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US-China Tensions and Financial Spillovers: Uncovering Asymmetric TVP-VAR Transmission

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Abstract:

This study investigates the transmission of geopolitical tensions between the United States and China to their stock markets within a dynamic and asymmetric framework. The analysis uses monthly returns of the S&P 500 and the Shanghai Composite Index, along with the log-difference of the US–China Tension Index (UCT), covering the period 1993–2024. An asymmetric TVP-VAR model is applied to capture time-varying and directional spillovers arising from positive and negative tension shocks. At the same time, a quantile-VAR connectedness analysis is employed for robustness. The results reveal pronounced asymmetries in spillover dynamics. Increases in geopolitical tensions lead to stronger and more widespread effects than periods of easing, particularly during crisis episodes, when spillover intensity rises markedly. The findings further show that while UCT shocks significantly impact financial markets, extreme market stress can also trigger feedback effects on geopolitical tension indicators. In addition, the Chinese stock market exhibits higher sensitivity to UCT shocks than the US market, indicating greater exposure to geopolitical risk. Overall, the results underline the persistent impact of geopolitical tensions on stock market dynamics.

Keywords: US-China Tension Index, Financial spillovers, TVP-VAR

JEL Classification: C32, F51, G15

1. Introduction

Although strategic, economic, and technological friction between the US and China has been building for decades, these tensions became more visible and financially consequential in 2018, when President Trump's announcement of strong measures against China's "unfair trade" triggered a series of mutual tariffs. This escalation transformed bilateral frictions into a systemic risk for global economic coordination (Liu and Woo, 2018; Kim, 2019). The impact of these tensions on the global stage stems from the two countries' decisive roles in the global economy. With its developed financial markets, high-tech production capacity, and its dollar as a reserve currency, the US is the country that shapes the financial and institutional architecture of the global economic order. China, with its high growth rate over the last three decades, its production- and export-oriented industrial structure, and its growing capacity in digital and green transformation, has positioned itself at the center of global supply chains. Approximately one-quarter of global trade passes directly through the US and Chinese economies. In 2024, the US was second in global exports with an 8.2% share and first in imports with a 13.9% share. China was first in exports with a 15% share and second in imports with a 10.7% share. This global weight demonstrates that the two countries are significantly influential not only for the global economy but also for each other. China's share of US total imports peaked at 9% in 2015 and declined to 6.4% in 2024. Similarly, the share of US imports from China in total imports peaked at approximately 22% in 2017 but has fallen to 13.8% by 2024 (The World Integrated Trade Solution (WITS) Database). This trend indicates a strengthening of decoupling in the two countries' trade relations and a relative decrease in economic interdependence. This restructuring process paves the way for changing risk perception and uncertainty dynamics in financial markets. Hence, geopolitical tensions between the US and China have become a potential factor shaping not only trade flows but also the distribution of investment decisions. The trade war appears to be affecting market sentiment and investor behavior, extending beyond direct flows of goods and services. Stock market reactions serve as a kind of sentiment indicator reflecting investors' future expectations. Negative news about the trade war fuels fear and uncertainty in markets, increasing volatility (Carlomagno and Albagli, 2022). Consequently, announcements and rhetoric regarding the US-China trade war have become a major trigger for periods of volatility in global financial markets (Bissoondoyal-Bheenick et al., 2022).

The theoretical framework explains why geopolitical tensions strongly impact financial market behavior. This has been widely confirmed in theoretical literature. The

Efficient Market Hypothesis is the fundamental approach to explaining how information flows in financial markets are reflected in prices (Fama, 1970). According to this view, asset prices rapidly reflect publicly available information, and uncertainty or new news is immediately incorporated into market values. Therefore, shocks such as trade policies, tariffs, and geopolitical tensions are expected to affect market pricing. Real Options Theory (Dixit and Pindyck, 1994) suggests that when uncertainty increases, firms postpone investment decisions and act more cautiously. This attitude weakens market performance and increases volatility. Integrated Markets Theory (Wahyudi and Sani, 2014) also argues that market integration increases when long-term common trends exist among financial assets. When considered together, these approaches reveal that uncertainty and information shocks have powerful and multifaceted effects on investor sentiment, market integration, and asset prices (Khan et al., 2025a).

Uncertainty, heightened correlations, and negative global returns have largely driven the impact of US-China tensions on financial markets. Generally, escalating tensions tend to affect stock market indices negatively (Peng et al., 2025; Şeyranlıoğlu, 2025). Analysis of corporate investment in the US shows that rising US-China tensions are associated with a significant decline in firm investment. This negative impact has been largely driven by a policy-uncertainty component, rather than by the imposed tariffs (Rogers et al., 2024). An in-depth examination of the markets reveals that US-China tensions both increase individual stock market volatility and strengthen the interdependence and long-term correlations between the two countries' market indices (Xu et al., 2025). Chinese markets have shown a stronger, more pronounced response to rising tensions than US markets. This is consistent with hegemony theory in international finance (Peng et al., 2025). Within China's multi-layered market structure, small and medium-sized enterprises and technology-focused segments are more sensitive to geopolitical changes than larger, corporate markets (Xu et al., 2025). Tensions increase shared volatility between the two countries, reducing portfolio diversification advantages (Xu et al., 2025), and coincide with periods of financial fragility (Wu, 2025; Tillmann and Yun, 2025). As tension levels rise, market risk appetite increases, intensifying volatility in safe-haven assets such as gold (Wu, 2025). The effects of tensions between the two countries spill over into Asian and frontier markets (Khan et al., 2025b) and produce both short- and long-term negative effects in emerging markets like Türkiye (Şeyranlıoğlu, 2025). Taken together, these findings suggest that the effects of US-China tensions on financial markets are widespread, persistent, and contagious.

These widespread and multifaceted influences in the literature clearly highlight the need for a reliable indicator that can systematically measure how and through which channels US-China tensions are reflected in financial markets. In response to this need, Rogers et al. (2024) developed a new index, the US-China Tension Index (UCT), by analyzing news content in the US press using text-mining techniques. By consistently measuring the level of tension in bilateral relations at a monthly frequency and over an extended period, the UCT provides a powerful analytical tool for examining the impact of geopolitical shocks on market behavior. Studies conducted after the index was developed (Hines et al., 2025; Li and Liu, 2025; Peng et al., 2025; Xu et al., 2025) investigated the effects of UCT on stock returns, volatility, and market linkages, demonstrating that this indicator is increasingly being used to measure the geopolitical sensitivity of financial markets. Thus, UCT is becoming an increasingly important indicator in the literature for analyzing the impact of political developments between two countries on the markets. This study, leveraging this index, examines the transmission dynamics arising from geopolitical tensions between the US and Chinese stock markets over an extended period.

This study focuses on the transmission dynamics of geopolitical tensions between the US and China to financial markets. Accordingly, the primary objective of this study is to demonstrate how these tensions affect the stock markets of both countries, particularly how this impact has changed over time and how it responds to positive and negative shocks. This motivation is reinforced by the growing evidence that the US-China rivalry, which has intensified over the last three decades, has destabilizing effects on financial markets, and by the limited number of studies in the literature that measure this impact in a high-frequency, directional, and dynamic manner. The methods used in this study allow separate analysis of the effects of escalating and de-escalating tensions on the stock market and demonstrate that these effects are particularly concentrated during market extremes. Thus, the study dynamically examines the financial linkages between UCT-induced shocks and the US and Chinese stock markets in terms of both direction and intensity, comprehensively demonstrating how these relationships evolve under different market conditions. Thanks to this holistic approach, the study addresses a significant gap in the literature by considering the role of US-China tensions in financial markets not only through average effects but also asymmetrically across time, shock direction, and market conditions.

The remainder of the paper proceeds as follows: Literature Review summarizes prior research. The data section introduces the variables. Methodology outlines the empirical approach. Findings and Discussion present the results. Conclusion offers final remarks.

