}_{1t}(\tau_1))}\sqrt{\sum_{t-k+1}^{T}\psi^2_{\tau2}(y_{2t-k}-\hat{q}_{2t-k}(\tau_2))}} \tag{10}$$

where $\hat{q}_{it}(\tau_i)(i=1.2)$ indicates the estimated quantile function.

4. Results and Discussion

4.1. Results of the short-run static connectedness

Table 2 (panels A and B) shows the spillover results among all return series in the short run. The TCI in the short run illustrates a high percentage of interconnections in the network (45.82%). This finding reduces the benefits of portfolio diversification during short-term periods. Therefore, investors should be cautious when relying on diversification for short-term risk management. According to the results, US and Chinese industry returns are the main net transmitters of shocks to the network. It implies that they impose the main shocks to other return series. Therefore, in the short-term, the industry sector plays a major role in transmitting shocks to the network. To justify this result, these two countries have the largest industrial production in the world. Moreover, the share of added value of the industrial sector in these two countries is the highest compared to other sectors (Mensi et al., 2024; Xiong, Y., & Wu, 2021; Lin & Wang, 2018; Yazdi et al., 2015). More importantly, industry is the leading sector for economic development, and growth in the industry sector can lead to growth in other sectors (Rizani, 2020). Our findings are confirmed by Cortina et al. (2023), who argue that Chinese industrial firms have experienced a considerable increase in their financial and investment activities since 2012, mostly because of their availability to international investors.

On the contrary, our findings show that the Chinese utility sector contributes minimally to overall market volatility. Its low shock transmission makes it a relatively stable component within a portfolio. Therefore, investors seeking defensive assets may consider exposure to this sector. The results also confirm that Chinese healthcare and the US utility sectors are the main net receivers of shocks from the network during the sample period. So, their role as net shock receivers highlights their vulnerability to external developments. As a results, investors should monitor broader market conditions when investing in these sectors.

Table 2-Panel A shows the pairwise spillover effect among the Chinese return series and the network. The results indicate that the Chinese utility return transmits the most volatility shocks to the Chinese industry return. The short-term results related to the Chinese healthcare return in the short term clearly show that it is mainly influenced by the Chinese telecom sector. Subsequently, the Chinese utility, real estate, and energy indices exhibited the highest fluctuation transfers to the Chinese healthcare index. The Chinese energy return has very low effectiveness in terms of US sector returns. As China imports most of its energy from Iran and Russia, and most Chinese energy producers are members of OPEC, its energy return is not considerably affected by the US sectoral returns. Our results confirm those of Liu (2021) and Gerlagh et al. (2020), who argue that the Chinese energy stock market is significantly linked to the overall Chinese stock market and that energy price volatilities can impose major changes

in other Chinese stock market sectors through energy stock returns. Therefore, it would be beneficial for investors to understand their connectedness with other stock returns to mitigate the risk of their investment portfolio.

Our findings show that in the short term, the Chinese real estate return is mainly influenced by the Chinese utility sector. The Chinese industry, energy, telecom, and healthcare sectors ranked next. The results for the Chinese utility sector indicate that the Chinese industry return had the greatest impact at 11%. In addition, the transfer rate of volatilities from the US sectors to the Chinese utility index is below 1%. Therefore, investing in the Chinese utility sector along with the US sectors could be beneficial for achieving optimal investment. The results for the Chinese telecom index show that it is mainly influenced by Chinese healthcare and industry returns.

The results of the volatility spillover effect between US sector's returns and the network are provided in Table 2-Panel B. The results related to the US telecom show that it is mainly influenced by the US industrial and healthcare returns. Our findings on US real estate returns clearly show that they are mainly influenced by the US utility return in the short term. It is obvious that the transfer of shocks from the US utility sector to the real estate sector is significant compared with the pairwise effects among the other network assets. This is not surprising because residential and nonresidential buildings consume significant amounts of electricity and natural gas. The impacts on other sectors include healthcare, telecommunications, industry, and energy. In addition, the results show that the US real estate sector has a very low impact on Chinese asset returns.

Based on the results, the US industry sector receives the most volatility from the US energy return. Contrary to the results obtained thus far from transmitting fluctuations in Chinese sector returns to US returns, the US industry receives a significant spillover effect from the Chinese stock returns, especially Chinese energy index. The US healthcare sector is mainly affected by the US industry index (11.98%). The effectiveness of the US healthcare return from the Chinese stock market is significant, similar to that of the US industry sector. Based on the short-term results obtained from the transfer of volatilities to the US energy return, the US industry sector is the most transmitter of volatilities. The results related to the utility return of the US market clearly show that it is less affected by Chinese sectors. Our findings indicate that the US real estate return is the most contributor to the US utility sector in the short-run.

Table 2. Estimates of static short-run spillovers

Panel A: Static short-run spillover effects between network returns and China's sectoral returns

	CN industry	CN healthcare	CN energy	CN real estate	CN utility	CN telecom
CN industry	23.52	7.89	9.69	8.47	11.00	9.02
CN healthcare	10.14	30.56	5.48	6.57	7.20	9.45
CN energy	10.18	4.92	26.96	8.61	10.92	6.44
CN real estate	9.68	6.20	8.81	27.26	9.41	7.64
CN utility	11.19	6.07	10.81	9.19	25.83	7.52
CN telecom	10.92	8.6	6.96	8.07	8.32	27.86
US telecom	0.92	0.94	0.76	0.67	0.61	0.62
US real estate	0.74	0.7	0.88	0.72	0.35	0.42
US industry	0.96	0.87	0.89	1.05	0.93	0.76
US healthcare	0.75	0.78	0.74	0.83	0.72	0.58
US energy	1.30	1.00	1.51	1.39	0.98	1.10
US utility	0.96	0.75	0.91	0.89	0.7	0.58
TO	57.74	38.74	47.44	46.46	51.15	44.13
Net	6.01	-6.53	-1.28	-0.65	0.94	-3.42

Panel B: Static short-run spillover effects between network returns and the US sectoral returns

	US telecom	US real estate	US industry	US healthcare	US energy	US utility	From
CN industry	0.82	0.97	1	1.29	1.02	0.56	51.72
CN healthcare	0.98	1.14	1.31	1.1	1.12	0.79	45.27
CN energy	0.82	1.03	1.44	1.59	2.1	0.66	48.71

CN real estate	0.77	0.78	1.08	1.1	1.09	0.54	47.11
CN utility	0.7	0.75	1.07	1.45	0.92	0.54	50.21
CN telecom	0.69	0.7	0.85	0.84	1.02	0.58	47.55
US telecom	34.39	7.59	10.12	9.61	5.79	5.45	43.08
US real estate	7.25	32.73	7.98	8.4	3.6	13.06	44.1
US industry	8.8	7.26	29.21	11.98	11.57	3.69	48.76
US healthcare	8.5	7.79	12.79	32.88	6.17	4.55	44.2
US energy	6.07	4.05	14.25	6.92	36.95	2.11	40.68
US utility	6.16	15.01	4.54	5.72	2.25	37.5	38.46
TO	41.56	47.06	56.42	50	36.63	32.54	TCI=45.82
Net	-1.52	2.96	7.66	5.79	-4.04	-5.92	

Notes: (1) CN stands for China. (2) The spillovers are from the respective variables to the networks that are in the "TO" rows, while the spillovers from the network to the respective variables are in the "FROM" columns. Net is the difference between To and From for each variable.

4.2. Results of the medium-run static connectedness

Panel A of Table 3 shows the results of the spillover effect between all Chinese returns and the network in the medium term. As is clear from the results in Table 3 (both panels A and B), the transfer of volatility from each sectoral return of the Chinese and US stock markets to the entire network significantly decreased compared to the short-term period. Therefore, there is a good opportunity for portfolio diversification in the medium term compared to the short term, with the highest amount of net volatility transferred from the US industry sector at 3.79%. Our findings confirm that the US industry sector is the main net contributors to the network in the medium and short run. In addition, the US energy return has the least connection in the network, which shows its potential in minimizing risk and making benefits for portfolio diversification. By contrast, the main net receiver of shocks from the network is the Chinese energy return.

Table 3-Panel A shows that the Chinese industry return receives the main shocks from utility sector in the medium term. The results related to the Chinese healthcare return show that

it is mainly influenced by the Chinese telecom return in the medium term. Based on our findings, the Chinese energy return receives the most volatility from the Chinese utility return in the medium term. In addition, the amount of volatility transmission from the US stock market returns to it decreases significantly in the medium term. The results related to the transfer of volatilities to the Chinese real estate sector in the medium term show that it is mainly influenced by Chinese industry and utility sector returns. China's utility sector is primarily affected by its energy sector. In addition, the effect of US financial market returns on the above index is less than 0.5% in the medium term. The results related to the transfer of volatilities to the Chinese telecom return in the medium term show that it is mainly affected by Chinese industry return.

Table 3-Panel B shows our findings about the spillover effect between the US stock market sectors and the network. This panel shows that the US telecom return is mainly influenced by the US industry and healthcare returns. In addition, the effects of the US sectoral returns are less than 0.4% in the medium term. Based on these results, the US real estate return is influenced mainly by the US utility sector. The US industry returns are mainly influenced by the US energy and healthcare returns. The results of the US healthcare index in the medium term show that it is mainly influenced by the US industry sector. The results for the US energy return indicate that it is mainly influenced by the US industry return. Our findings on the transfer of volatilities to the US utility index in the medium term show that it is mainly influenced by the US real estate sector by 3.40%.

Finally, the TCI in the medium term is 11.45%. The interconnectedness between the US and Chinese stock market returns decreases considerably compared with the short term. Therefore, sectoral diversification could be beneficial for optimal investment in the medium term compared to the short term.

Table 3. Estimates of static medium-run spillovers

Panel A: Static medium-run spillover effects between network returns and China's sectoral returns

	CN industry	CN healthcare	CN energy	CN real estate	CN utility	CN telecom
CN industry	5.85	2.16	2.26	2.50	2.49	2.39
CN healthcare	2.29	7.99	1.12	1.71	1.64	2.35
CN energy	2.81	1.12	6.36	2.33	2.6	1.50
CN real estate	2.45	1.53	2.22	7.47	2.47	1.97
CN utility	2.88	1.54	2.39	2.36	6.19	1.86
CN telecom	2.70	2.33	1.63	2.13	2.21	7.08
US telecom	0.23	0.25	0.22	0.14	0.12	0.18
US real estate	0.14	0.15	0.19	0.10	0.08	0.07
US industry	0.21	0.21	0.13	0.25	0.22	0.15
US healthcare	0.11	0.19	0.12	0.18	0.13	0.08
US energy	0.38	0.29	0.27	0.3	0.23	0.3
US utility	0.22	0.20	0.26	0.25	0.15	0.14
TO	14.42	9.98	10.81	12.25	12.33	10.99
Net	0.46	-1.38	-2.30	-0.77	-0.65	-1.60

Panel B: Static medium-run spillover effects between network returns and the US sectoral returns

	US telecom	US real estate	US industry	US healthcare	US energy	US utility	From
CN industry	0.35	0.28	0.47	0.47	0.44	0.15	13.96
CN healthcare	0.4	0.3	0.47	0.44	0.38	0.26	11.36
CN energy	0.27	0.27	0.66	0.44	0.95	0.16	13.11
CN real estate	0.34	0.34	0.55	0.46	0.5	0.19	13.02
CN utility	0.24	0.23	0.46	0.55	0.34	0.13	12.99
CN telecom	0.3	0.16	0.34	0.33	0.34	0.12	12.59
US telecom	8.43	1.73	2.25	1.93	1.29	1.3	9.64
US real estate	1.8	8.06	1.74	1.95	0.88	3.4	10.5
US industry	1.93	1.52	6.94	2.59	2.8	0.71	10.73
US healthcare	1.93	2.03	3	7.97	1.35	1.24	10.37
US energy	1.4	0.82	3.52	1.53	8.53	0.36	9.4
US utility	1.45	3.99	1.06	1.5	0.53	9.48	9.74
TO	10.42	11.67	14.52	12.19	9.79	8.02	TCI=11.45
Net	0.79	1.17	3.79	1.82	0.39	-1.72	

Notes: (1) CN stands for China. (2) The spillovers are from the respective variables to the networks that are in the "TO" rows, while the spillovers from the network to the respective variables are in the "FROM" columns. Net is the difference between To and From for each variable.

4.3. Results of long-run static connectedness

Panels A and B of Table 4 show the results of the spillover effect between the US and Chinese stock market returns in the long run. The transmission rate of volatilities between the return series is below 1%. This result indicates that in the long term, the risk of portfolio diversification among the six sectors of the US and Chinese stock markets decreases, which can help investors decrease portfolio risk and create opportunities for diversification in their asset portfolios.

The results show that the main net contributor in the network is the US industry return. However, the Chinese industry return is responsible for the lowest amount of connection in the network. On the other hand, Chinese energy return is the major net recipient of volatility from the network in the long term. Our findings imply that policymakers should focus on stabilizing U.S. industrial markets to reduce global volatility spillovers. Moreover, given China's energy sector is a major long-term volatility recipient, strengthening risk-hedging mechanisms is essential.

The results of the pairwise spillover effect between the Chinese industry return and other sectors (Table4-Panel A) show that it receives the most volatility from the utility sector. In addition, the amount of shock transfer from US stock market returns significantly decreased compared to the short term. The long-term results for the Chinese healthcare sector show that it is influenced mainly by the telecom return. The results show that the Chinese healthcare return is mainly influenced by Chinese telecom and industry returns. Moreover, the effect of the US stock market indices on the Chinese market industry index is very low (even lower than 0.07%) in the long run. Our findings on Chinese energy returns indicate that they are mainly influenced by Chinese utility returns. The research findings show that Chinese real estate returns are influenced mainly by Chinese industrial returns. However, the Chinese healthcare return had the lowest effect. The results for Chinese utility returns indicate that they are mainly influenced by the Chinese energy sector. The Chinese telecom return is primarily influenced by the Chinese industry return. Moreover, as can be seen in Table 4-Panel A, the effect of US stock market returns on Chinese sectoral returns is very low in the long run. These findings imply that strengthening inter-sectoral resilience within China is crucial, as domestic sectors like telecom, utilities, and industry significantly drive returns in healthcare, energy, and real estate. In addition, the minimal long-term influence of U.S. stock markets on Chinese sectors highlights the importance of focusing on internal economic dynamics for market stability.