2. Literature Review

As the global economy is increasingly shaped by geopolitical dynamics, economic and political tensions between the US and China have become a key factor determining not only the relationship between the two countries but also the stability of global financial markets (Rogers, Sun, and Sun, 2024; Egger and Zhu, 2020). The US-China Tension Index, developed in this context, enables quantitative monitoring of tension between the two countries, providing an essential analytical tool for understanding investor behavior, market volatility, and capital flows (Rogers et al., 2024). Recent studies have used UCT to investigate the economic and financial consequences of geopolitical uncertainty, particularly its effects on stock returns, volatility, and markets (Peng et al., 2025; Cai et al., 2025a; Xu et al., 2025; Hines et al., 2025), energy markets (Caporin et al., 2025; Cai et al., 2025b; Li et al., 2025; Inglesi-Lotz et al., 2025), and commodity prices (Khan et al., 2025a; Wu, 2025). Furthermore, some studies have highlighted the broader relationship between uncertainty, financial spillover effects, and systemic market risk. For example, AlGhazali et al. (2025) show that policy distortions, such as energy subsidies, can amplify inter-market financial spillover effects, and that structural policy environments can strengthen inter-market transmission channels. Similarly, Yeh et al. (2025) emphasize the link between spillover dynamics and stock market crash risk, demonstrating that stronger market linkage can increase the fragility of financial systems during periods of stress. Building on this line of research, Xu et al. (2026) developed composite uncertainty indicators using supervised dimensionality-reduction techniques and found that multidimensional uncertainty measures contain significant predictive information for stock market returns. Taken together, these studies demonstrate that uncertainty-related shocks and policy factors can intensify financial spillover effects and increase inter-market systemic risk.

Egger and Zhu (2020) are among the first studies to examine the stock market reactions to trade wars. They show that protective tariffs imposed by the US and China negatively affect not only target-country firms but also firms in other countries. This impact spreads to other countries' markets through indirect channels, particularly through global supply chains. The findings suggest that trade wars create contagion shocks through global financial linkages. He, Lucey, and Wang (2021) analyzed the dynamic impact of US-China trade tensions on stock markets using the TVP-SV-VAR model, using the concept of trade policy uncertainty (TPU). Their findings indicate that US-sourced TPU increases volatility in both the US and Chinese stock markets; however, it has a positive short-term effect on the US market and a negative short-term effect on the Chinese market. This suggests that market reactions are asymmetrical depending on the countries' economic resilience and political stability. Chen and Pantelous (2022) stated that Chinese industries are more exposed to trade tensions than their US counterparts. Nishimura and Sun (2021) analyzed the effects of US President Donald Trump's China-related tweets on market volatility and showed that these messages increased global volatility. They found that negative tweets, in particular, caused sharp declines in the Chinese stock market and increased short-term volatility in the US.

Chengying, Rui, and Ying (2022) used an event study approach to examine the impact of the trade war, which began in 2018, on the Chinese stock market. The results revealed that trade war announcements created contagion effects across sectors, but that inter-sectoral differences diminished in the long run. These findings are supported by a study by Oh and Kim (2024) using high-frequency financial data. The researchers developed a continuous-time jump-diffusion model to examine volatility contagion between the US and Chinese stock markets. The study shows that risk contagion from the US to China occurred following the trade war, with the contagion channel shifting from integrated volatility to negative price-jump variation.

Rogers et al. (2024), who developed the UCT, demonstrated that rising US-China tensions reduce investment intentions among American firms, particularly those with high export dependence on China, and accelerate the shift away from China in their supply chains. Furthermore, an increase in the index leads to a systematic decline in stock returns through the uncertainty channel. Similarly, Cai et al. (2025a) used this index, developed by Rogers et al. (2024), to examine the causal relationship between US financial conditions and US-China political tensions. According to Granger causality analysis, the US financial conditions index (specifically the Chicago Fed's NFCI indicator) can predict political tensions with China; a reverse relationship is found in only a few cases. This finding suggests that geopolitical risks intensify during periods of financial stress and that financial markets are sensitive to political tension.

Li and Liu (2025) used a GJR-GARCH-MIDAS model to examine how UCT fluctuations affect the volatility of the S&P 500 and NASDAQ indices. They found that increases in UCT significantly increase long-term volatility, while decreases reduce it. The results highlight the asymmetric response of US equities to positive and negative tension shocks, suggesting that financial markets internalize geopolitical signals as persistent risk factors rather than short-term noise. Complementing this, Hines et al. (2025) analyzed how activist short-sellers strategically time their campaigns against US-listed Chinese firms during periods of high tension. Their findings suggest that rather than contributing to information efficiency, short sellers capitalize on prevailing political views, with campaigns launched during peaks of tension producing sharper short-term price declines but larger subsequent returns. This evidence points to geopolitically induced distortions in US market efficiency. Peng et al. (2025) find that Chinese stock markets respond more strongly to UCT than US markets do. UCT has a growing impact on Chinese stock markets, which exhibit significant time-varying characteristics. Furthermore, the US stock market is more sensitive to positive news about US-China relations and reacts with lagged reactions to deteriorating ties, demonstrating an asymmetric pattern. Xu et al. (2025) use a DCC-DAGARCH-MIDAS framework to analyze dynamic co-movement between the US and Chinese stock markets. Their results indicate that escalating tensions, especially during trade wars, increase volatility co-movement and reduce the diversification benefits of cross-country portfolios. Similarly, Wu (2025) and Tillmann and Yun (2025) emphasize that US-China relations co-vary with periods of financial instability, with Chinese markets in particular being more sensitive to external shocks.

The effects of the US–China Tension Index are not limited to the stock markets of the two countries alone. Khan et al. (2025b) examine the transmission of US–China tensions to emerging and frontier markets in Asia using the TVP-VAR and wavelet coherence methods. They find a stronger linkage between the UCT and frontier markets (e.g., Sri Lanka, Pakistan, Kuwait) compared to emerging markets, indicating that more fragile economies are more susceptible to geopolitical spillovers. Furthermore, low-frequency co-movements between UCT and stock returns suggest that geopolitical shocks have persistent, long-term effects. Şeyranlıoğlu (2025) applies an ARDL bounds test to assess the transmission of US-China tension to Türkiye's Borsa Istanbul (BIST-100) index. The results show that increases in UCT negatively affect Turkish stock returns in both the short- and long-term, confirming the global impact of Sino-American geopolitical risk across non-Asian emerging markets.

Existing literature demonstrates that the US-China Tension Index and similar indicators provide valuable insights into financial contagion and investor expectations. The effects of geopolitical tensions, by their nature, evolve, and markets react differently to these developments in different periods. Accurately capturing this dynamic structure allows for a more realistic analysis of market dynamics. In this study, the impact of US–China tensions on financial markets is analyzed using a dynamic, asymmetric, time-varying framework, which enables the separate identification of positive and negative tension shocks and their evolving effects. To ensure robustness, the analysis is complemented with a quantile-VAR-based connectedness approach, allowing the investigation of how geopolitical tensions influence markets under different distributional conditions, particularly during extreme market states. By adopting these methodologies, the study reveals how the relationship between geopolitical tensions and stock markets has shifted across different economic regimes and market environments. Thus, it contributes to the literature not only by treating geopolitical effects as a dynamic rather than static process but also by expanding the scope of prior research, which largely focused on limited crisis periods.

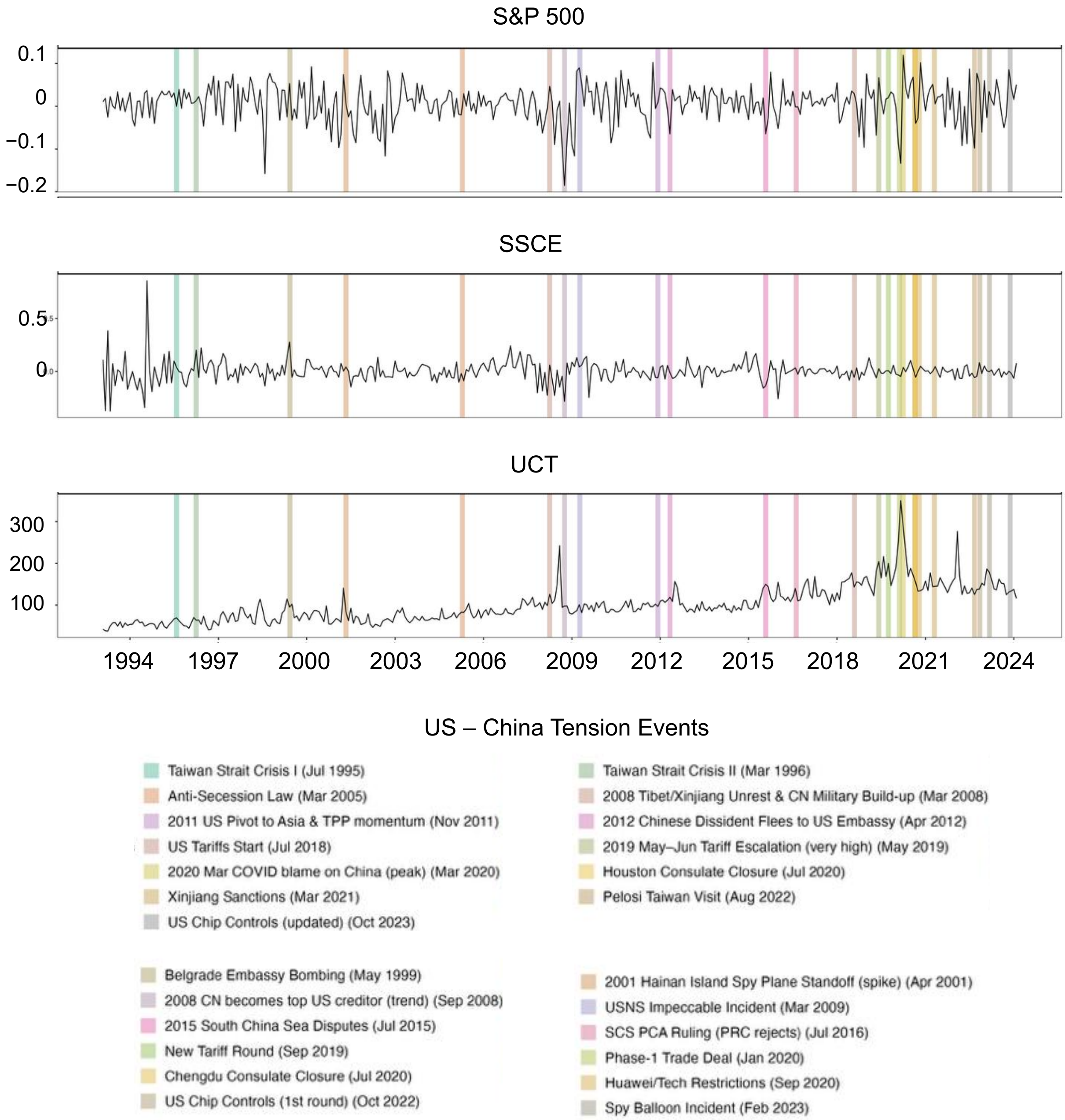
3. Data

This study uses monthly data from February 1993 to February 2024 for the US–China Tension Index (UCT), the US S&P 500 index (US500), and China's Shanghai Composite equity index (SSCE). The US–China Tension Index (UCT) is a text-based indicator developed by Rogers et al. (2024) to quantify geopolitical tensions between the United States and China. The index is constructed using large-scale textual analysis of leading US newspapers. Specifically, the methodology identifies news articles that combine keywords related to the United States and China with conflict-related terms such as tensions, disputes, sanctions, or trade restrictions. The frequency of these articles is then normalized to the total volume of news coverage to produce a monthly indicator that captures the intensity of bilateral tensions. This approach follows the broader tradition of text-based economic indicators, such as the Economic Policy Uncertainty (EPU) index, which also relies on newspaper coverage to measure policy-related uncertainty. By aggregating information from media narratives, the UCT provides a systematic, high-frequency proxy for geopolitical tensions that would otherwise be difficult to quantify directly. Although the index is based on media coverage and may therefore reflect the framing of geopolitical events in the press, previous studies have shown that such text-based indicators provide valuable information about market expectations and uncertainty dynamics. In this sense, the UCT should be interpreted as a proxy for perceived geopolitical tension rather than a direct measure of objective political conflict.

For financial market data, we collected monthly closing prices of the S&P 500 index and the Shanghai Stock Exchange Composite Index from investing.com. We computed logarithmic returns for each index by taking first differences of the natural logarithm of the monthly closing price series.

The Shanghai Composite Index was chosen as the benchmark for the Chinese market (rather than alternatives such as the CSI 300) for its broad market coverage. The SSCE Composite is a market-capitalization-weighted index that includes all A-shares (mainly open to domestic investors) and B-shares (initially designed for international investors) traded on the Shanghai Stock Exchange. Therefore, it provides a comprehensive representation of China's stock market, capturing the performance of a wide array of listed firms. In the context of our study, this broad market index serves as an appropriate indicator of Chinese equity performance, against which we can examine spillover effects stemming from geopolitical and policy-related tensions.

Figure 1. UCT and Stock Returns with Major Events (1993–2024)



Source: Event dates are based on the Council on Foreign Relations (2025). Event windows were defined by the authors.

Fig. 1 shows the UCT alongside monthly returns for the S&P 500 and SSCE, highlighting periods of heightened bilateral tension events. During the 1990s, the UCT hovered at lower levels with brief rises, like in the 1995-1996 Taiwan Strait Crisis or the 1999 US bombing of the Chinese embassy in Belgrade, which overlapped with small return dips (Gries, 2001), but global shocks such as the 1997-1998 Asian Financial Crisis led to sharper negative returns in Shanghai than in the S&P, underlining regional sensitivities over direct US-China strains (Du et al., 2017; Kan, 2000). The 2000s featured slightly elevated average UCT readings, with events like the 2001 Hainan Island plane collision adding spikes. Nevertheless, the 2008 global financial crisis marked a low in the index amid China's position as a significant US debt holder, fostering interdependence, even as both markets suffered negative returns, illustrating that global downturns often eclipse quieter bilateral relations (Drezner, 2009). Obama's terms (2008-2016) included the 2011 pivot to Asia that nudged tensions up steadily without triggering extreme market fallout, whereas global strains like the 2010-2012 Eurozone crisis burdened the US returns more (Lieberthal, 2011). During the early Trump period (2017–2018), tariffs significantly boosted the index; in the later phase (2019–2020), the scope expanded to include tech controls, blacklists, and COVID-19 blame-shifting, maintaining UCT at elevated levels (Cai, 2025; Farrell and Newman, 2019; Luo et al., 2025). It remains high afterwards with semiconductor/export rules and security incidents.

To prepare the data for modeling, we need to address the index level's nonstationarity. Similar to the S&P 500 and SSCE returns, we transform the UCT into a stationary series by taking its monthly log-difference to focus on volatility, defined as $\ln(UCT_t) - \ln(UCT_{t-1})$. This transformation enables our models to assess the impact of shocks in tension, rather than focusing on the absolute level of the index.

Table 1. Descriptive Statistics

	UCT	US500	SSCE
Mean	0.003	0.007	0.002
Variance	0.187	0.044	0.009
Skewness	–0.027	–0.768***	1.494***
Kurtosis	5.713***	4.400***	20.263***
JB	114.511***	67.130***	4770.401***
ADF	–25.473***	–18.988***	–22.137***
Q(20)	47.538***	12.362	29.353***
Q2(20)	31.867***	61.641***	28.943***
kendall	***UCT***	***US500***	***SSCE***
UCT	1.000***	–0.05	–0.014
US500	–0.05	1.000***	0.130***
SSCE	–0.014	0.130***	1.000***

*** indicates 1% confidence level.
Source: Own calculations

Table 1 presents the descriptive statistics of the series, and all of them are confirmed to be stationary, as indicated by the ADF unit root test. The unconditional correlations (Kendall's τ) between UCT shocks and the two market returns are modest, meaning that a simple linear analysis would be insufficient. The highly significant Jarque-Bera (JB) statistics for all series strongly reject the null hypothesis of normality. This non-normality is primarily driven by a significant fat-tailed pattern across all variables, most notably in the SSCE, and pronounced negative skewness in the S&P 500. Finally, the significance of the Ljung-Box Q-statistics for returns indicates robust volatility clustering. The evidence of asymmetry (skewness) and time-varying volatility (volatility clustering) necessitates the Asymmetric TVP-VAR model to capture how the direction of shocks and the overall level of connectedness change over time. At the same time, these findings motivate the use of a quantile connectedness approach to move beyond average relationships and model behavior under extreme market conditions.

4. Methodology

To examine how shocks move between the UCT and stock returns, we use two methods. First, we use the asymmetric time-varying parameter vector autoregression (Asymmetric TVP-VAR) connectedness approach from Antonakakis et al. (2020), which builds on the original connectedness idea by Diebold and Yilmaz (2012). This method helps us see differences in spillovers from positive and negative shocks, which change over time.

First, we separate each return series p_t (for the UCT, the S&P 500, and the SSCE) into its positive and negative components (Adekoya et al., 2022). This allows us to study "good news" and "bad news" shocks individually. However, the economic interpretation of these components is variable-specific. For UCT, a positive component represents an increase in perceived tension, whereas a negative component represents a decrease in tension. For stock returns, positive and negative components represent market gains and losses, respectively:

$$p_t^+ = p_t . \frac{1+sgn(p_t)}{2} \tag{1}$$

$$p_t^- = p_t . \frac{1-sgn(p_t)}{2} \tag{2}$$

Here, p_t^+ (p_t^-) represents positive components (negative components) and *sgn* denotes the signum function. We estimate three specifications: a symmetric benchmark using the original transformed series, a positive-component system, and a negative-component system. Each specification contains the same three variables.