Table 4-Panel B provides the spillover effect between the US sectoral returns and their counterparts in the Chinese stock market. The results related to the US telecom sector in the long term show that it is mainly influenced by the US industry and healthcare returns. The US real estate returns are mainly influenced by the US utility sector (similar to what we obtained in the medium term). Regarding our findings, the order of the Chinese stock market indices did not change compared with the middle-term period, and only the intensity of their influence decreased. The weak long-term connectedness allows China to prioritize human capital accumulation (as main driver of economic growth (Ahmadian Yazdi et al., 2015)) in key sectors without being overly exposed to external financial shocks. The results of the US industry return show that it is mainly influenced by the US energy and healthcare sectors in the long term. The US healthcare return is mainly influenced by the US industry sector. The US energy returns are mainly influenced by the US industry return. The results related to the transfer of volatilities to the return of the US utility sector in the long term show that it is mainly influenced by the returns of the real estate sector.

In general, our findings show that the energy and industry sectors in the US and China are closely related and that there is high effectiveness between the stocks of these two sectors in the stock markets of these two countries. Steeves and Ouriques (2016) argue that, owing to the rapid industrialization of these two economies and the growing global population, the energy sector and its security are important political issues for these economies. Therefore, considering the high spillover effects between these two sectors in all time horizons, optimal diversification is required to reduce portfolio investment risk. Finally, the results for the TCI in the long run illustrate a low percentage of connectedness with the network (2.85%), which implies a weak relationship between the US and Chinese returns in the long term. Thus, the weak long-term return connectedness offers an opportunity for policymakers and institutional investors to promote cross-country diversification strategies to enhance risk-adjusted returns. Furthermore, given the strong short- and medium-term connectedness between U.S. and Chinese energy and industry sectors, coordinated energy security and industrial policy can help mitigate cross-border volatility risks.

Table 3. Estimates of static long-run spillovers

Panel A: Static long-run spillover effects between network returns and China's sectoral returns

	CN industry	CN healthcare	CN energy	CN real estate	CN utility	CN telecom
CN industry	1.45	0.54	0.56	0.63	0.62	0.60
CN healthcare	0.56	2.00	0.27	0.43	0.40	0.58
CN energy	0.71	0.28	1.57	0.59	0.64	0.37
CN real estate	0.61	0.38	0.55	1.88	0.62	0.49
CN utility	0.72	0.39	0.58	0.59	1.54	0.46
CN telecom	0.67	0.58	0.40	0.53	0.56	1.77
US telecom	0.06	0.06	0.06	0.03	0.03	0.05
US real estate	0.04	0.04	0.05	0.02	0.02	0.02
US industry	0.05	0.05	0.03	0.06	0.06	0.04

US healthcare	0.03	0.05	0.03	0.05	0.03	0.02	
US energy	0.10	0.07	0.07	0.08	0.06	0.08	
US utility	0.05	0.05	0.07	0.06	0.04	0.03	
TO	3.60	2.50	2.65	3.08	3.07	2.73	
Net	0.10	-0.32	-0.64	-0.18	-0.17	-0.42	

Panel B: Static long-run spillover effects between network returns and the US sectoral returns

	US telecom	US real estate	US industry	US healthcare	US energy	US utility	From
CN industry	0.09	0.07	0.12	0.12	0.11	0.04	3.50
CN healthcare	0.10	0.08	0.12	0.11	0.10	0.07	2.82
CN energy	0.07	0.07	0.17	0.11	0.24	0.04	3.29
CN real estate	0.09	0.09	0.14	0.12	0.13	0.05	3.26
CN utility	0.06	0.06	0.12	0.14	0.09	0.03	3.24
CN telecom	0.08	0.04	0.09	0.09	0.08	0.03	3.15
US telecom	2.10	0.42	0.55	0.47	0.31	0.32	2.37
US real estate	0.45	2.00	0.43	0.49	0.22	0.85	2.61
US industry	0.48	0.37	1.73	0.63	0.69	0.17	2.64
US healthcare	0.48	0.51	0.75	1.99	0.33	0.31	2.58
US energy	0.35	0.20	0.87	0.38	2.11	0.08	2.33
US utility	0.36	0.99	0.26	0.38	0.13	2.38	2.44
TO	2.60	2.89	3.62	3.03	2.44	1.99	TCI=2.85
Net	0.24	0.28	0.98	0.45	0.12	-0.44	

Notes: (1) CN stands for China. (2) The spillovers are from the respective variables to the networks that are in the "TO" rows, while the spillovers from the network to the respective variables are in the "FROM" columns. Net is the difference between To and From for each variable.

4.4. Results of the dynamic connectedness under different time horizons

Figure 2 shows the dynamics of total connectedness among network returns of the US and China six major sectors during the sample period. As is clear from this figure, TCI is affected by many shocks during three different time horizons: short, medium, and long term. The results of TVP-VAR-BK suggest that the TCI has experienced a volatile trend in all time frames (except for its volatilities in the long term, which have more moderate volatilities in comparison to the short and medium terms). The results show that TCI volatilities increased significantly in the post-global financial crisis (GFC) era, after which they decreased until the end of 2017. Increasing the TCI creates signals for investors to prevent the diversification of their investment portfolios. However, there is a good opportunity for diversification during periods in which the TCI has a decreasing trend. Our findings show that the TCI of networks experienced a growing trend at the time of the China trade tensions. In addition, it increased again during the spread of the COVID-19 pandemic and during the conflict between Russia and Ukraine. Thus, the recent health and political crises have changed investors' and speculators' investment decisions regarding their risk appetites and investment horizons.