Next, we estimate a TVP-VAR(1) model using the Bayesian Information Criterion (BIC) as the support criterion. A standard VAR assumes that coefficients are constant over the entire 1993-2024 period. The TVP-VAR, however, allows coefficients and variances to vary by month. This flexibility captures crises or structural policy shifts. The model is expressed as follows:

$$p_t = \beta_t p_{t-1} + u_t \qquad u_t \sim N(0, \Sigma_t) \tag{3}$$

$$vec(\beta_t) = vec(\beta_{t-1}) + v_t \quad v_t \sim N(0, R_t) \tag{4}$$

In this system, p_t is the vector of asymmetric components containing UCT, US500, and SSCE. In the symmetric specification, p_t contains the original transformed series; in the component-specific specifications, it contains either their positive or negative components. β_t is the time-varying coefficient matrix, Σ_t is the time-varying variance-covariance matrix of the observation errors (u_t), and R_t represents the time-varying variance-covariance matrix of the state equation errors (υ_t). The $vec(\beta_t)$ operator vectorizes a matrix. This model allows the parameters to be estimated for every period using the Kalman Filter.

After estimating the TVP-VAR, we obtain a time-varying moving-average representation (TVP-VMA) via the Wold decomposition, enabling variance decompositions. In this representation, A_t denotes the time-varying moving-average coefficient matrices that capture the dynamic impulse responses to structural shocks over time. We then compute the spillover measures using the generalized forecast error variance decomposition (GFEVD) approach introduced by Diebold and Yilmaz (2012). This GFEVD method, based on the techniques of Koop et al. (1996) and Pesaran and Shin (1998), yields variance decomposition entries that are invariant to variable ordering. In practice, for each horizon H (we use H = 24 months), the GFEVD produces the fraction of the H-step ahead forecast error variance of variable *j* that is attributable to shocks in variable *i*, denoted $\psi^{g}_{ij,t}(H)$ as:

$$\psi^{g}_{ij,t}(H) = \frac{\Sigma^{-1}_{ii,t}\sum_{t=1}^{H-1}(\iota_i' A_t \Sigma_t \iota_t)^2}{\sum_{j=1}^{k}\sum_{t=1}^{H-1}(\iota_i' A_t \Sigma_t A_t' \iota_i)} \tag{5}$$

where ι_t is a selection vector (1 for *i*), and $\Sigma^{-1}_{ii,t}$ is the *j*th diagonal element. Intuitively, $\psi^{g}_{ij,t}(H)$ is the proportion of *i*'s forecast error variance (up to horizon *H*) accounted for by shocks in *j* at time *t*. We normalize these fractions so that for each *i*, the contributions from all sources (including itself) sum to 100%, due to shocks that are not orthogonal in the generalized framework. The normalized (scaled) share is denoted by $\tilde{\psi}^{g}_{ij,t}(H)$ and represents the pairwise directional connectedness from variable *j* to *i* at time *t*:

$$\tilde{\psi}^{g}_{ij,t}(H) = \frac{\psi^{g}_{ij,t}(H)}{\sum_{j=1}^{k}\psi^{g}_{ij,t}(H)} \tag{6}$$

In other words, $\tilde{\psi}^{g}_{ij,t}(H)$ is the fraction of *i*'s *H*-step-ahead forecast-error variance attributable to shocks in variable *j*. This pairwise measure is the building block for broader indices of connectedness.

From the 3 × 3 GFEVD matrix, calculated for each time *t*, we construct total, net total and net pairwise directional connectedness indices. For each variable *i*, the total directional connectedness to others is the sum of spillovers from *i* to all other variables. Using the pairwise terms:

$$C^{g}_{i\to j,t}(H) = \sum_{j=1,i\neq j}^{k}\tilde{\psi}^{g}_{ji,t}(H) \tag{7}$$

$$C^{g}_{i\leftarrow j,t}(H) = \sum_{j=1,i\neq j}^{k}\tilde{\psi}^{g}_{ij,t}(H) \tag{8}$$

For each variable *i*, the total directional connectedness to others is the sum of spillovers from *i* to all other variables ($C^g_{i\to j,t}(H)$) while the total directional connectedness from others for variable *i* is the sum of variance shares that *i* receives from all other variables' shocks ($C^g_{i\leftarrow j,t}(H)$). A higher $C^g_{i\to j,t}(H)$ means that variable *i* is a major transmitter of shocks to the system while larger $C^g_{i\leftarrow j,t}(H)$ means *i* is highly influenced by shocks originating elsewhere in the network. The difference between spillovers transmitted and received gives net total directional connectedness (NET). If $C^g_{i,t}(H) > 0$, variable *i* is a net transmitter of shocks. If $C^g_{i,t}(H) < 0$, it is a net receiver.

$$C^g_{i,t}(H) = C^g_{i\to j,t}(H) - C^g_{i\leftarrow j,t}(H) \tag{9}$$

While the NET index (Eq. 9) shows if a variable is a net transmitter or receiver to the system, the net pairwise directional connectedness (NPDC) provides a net flow, between a single pair, *i* and *j*:

$$NPDC_{ij,t}(H) = \tilde{\psi}^g_{ij,t}(H) - \tilde{\psi}^g_{ji,t}(H) \tag{10}$$

If $NPDC_{ij,t}(H) > 0$, it signifies that variable *j* is a net transmitter of shocks specifically to variable *i*. A negative value indicates that variable *j* is a net receiver of shocks from variable *i*.

By employing an asymmetric TVP-VAR approach, we can compare these connectedness measures under positive and negative conditions. The model allows us to explore whether an increase in tension (UCT_t^+) leads to more volatility during stock market downturns ($US500_t^-, SSCE_t^-$), or whether declines in the S&P 500 and SSCE ($US500_t^-, SSCE_t^-$) influence the tension index.

As a robustness check, we also apply the quantile VAR (QVAR) connectedness methodology, which allows the connectedness to be analyzed at different points of the return distribution. Our first method, the Asymmetric TVP-VAR, captures how connectedness evolves dynamically over time and distinguishes between the impact of positive and negative shocks. The Quantile Connectedness model, by contrast, examines how the strength of connectedness varies with market conditions. In essence, the first model examines asymmetry over time, while the second model examines connectedness in the tails of the distribution. This approach is based on the quantile VAR model introduced by Ando et al. (2022) and applied to connectedness analysis by Chatziantoniou et al. (2021). The main idea is to analyze the system's interdependence during different states, such as periods of extreme market stress (bear markets, represented by the lower quantiles of the return distribution), normal periods (the median, or 0.50 quantile), and periods of extreme positive performance (bull markets, or the upper quantiles). To provide a clear contrast to the first method, this analysis is conducted on the original (symmetric) 3-variable system $p_t =′$.

The QVAR model estimates parameters that vary across quantiles (τ), where τ ranges from 0 to 1. We estimate the following system:

$p_t = \mu(\tau) + \sum_{j=1}^{K} \Phi_j(\tau) p_{t-j} + u_t(\tau)$ from τ = 0.05 to τ =0.95. p_t is the vector of endogenous variables. $u(\tau)$ is the quantile-specific intercept vector, K denotes the optimal lag length, and j acts as the subscript indicating the lag index. $\Phi_j(\tau)$ represents the matrix of autoregressive coefficients at lag j for the τth quantile, capturing the specific dynamic linkages at that state. Finally, $u_t(\tau)$ is the quantile-specific vector of structural error terms. The GFEVD and the resulting connectedness indices (TO, FROM, NET, NPDC) are calculated in the same manner as described in Eq. (6) through (10). However, the resulting indices $\tilde{\psi}_{ij}^{g}(H,\tau)$ and $C_i^{g}(H,\tau)$ are functions of the quantile (τ) rather than time.

It is important to note that the TVP-VAR connectedness framework relies on generalized forecast error variance decompositions. Like many text-based macroeconomic indicators, the UCT index may be subject to endogeneity. Severe financial market downturns can trigger increased media coverage of geopolitical frictions, creating a potential for simultaneity bias. However, the advantage of using directional connectedness indices is that they allow us to empirically observe and quantify these bidirectional feedback loops between market conditions and media coverage over time (Eq. 9 and Eq. 10).