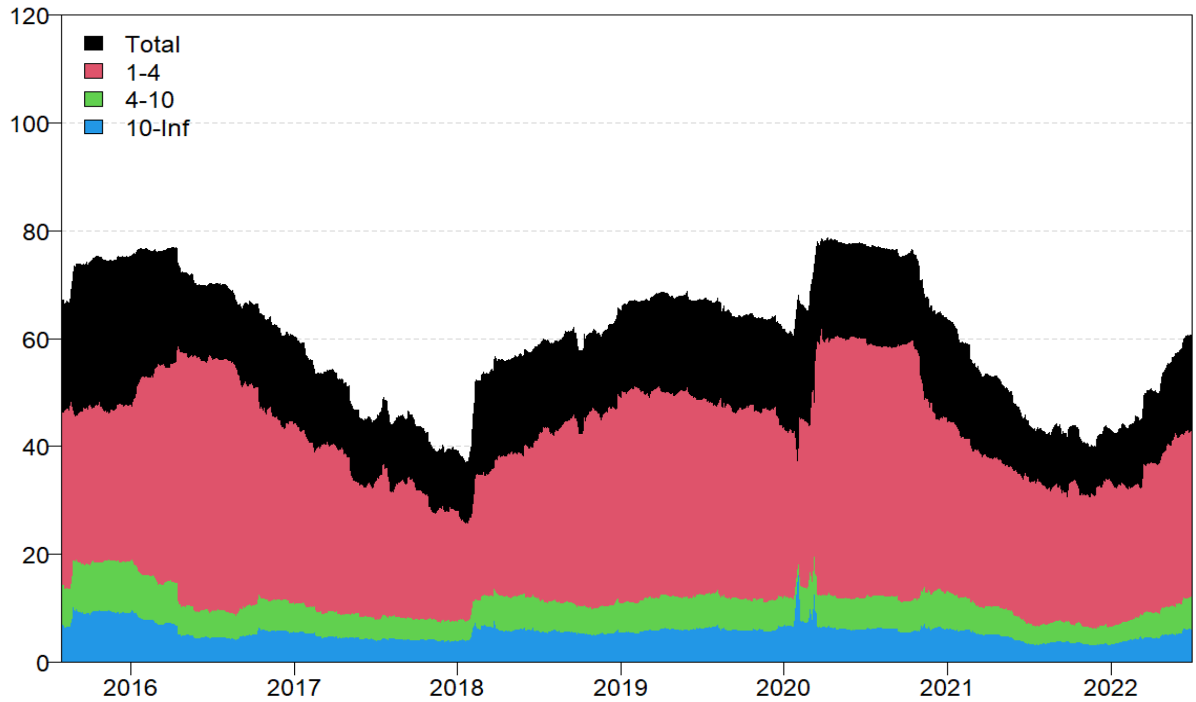


Figure 2. Dynamic frequency total spillovers in the US and Chinese stock markets indices in the network

Notes:

(1) The window size=200, nfore=20, and lag=1.

(2) The red area indicates the total spillover in the short-term investment period, from 1 up to 4 days. The blue area reflects the total spillover in the medium-term horizon of 4–10 days. The green area reflects the total spillover in the long-term horizon of more than 10 days. The black area reflects the total spillover during the entire period. The horizontal axis shows the time horizon.

Figure 3 depicts the net transfer of volatilities of each US and Chinese stock market return to the network over different time horizons. Black shows the average transfer of the net fluctuations of each return over the entire period, whereas red, green, and blue correspond to the short-, medium-, and long-term period, respectively. Generally, as is clear in this figure, the Chinese industry, US real estate, and US industry indices are primarily the net transmitters of volatilities in the network; by contrast, the Chinese healthcare, energy, real estate, and telecom, along with the US energy and utility sector indices, are the net receivers of volatilities from network variables in all four periods.

Specifically, our findings indicate that the Chinese industry, energy, and utility sectors are net transmitters of shocks to the network during the COVID-19 outbreak in the first months of 2020 in the total, short-, medium-, and long-term periods. However, the other Chinese sectoral returns are net receivers of volatilities from the network during the same period. The main recipient of volatilities from the network is China's health care, which receive the highest shocks during the period of the COVID-19 pandemic in all time horizons. This finding is confirmed by He et al. (2021) and Tang et al. (2022) whom showed that the sectoral stock market returns of China were influenced by COVID-19 pandemic. By contrast, the US healthcare return is a net transmitter of shocks to the network during the same period and investment horizons. In general, utility returns in both the US and China's stock markets received the least volatility from the network in the long-term investment horizon. Therefore, this is a suitable long-term asset. The same analysis holds for most sectors in the two stock markets.

Although the Chinese industry sector is one of the main risk transfers to the network during the entire period, the intensity of this sector's impact on the network decreased significantly during the Russia-Ukraine war. Meanwhile, the US industry has a considerable impact on the network during this tensions, especially in the short term. Our results confirm those of Choi (2023), which highlight the significance of the US industrial sector during the Russia–Ukraine tensions in 2022 and Roudari et al. (2023) who showed the impacts of political shocks on stock market returns. Compared with the energy sector in the Chinese stock market, the US energy sector is a significant risk transmitter to the network, especially in the short term. Therefore, this asset can be suitable for investors rather than speculators, who have a short-term view of the market. The magnitude of the energy returns risk increases during crisis periods, which is also confirmed by Xing et al. (2023), who showed the increasing impact of the US energy sector during the conflict era.

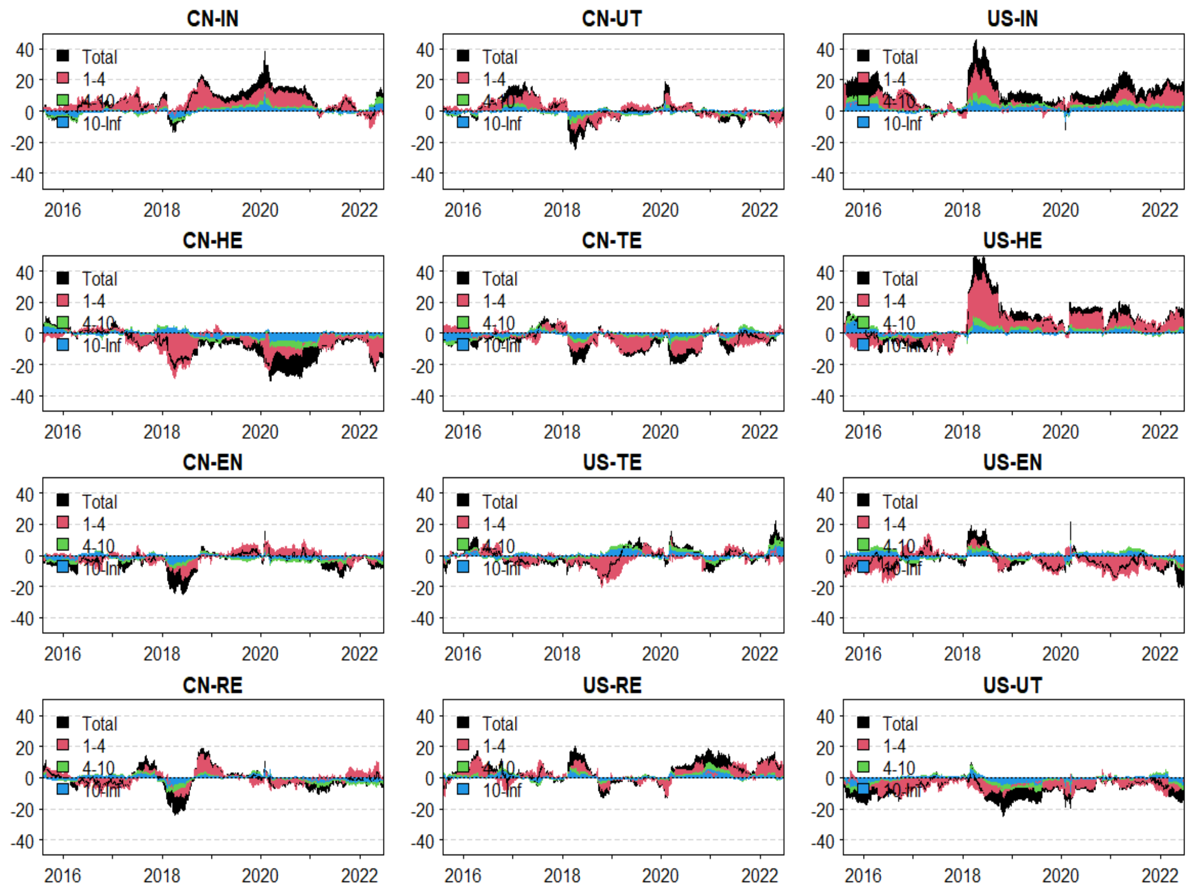


Figure 3. The net transmission of fluctuations of each of the return series to the network.

Notes: Red represents the net-time frequency of each variable in the short term, green captures the medium term, and blue color characterizes the long term. Additionally, black symbolizes the total of all periods. The US and CN refer to the US and Chinese stock markets, respectively. IN, HE, EN, RE, UT, and TE donote industry, healthcare, energy, real estate, utility, and telecom sectors, respectively.

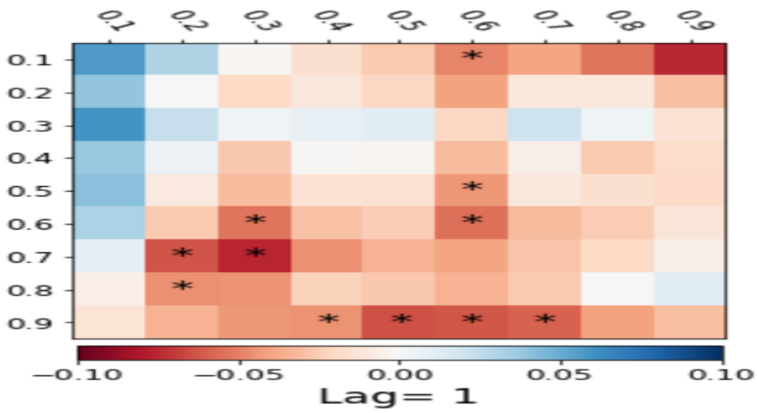
4.5. Results of Cross Quantilogram

Figure 4 displays the cross-quantile dependence and spillover effect between the two-sector stock markets of China and the US. The results are illustrated in the form of heat maps with 81 (9×9) cells per lag. Each cell in the heat maps corresponds to the cross-quantile unconditional bivariate correlation between one pair of indices (the first on the x-axis and the second on the y-axis). The strength and direction of the correlation are indicated by the color scale, with a statistically insignificant correlation set to zero.

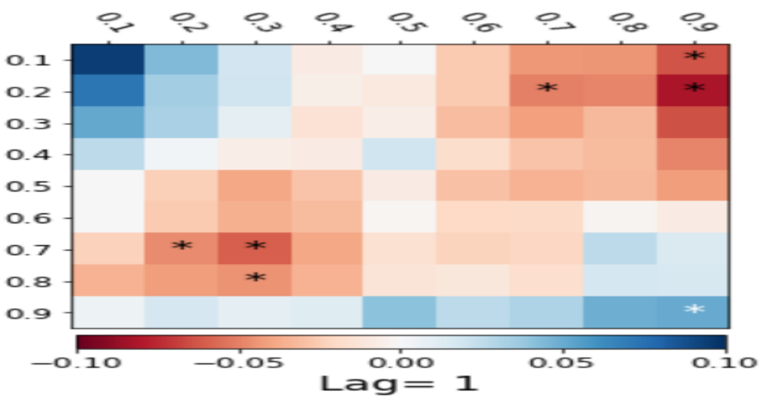
For a further explanation, we note that each of these heat maps shows the effect of the variable on the horizontal axis on the variable on the vertical axis. The closer the color of the cells is to blue, the more positive the effect; in contrast, the closer it is to red, the more negative the effect. In addition, each of these cells shows how this effect occurred for each decimal place. In addition, cells with stars indicate the significance of this relationship at the 0.95% level. In addition, cells that are not statistically significant (cells without stars) indicate a lack of predictable directionality. In this study, we use the returns of each asset in selected sectors of the US and China's stock markets as data. Therefore, the further we move away from the origin of the coordinates on the axes, the higher the efficiency of the desired asset return. In addition, the number of lags in the CQ is determined based on the three levels of the lower, middle, and upper quantiles, and at all three levels, the optimal lag based on SBC, Hannan-Quinn and AIC criteria is equal to one.

The CQ methodology was used to determine directional predictions between the different sectoral returns of the Chinese and US stock markets. Therefore, using this technique, an image of the relationship between the predictor and the share return is provided. As is clear from Figure 4.A, the influence of Chinese industry return on the US industry return is depicted in different quantiles. In addition, the detailed features depend on the quantiles of the US and Chinese returns.

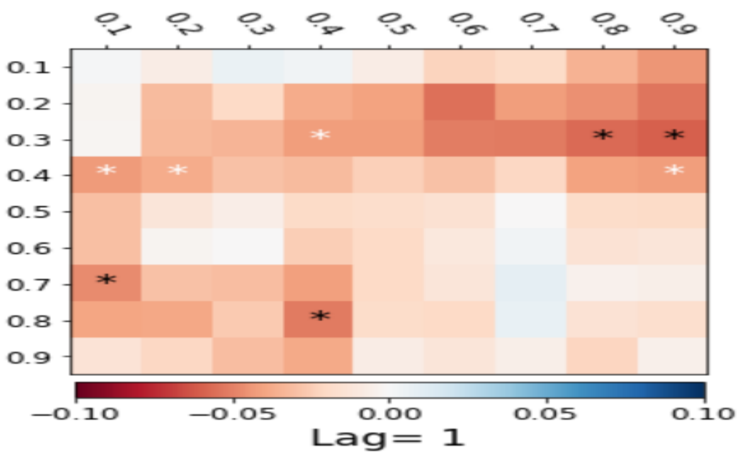
First, note that in this figure, the quantiles of the US industry return are in the vertical axis, and the quantiles of the Chinese industry return are in the horizontal axis. Taking a general look at Figure 4.A, and considering the color of the starred cells, it is clear that the influence of the Chinese industry return on the US industry return is negative. This means that, mainly in the higher quantiles of industry returns in the US market and the medium and lower quantiles of China's industry returns, the effect of Chinese industry returns on the US industry returns is negative. Consequently, Chinese industry returns offer good diversification for US industry sector investors when these two markets are in contradictory positions (i.e., the US industry return is in a bullish status and the Chinese industry index is in a mean or bearish position).