Taken together, these approaches provide complementary insights into how geopolitical tensions interact with financial markets across time and different market states. However, the empirical framework employed in this study should not be interpreted as identifying structural causal effects. These approaches capture predictive relationships and time-varying interdependencies rather than strict causal mechanisms. In addition, because the UCT index is constructed from media coverage, developments in financial markets may themselves influence the intensity of news reporting and thus the index values. Accordingly, the results should be interpreted as evidence of dynamic spillover relationships associated with geopolitical tensions rather than as definitive causal effects.

5. Findings and Discussion

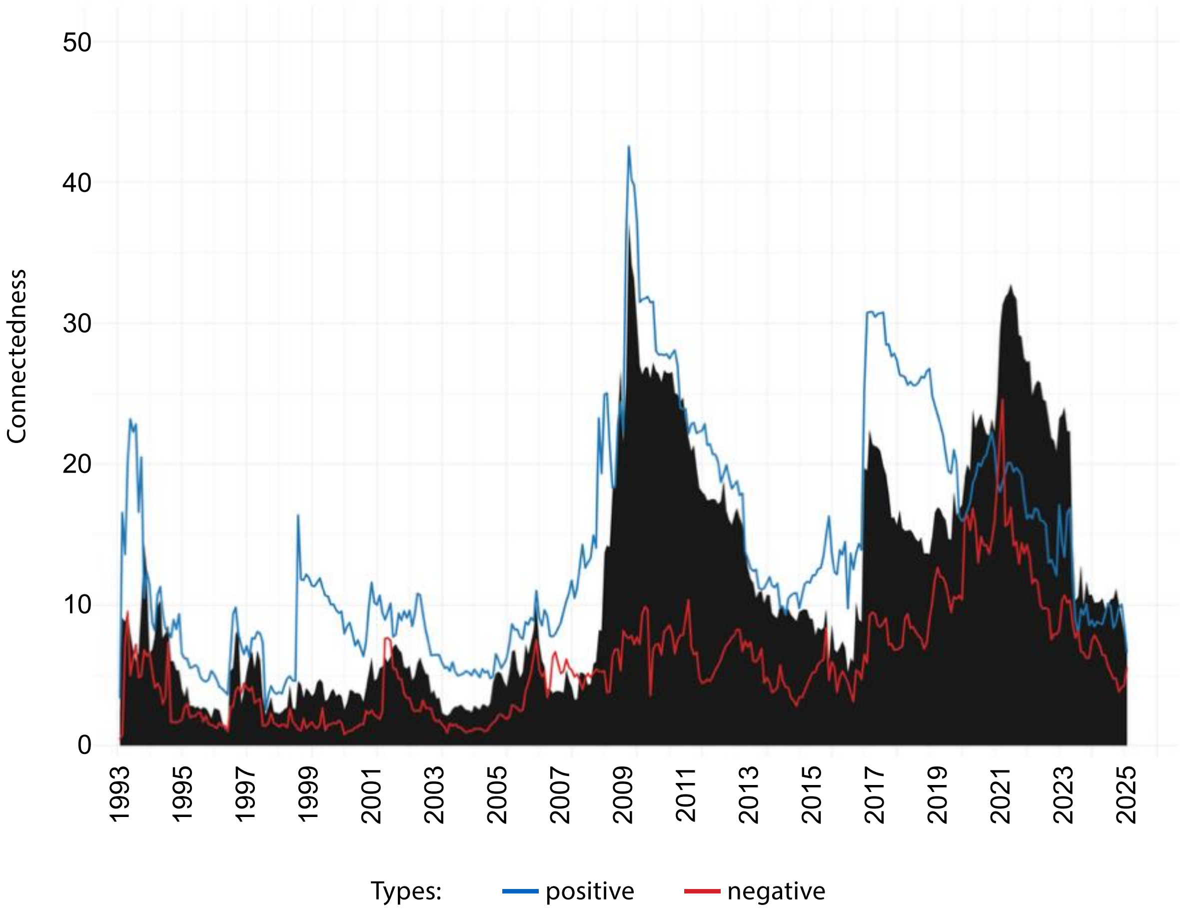
The results in Table 2 show that the three series are strongly connected in both positive and negative regimes. The UCT remains the transmitter of positive shocks, implying that the impact of escalation episodes spreads more widely than that of tension relief, while the S&P 500 and SSCE act mainly as receivers. At the same time, the US500 has higher "from others" and "to others" values than the SSCE, indicating greater average integration of the US market within the connectedness system, both as a receiver and a transmitter of shocks.

Table 2. Asymmetric TVP-VAR Connectedness Table

	UCT	US500	SSCE	FROM others
UCT	91.53 + → 92.13 − → 95.56	5.60 + → 4.42 − → 2.93	2.87 + → 3.46 − → 1.51	8.47 + → 7.87 − → 4.44
US500	5.31 + → 7.83 − → 2.98	86.63 + → 81.59 − → 92.93	8.06 + → 10.58 − → 4.10	13.37 + → 18.41 − → 7.07
SSCE	4.55 + → 6.07 − → 1.65	7.86 + → 9.69 − → 3.87	87.60 + → 84.24 − → 94.48	12.4 + → 15.76 − → 5.52
TO others	9.86 + → 13.90 − → 4.63	13.45 + → 14.10 − → 6.80	10.93 + → 14.04 − → 5.61	34.24 + → 42.05 − → 17.04
Inc.Own	101.39 + → 106.03 − → 100.19	100.08 + → 95.69 − → 99.73	98.53 + → 98.28 − → 100.09	
NET	1.39 + → 6.03 − → 0.19	0.08 + → −4.31 − → −0.27	−1.47 + → −1.72 − → 0.09	17.12/11.41 + → 21.02/14.02 − → 8.52/5.68

Source: Own calculations

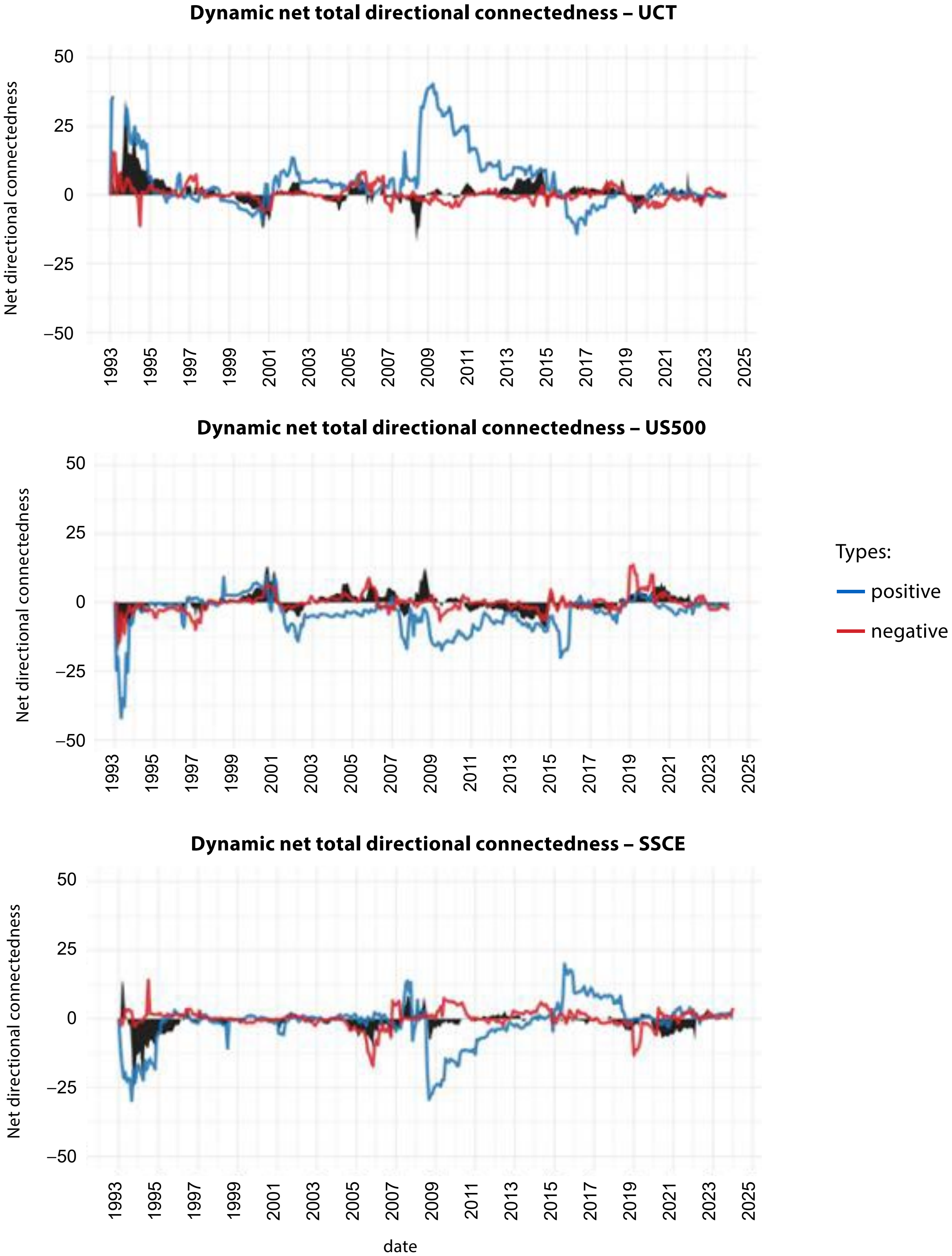
Figure 2. Asymmetric Dynamic Total Connectedness Index (TCI)



Source: Author(s)

Fig. 2 shows the dynamic total connectedness index (TCI). In this figure, as well as in Figures 3 and 4, the blue and red lines represent the connectedness generated by isolated positive and negative shocks, respectively. The black shaded bounded area represents the connectedness index estimated from the standard, symmetric TVP-VAR model. Linking these dynamics to the events in Fig. 1 shows that spikes match tension periods. The early rise in the mid-1990s corresponds to the Taiwan Strait crises and the 1999 Belgrade embassy bombing, when uncertainty sharply increased. The next surge around 2008-2010 aligns with the global financial crisis and the Eurozone crisis, during which China became a key creditor of the US, showing that the system is highly sensitive to major global financial shocks, not just bilateral tensions. One of the highest levels occurred during Trump's first term (2017-2020), covering the tariff and technology wars, where both positive and negative spillovers intensified. Another peak appears in 2020-2022, reflecting the COVID-19 blame episode, chip export controls, and renewed diplomatic frictions. This strongly suggests that, while the GFC was a major external shock, the recent high-spillover environment is driven by the ongoing and escalating US-China tensions.

Figure 3. Asymmetric Dynamic Net Total Directional Connectedness

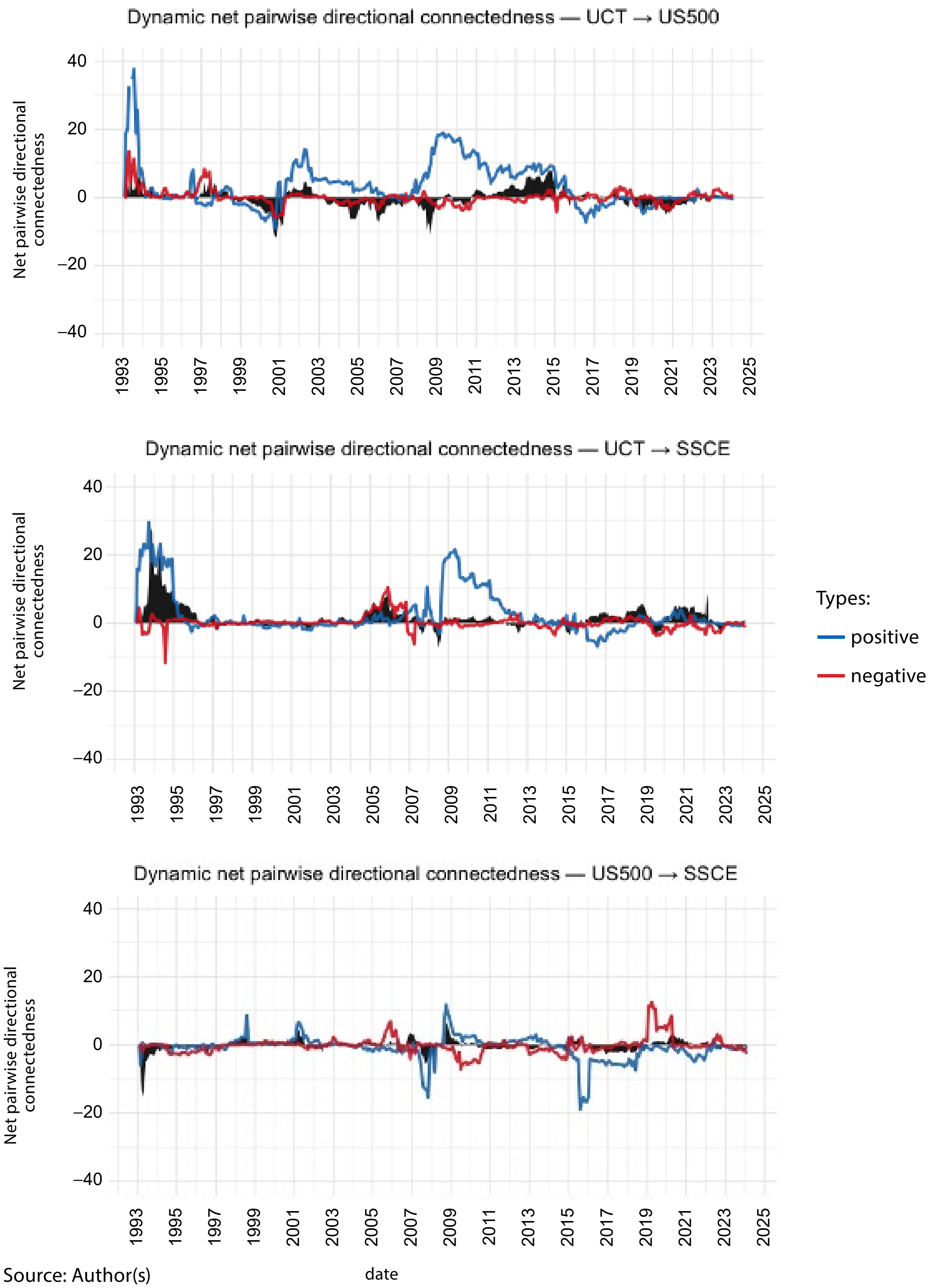


Source: Author(s)

Figs. 3 and 4 show the directional and pairwise connectedness measures. For the UCT, positive-component net connectedness is more pronounced in several periods, particularly in the early part of the sample and around 2008-2014, whereas negative-component net connectedness remains closer to zero for much of the sample. This pattern indicates that increases in the tension index are associated with stronger directional connectedness than decreases in the index. The S&P 500 behaves almost oppositely; it acts as a net receiver during most geopolitical or financial stress episodes. The SSCE has a more mixed role. In several global downturns, it has been a receiver. Still, in some periods, it becomes a transmitter around the 2015 South China Sea disputes and the 2020 tech-sanction period, which already suggests that China is not always a receiver. This asymmetry indicates that financial markets exhibit a strong negativity bias, where investors react aggressively to escalating geopolitical risks but largely ignore improvements in bilateral relations. From a behavioral finance perspective, this aligns with loss aversion, suggesting that the fear of geopolitical losses weighs far more heavily on investor sentiment than the potential gains from diplomatic stability.

The pairwise graphs reveal the specific channels of risk (Fig. 4). The UCT index transmits volatility to both the S&P 500 and the SSCE, but the intensity differs across the two. The Chinese market exhibits significantly higher sensitivity to these geopolitical shocks than the US market. This vulnerability aligns with previous findings in the literature suggesting that emerging markets often bear the brunt of global political uncertainty due to higher capital flow volatility and the dominance of retail investors (Chen and Pantelous, 2022; Peng et al., 2025). The impact on Chinese equities peaked during the 2018-2020 trade war, confirming that direct economic confrontations serve as the most potent transmission channel for the UCT index. The bilateral relationship between the US and Chinese stock markets displays a time-varying dominance. Historically, the US market has functioned as a net transmitter of risk to China. Especially during the 2008 global financial crisis and the 2018 trade war, negative return shocks originating from the US market spilled over into China, supporting the view that the US remains the central driver of global equity volatility. However, a significant structural shift occurred between 2015 and 2016. This period aligns with the "China Stock Crash" event, during which the Chinese market was a net transmitter of risk to the US market for a short time. This implies that China is not solely a passive receiver of geopolitical risk. When a massive internal bubble bursts in China, it generates sufficient volatility to affect the US financial system. Thus, the transmission channel is bidirectional during extreme domestic crises. This reversal indicates that during localized liquidity shortages, the contagion effect surpasses the typical directional