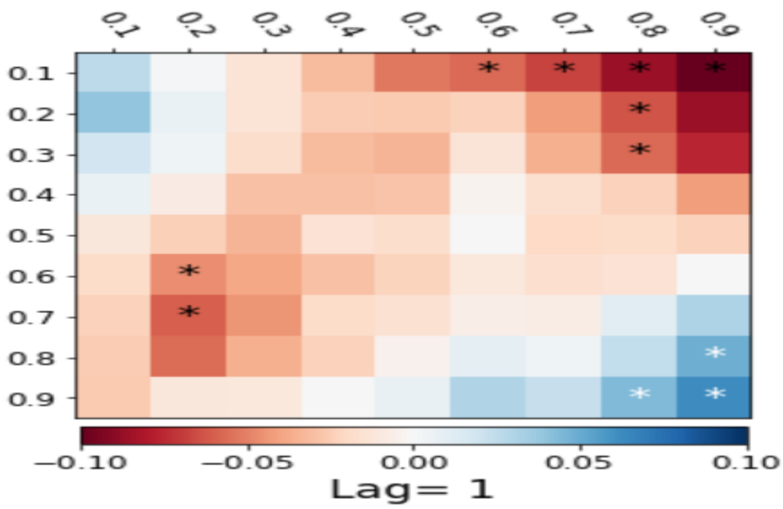
A. Spillover from CN industry to the US industry



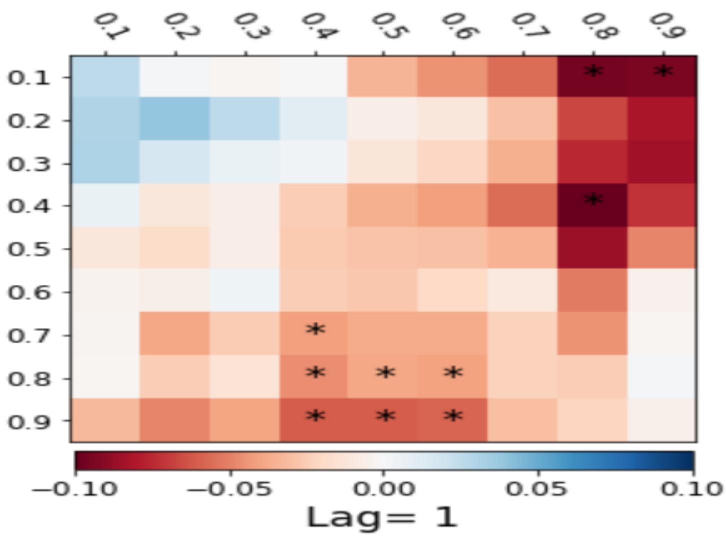
B. Spillover from CN health care to the US healthcare



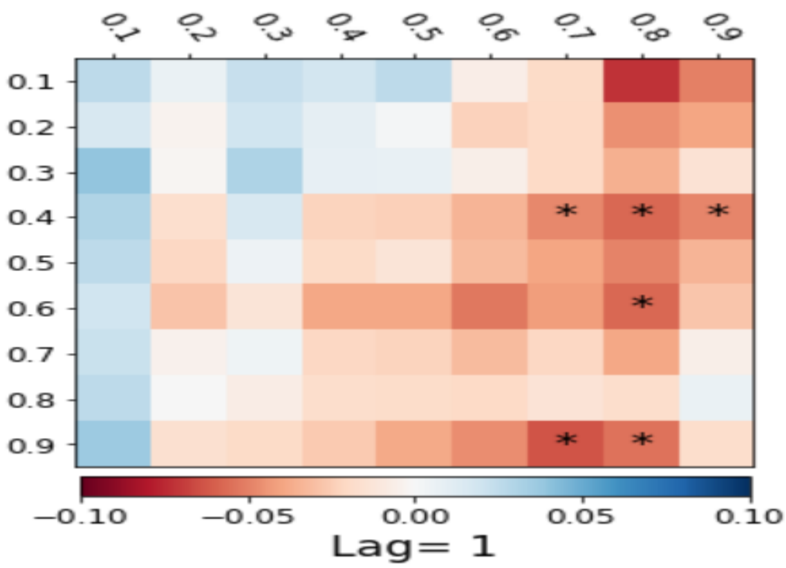
C. Spillover from CN utility to the US utility



D. Spillover from CN energy to the US energy



E. Spillover from CN real estate to the US real estate



F. Spillover from CN telecom to the US telecom

Figure 4. The heat map of directional causality in quantiles from each Chinese market sector to the US counterpart market – full sample using 1-day lag.
Note: CN indicates China.

Figure 4.B depicts the CQ analysis of the healthcare returns in the US and Chinese markets. First, note that in this figure, the US healthcare index is in the vertical axis and the Chinese financial market healthcare index is in the horizontal axis. As shown in Figure 4.B, the heat map is a mix of red and blue cells. However, according to the starred cells, this effect is statistically significant only in red cells; the effect of Chinese healthcare returns on the US healthcare returns is negative. Moreover, this negative connectedness between these two returns mainly occurs when the US healthcare return is in a bullish (bearish) status and the Chinese healthcare return is in a bearish (bullish) status. Thus, in the upper quantiles of the US industry return and lower quantiles of the Chinese industry return (and vice versa), investors have a good opportunity to diversify.

The results of the CQ analysis of the utility return in the US and Chinese markets are shown in Figure 4.C. Note that in this figure, the US utility return is on the vertical axis and the Chinese utility return is on the horizontal axis. The results of CQ, in connection with the effect of the Chinese utility return on the US utility return, indicate that this effect is negative in all quantiles. In addition, a significant negative connection mainly occurs in the mean and lower quantiles of US utility returns and in the lower and higher quantiles of Chinese utility returns. This implies that when the US utility market return is in a mean state and the Chinese utility return is in bearish and bullish statuses, the Chinese utility return has a negative effect on the US utility return. In general, this figure indicates that the Chinese utility sector could provide good diversification for the US utility investors.

Figure 4.D depicts the CQ analysis of the energy returns in the US and Chinese stock markets. Similarly, the US energy returns are on the vertical axis and the Chinese energy returns are on the horizontal axis. The figure shows that Chinese energy returns have a negative and significant effect on the US energy returns. Although this effect is reversed in the highest quantiles of both markets, therefore, there is a directional positive predictability from the Chinese energy returns to the US energy returns. This means that when the US energy and Chinese energy returns are in a bullish position, the Chinese energy index is not a good source of diversification for US energy sector investors. However, as presented in this heat map, the greatest negative impact was achieved when the US energy return is in a bearish position and China's energy return is in a bullish position.

The results of the CQ analysis of real estate returns in the US and Chinese markets are shown in Figure 4.E. The US real estate returns are shown in the vertical axis, and the Chinese real estate returns are shown in the horizontal axis. The impact of Chinese real estate returns on their counterparts in the US real estate market is positive in some quantiles and negative in others. However, importantly, the negative effect of Chinese real estate return on the US real estate return is statistically significant at the 95% level, while the positive effect is not statistically significant. In addition, the most negative impact occurred in the lowest quantiles of the US real estate returns and the highest quantiles of Chinese real estate returns. This means that when the return on US real estate is in bearish and the return of Chinese real estate is in bullish positions, Chinese real estate returns are a good source of diversification for US real estate investors.