Figure 4. Asymmetric Dynamic Net Pairwise Connectedness

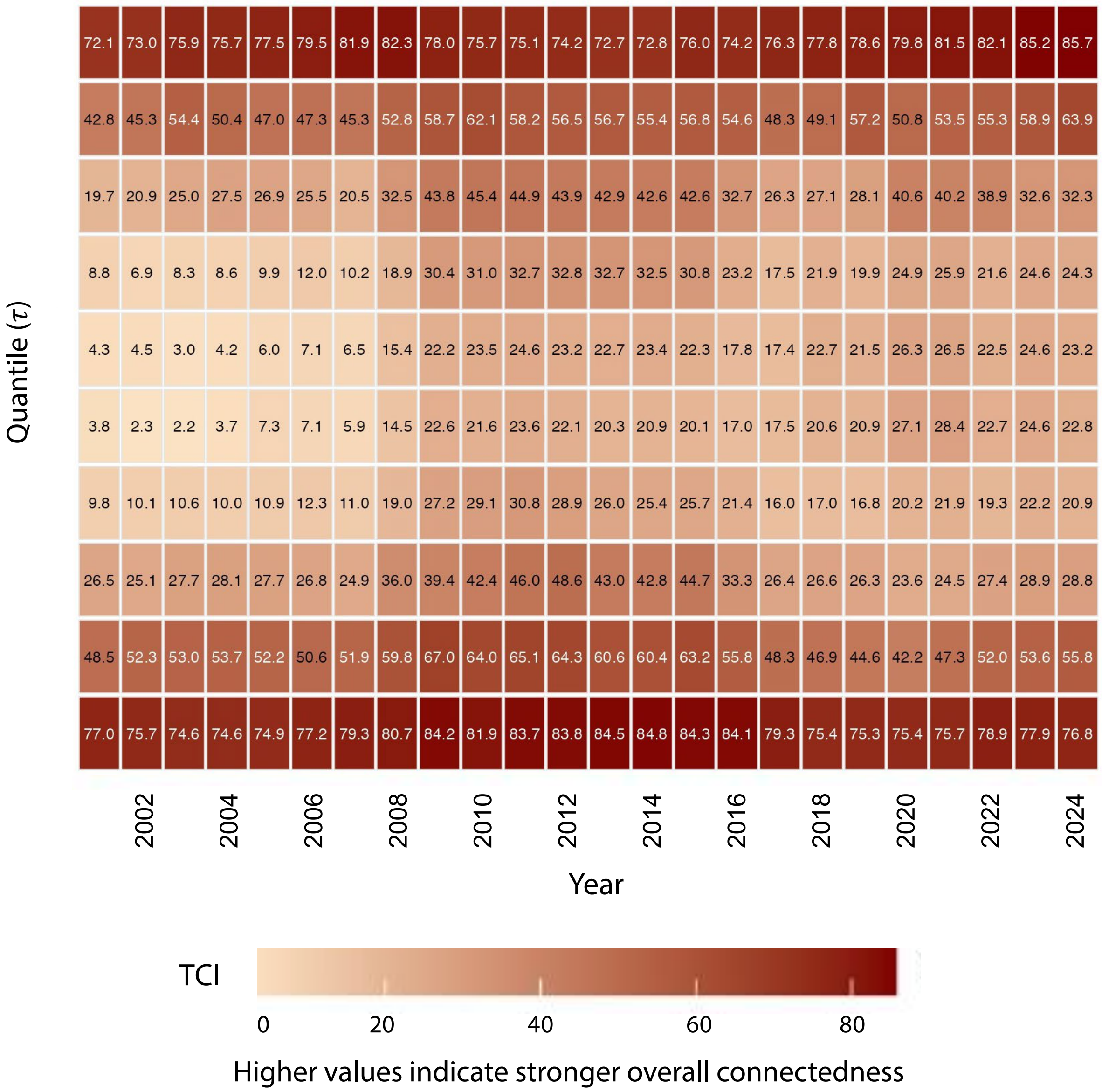


Source: Author(s)

hierarchy. This finding directly addresses reverse causality and simultaneity bias inherent in text-based indicators. The empirical results show that financial markets are not merely passive recipients of geopolitical shocks. The fact that the SSCE and S&P 500 occasionally act as net transmitters to the system suggests that deteriorating financial conditions can drive media coverage and influence the UCT index. This confirms a cyclical feedback mechanism where market crashes amplify the media's focus on bilateral frictions, which in turn feed back into predictive market volatility.

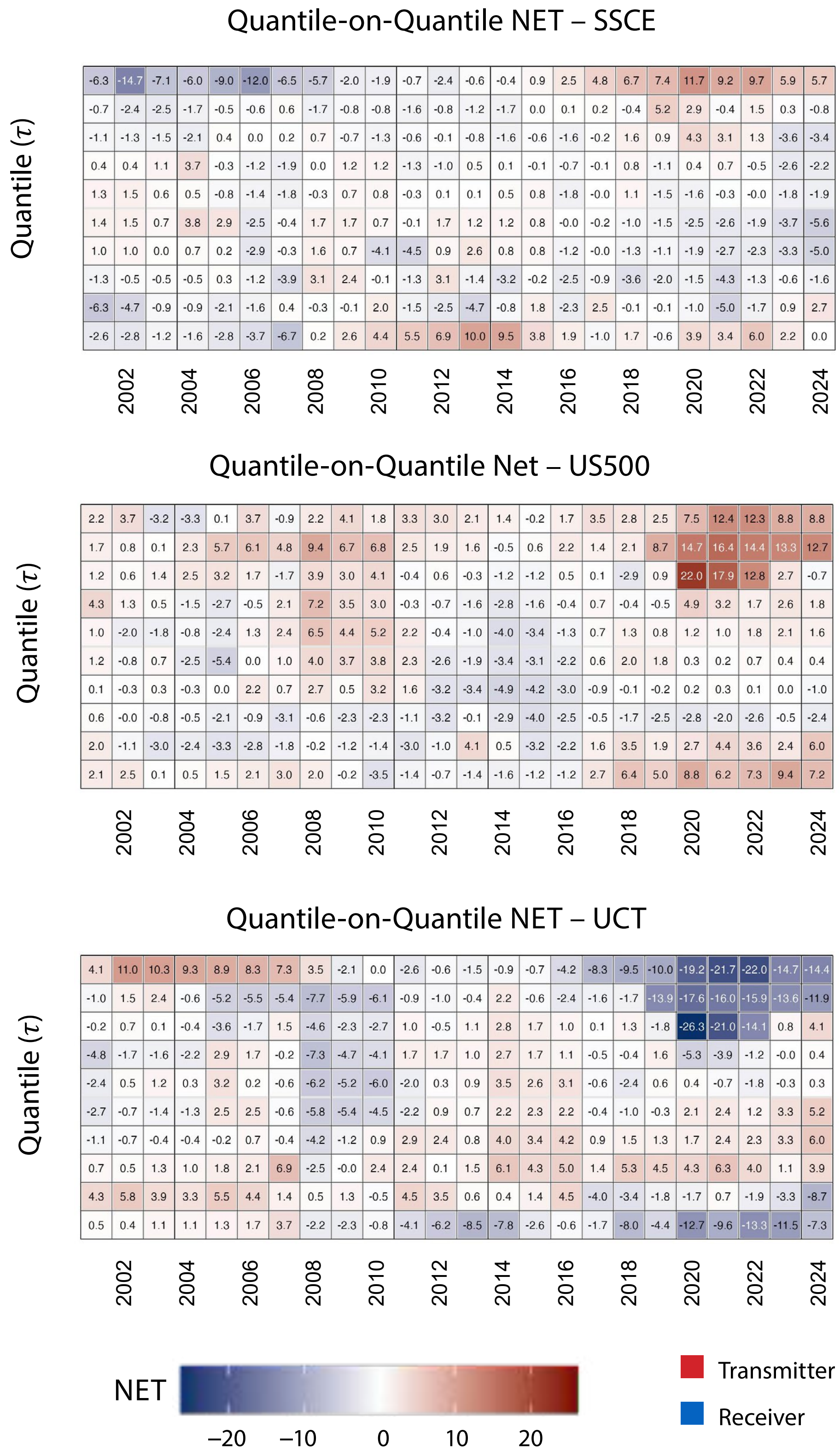
To ensure the robustness of the primary Asymmetric TVP-VAR results, we employed a Quantile-VAR connectedness approach. This methodology shifts the analytical focus from time-varying parameters to specific market states, enabling examination of how geopolitical tensions interact with stock markets under bull, bear, and normal market conditions. The TCI aggregates the pairwise directional spillovers into a single, system-wide metric of market interdependence. The Quantile-on-Quantile TCI results in Fig. 5 clearly demonstrate that spillovers are not uniform across the distribution. Instead, the total connectedness is highly asymmetric and exhibits significant strength primarily at the extreme tails (both bull and bear markets). This finding strongly corroborates the tail dependence hypothesis frequently observed in financial networks, confirming that the US-China financial system becomes tightly coupled and highly contagious predominantly during periods of severe market stress or irrational exuberance, rather than during normal market conditions (Chatziantoniou et al., 2021).