Figure 4.F depicts graphical evidence of the CQ results regarding the effect of Chinese telecom return on its counterpart in the US telecom market. In this figure, the US telecom return is on the vertical axis and the Chinese telecom return is on the horizontal axis. As can be seen in this heat map, a significant negative relationship exists between these two returns in the mean and upper quantiles of US telecom returns and higher quantiles of Chinese telecom returns. This shows that negative connectedness between these two returns occurs in the mean and bullish modes of the US telecom returns and the bullish mode of Chinese telecom returns. Consequently, Chinese telecom returns are a good diversification for US telecom investors when the first is in a bullish position and the second is in a mean and bullish position. Our findings align with the results of Chen and Zhou (2024), who highlight the dynamic and evolving interdependence between Chinese and U.S. stock markets. Similar to their study, we observe that certain sectors play leading roles in cross-market connectedness, while others have less influence. Therefore, based on our results the degree of interaction between the two markets varies over time and is negatively correlated, supporting the importance of considering sector-specific and temporal dynamics in risk spillover analyses.

5. Conclusions

This study examines the connectedness between the six main sectors of the US and Chinese stock markets, as these two major stock markets in two of the leading countries in the world have been the focus of research. The TVP-VAR-BK and cross-quantilogram techniques were employed for this purpose. The TVP-VAR-BK results show that, in all investment horizons (the short, medium, and long term), the US industry sector is the main net transmitter of volatility in the network. Chinese industry sector is in the second place and transfer major shocks to the network (in the short term). By contrast, Chinese energy return is the major volatility net receiver in the network during medium and long terms. However, Chinese health care return is the most net receiver of shocks in the short term. Our findings imply that US energy, Chinese industry, and Chinese real estate have the lowest connectedness the network in the long, medium, and short term, respectively.

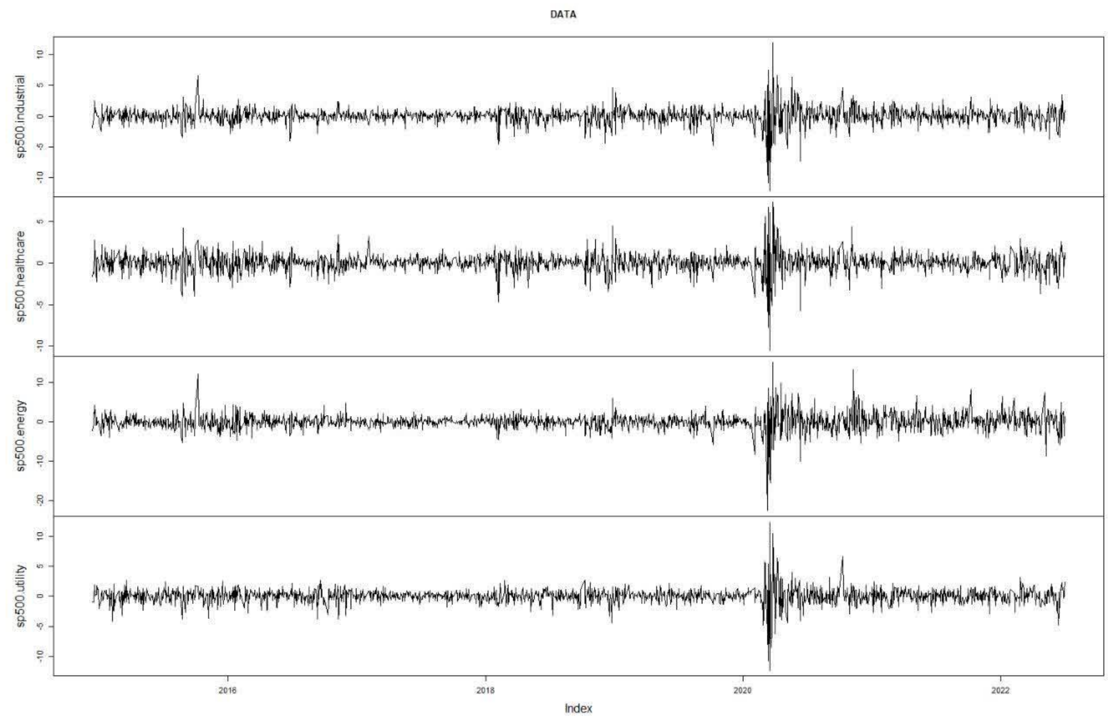
The Total Connectedness Index (TCI) exhibits significant volatilities across short, medium, and long-term horizons, with volatility being more moderate in the long term. Our TVP-VAR-BK analysis shows that TCI spiked notably after the Global Financial Crisis (GFC), declined until 2017, and rose again during major global disruptions such as the U.S.-China trade tensions, the COVID-19 pandemic, and the Russia-Ukraine war. These fluctuations reflect heightened systemic risk and shifts in investor sentiment during times of uncertainty. An increasing TCI signals reduced diversification benefits, while a declining TCI indicates more favorable conditions for portfolio diversification. Policymakers and financial regulators should monitor the TCI as an early-warning indicator of systemic risk, especially during geopolitical and health crises. By doing so, they can implement timely macroprudential measures to stabilize markets and guide institutional investors in managing systemic shocks more effectively.

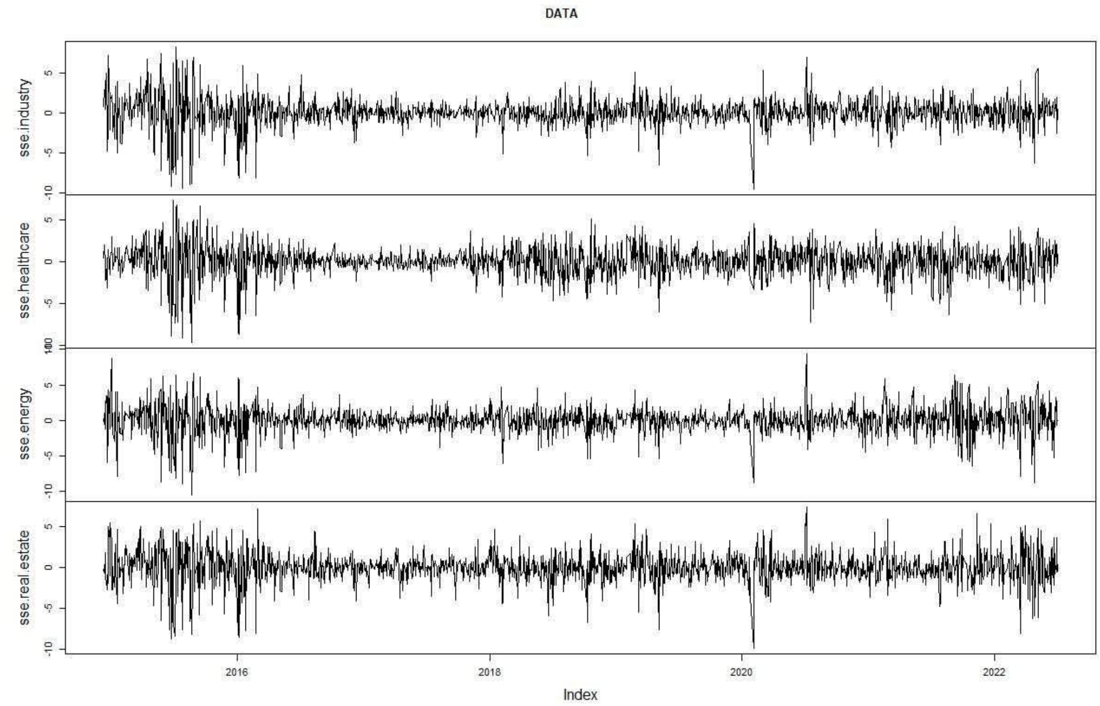
Using the cross-quantilogram (CQ) approach, we find consistent evidence that returns in China's sectoral returns exert a statistically significant negative impact on their US counterparts, particularly when the sectors are in opposite market conditions—that is, when one market is bullish and the other bearish. Investing in different stock markets and sectors provides diversification benefits when the stock returns exhibit negative relationships. For example, Chinese industry returns negatively affect US industry returns, especially when the US market is in a bullish state and the Chinese market is in neutral or bearish conditions, highlighting strong diversification potential for US investors. Similarly, the strongest negative dependence in the healthcare sector appears when one market is bullish and the other bearish, making Chinese healthcare stocks a useful hedge against opposite US market states. In the utilities sector, Chinese utility returns offer diversification benefits when the US market is in mid-to-high return quantiles and the Chinese market is in high or low quantiles, due to significant negative interdependence. In the energy sector, diversification advantages are clearest when the US and Chinese markets are in opposite return states; however, when both are bullish, a positive correlation emerges that reduces the effectiveness of diversification. In the real estate sector, Chinese returns are particularly effective for diversification when the US real estate returns are bearish and Chinese real estate is bullish. The Chinese telecom sector also offers diversification potential, especially when both markets are in bullish or neutral conditions, driven by a significant negative linkage.

These findings imply that policymakers and institutional investors should promote cross-border sectoral diversification, especially in asynchronous market conditions, as a strategic tool to stabilize portfolios and mitigate systemic risk exposure, particularly in times of geopolitical or health-related shocks. Therefore, the results of this study help us understand the co-movements of assets, informing portfolio diversification for investors and speculators and their investment decisions. From an asset allocation perspective, investors should pay attention to the status of each stock and its pairwise relationships to prepare for diversification in their investment portfolios.

The findings of this study offer several policy-relevant insights. The relatively low volatility transmission observed in China’s energy, utility, and real estate sectors—as well as the U.S. telecom sector—particularly after 2019 and during major shocks such as COVID-19 and the Russia–Ukraine war, suggests that these sectors may serve as effective safe-haven assets. Policymakers and financial regulators can promote investment diversification by encouraging awareness of these stable sectors. In contrast, the healthcare and industrial sectors in both countries exhibit strong and persistent connections within the return network, implying higher systemic sensitivity. While this may raise concerns for short-term investors, it is less critical for medium- and long-term horizons. Nevertheless, enhanced risk management strategies and greater transparency in these sectors are advisable. Moreover, the results from the cross-quantilogram approach reveal asymmetric and negative return spillovers between similar sectors in China and the U.S., particularly under divergent market conditions. This underscores the need for macroprudential monitoring frameworks that capture conditional dependence structures and for greater international coordination, especially in sectors with strong cross-border linkages such as real estate, healthcare, and energy.

Appendix





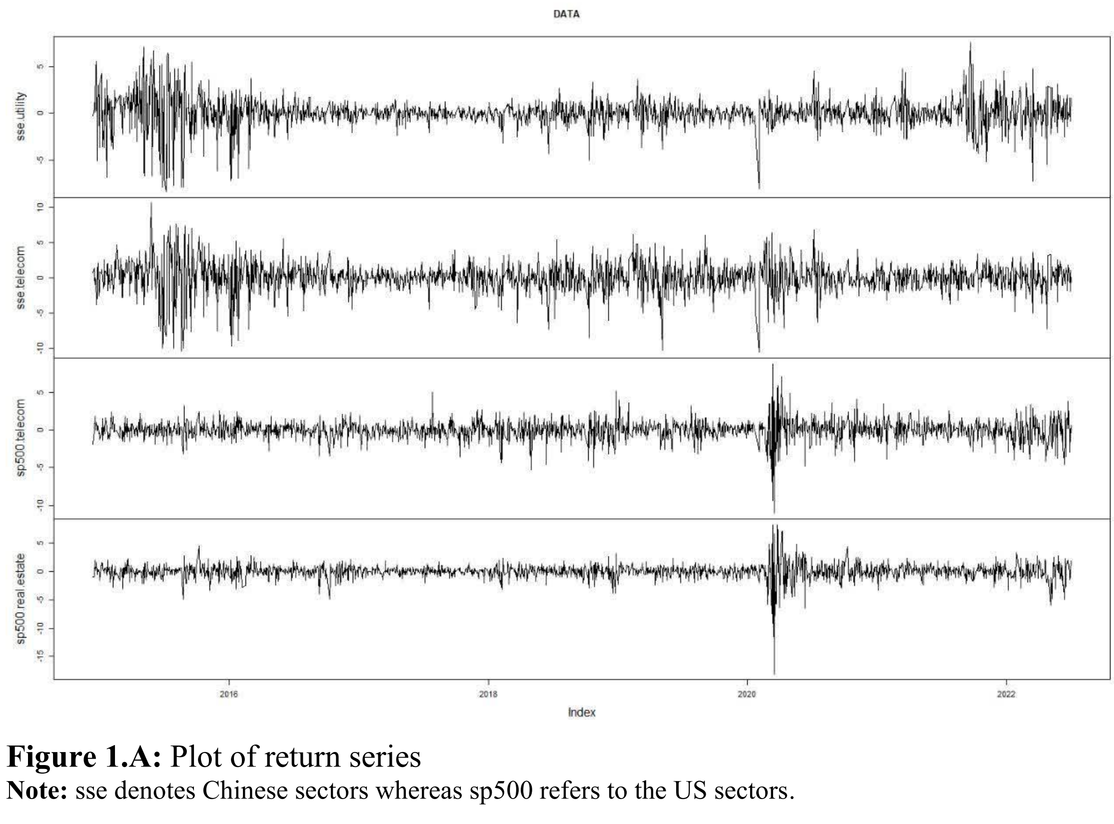


Figure 1.A: Plot of return series
Note: sse denotes Chinese sectors whereas sp500 refers to the US sectors.

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