Figure 5. Quantile-on-Quantile Total Connectedness Index (TCI)



Source: Author(s)

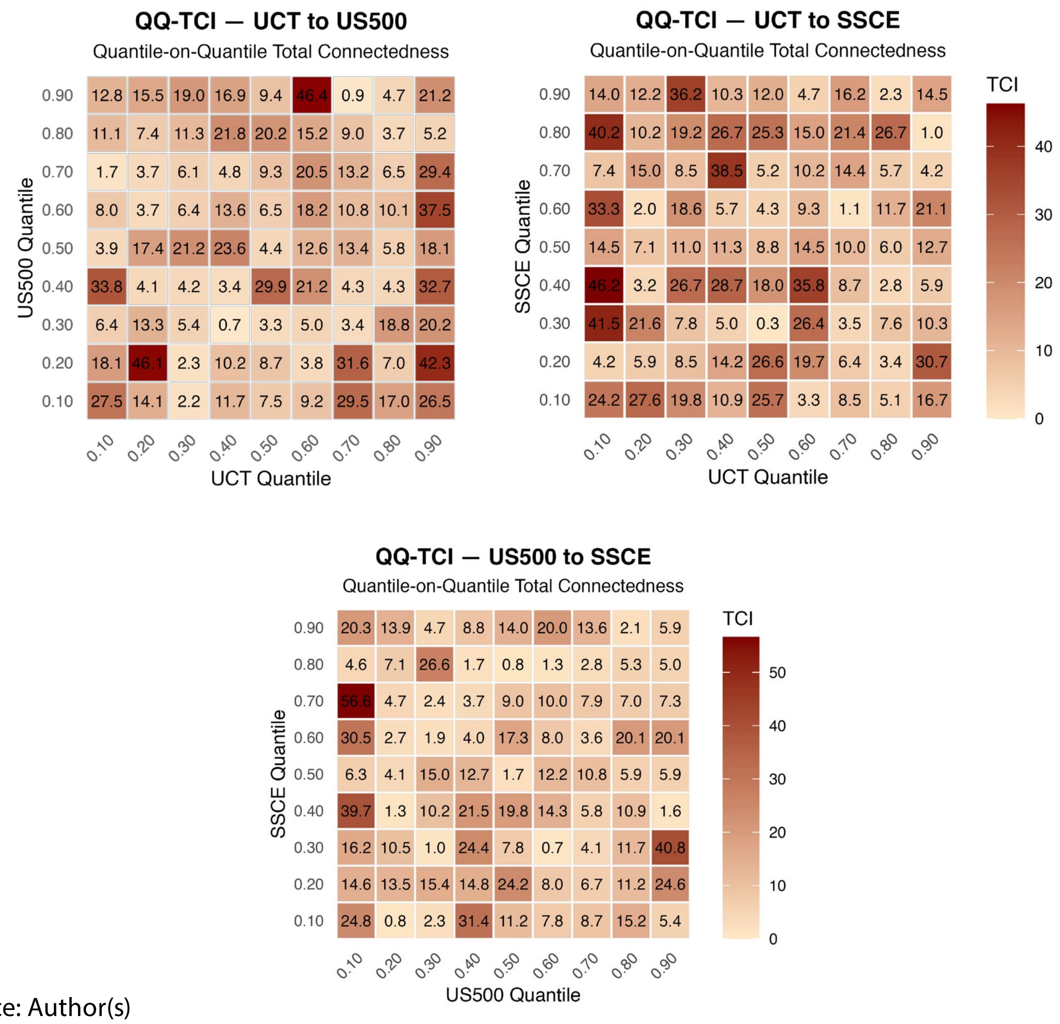
Figure 6. Quantile-on-Quantile Net Total Connectedness (NET)



Source: Author(s)

The time-varying quantile results in Fig. 6 provide a granular view of the net total connectedness over the period. The heatmap displays intense clusters of positive transmission, indicated by red zones, specifically during the 2018-2020 trade war and the COVID-19 pandemic, aligning with asymmetric results that identified these periods as peak transmission windows for geopolitical risk. However, the quantile analysis offers a refinement to the time-domain results. Unlike the continuous volatility transmission suggested by the time-varying model, the graph reveals that the UCT acts as a dominant transmitter only under specific crisis conditions. In calmer periods, such as the early 2000s, the transmission is neutral or weak across the median quantiles. This indicates that geopolitical risk does not automatically spillover to equity markets; rather, it requires a fragile market environment to trigger significant contagion.

Figure 7. Averaged Dynamic Quantile-on-Quantile Total Connectedness



Source: Author(s)

Fig. 7 looks at how an event in one variable's quantile (x-axis) connects to another variable's quantile (y-axis). In all three pairs, the dependence structure is heavily skewed toward the lower quantiles. The strongest spillovers occur when the tension index is at its upper extreme and stock returns are at their lower extreme. This confirms that investors price in geopolitical risk aggressively during bear markets but tend to disregard it during bullish trends. This indicates a 'flight-to-safety' behavior where investors correlate all assets during panic, negating diversification benefits. A similar asymmetry characterizes the relationship between the two equity markets. When the US market experiences a downturn (in low quantiles), it exerts a powerful drag on the Chinese market, with connectedness often exceeding 40%. Conversely, US market increases (high quantiles) generate significantly weaker spillovers to China.

The spillover patterns documented above may operate through several underlying economic transmission channels. First, the strong trade interdependence between the United States and China implies that geopolitical tensions can directly affect firm expectations through tariffs, export restrictions, and disruptions in global supply chains. Such developments alter expected cash flows and are therefore rapidly incorporated into stock prices. Second, geopolitical tensions may influence cross-border capital flows by increasing global risk perception and reshaping portfolio-allocation decisions, thereby generating synchronized movements across international equity markets. Third, tensions between the two countries often heighten broader policy uncertainty, affecting investor sentiment and amplifying market volatility. Through these trade, financial, and uncertainty channels, geopolitical developments between the US and China can propagate to financial markets and reshape the dynamic linkages between their stock markets.

The comparison of the Asymmetric TVP-VAR and Quantile-VAR results reveals a high degree of consistency regarding the transmission of geopolitical risk. Both methodologies confirm that a distinct negativity bias drives the financial system. This empirical evidence supports Peng et al. (2025), who observe that tension shocks induce stronger downside co-movements than periods of relief. Similarly, the intense spillovers observed during extreme market states in the quantile heatmaps are consistent with the findings of He et al. (2021) and Egger and Zhu (2020). These studies suggest that crisis periods and policy shocks function as the primary catalysts for cross-market contagion, a view that our dual-methodology approach validates.

The distinct contribution of the quantile approach lies in its ability to isolate tail dependence. While the TVP-VAR model identifies the specific historical timing of high spillovers, such as during the trade war, the quantile model confirms that this connectivity is a structural feature of bear markets. This aligns with Chatziantoniou et al. (2021), who argue that financial networks tighten specifically during tail events. Furthermore, this intensified tail dependence directly supports the empirical evidence of Yeh et al. (2025), confirming that stronger inter-market linkages under extreme stress significantly elevate crash risk. In a broader context, just as structural policy environments and distortions like energy subsidies amplify cross-market financial spillovers (AlGhazali et al., 2025), our results demonstrate that heightened geopolitical tensions act as a similar systemic catalyst, structurally propagating fragility across the US-China financial nexus during crisis periods. Additionally, the finding that Chinese markets exhibit greater sensitivity to these geopolitical shocks than the US market corroborates the findings of Xu et al. (2025) and Rogers et al. (2024). Unlike prior studies that rely on average effects, this framework demonstrates that the US-China financial decoupling is not a static condition. Instead, the markets remain highly synchronized during periods of stress, confirming that geopolitical tension acts as a state-dependent systemic risk that negates diversification benefits precisely when they are most needed.

6. Conclusion

This study examines how geopolitical tensions between the US and China are transmitted to financial markets within a holistic framework spanning a long-time horizon and accounting for their dynamic characteristics. Findings using the UCT clearly demonstrate that tensions between the two countries have significant, time-varying, and heterogeneous effects on stock markets. Specifically, escalations in tensions produce stronger and more widespread market reactions than de-escalations, and this effect is concentrated through channels of volatility, interdependence, and risk perception. Empirical findings indicate that shocks stemming from geopolitical tensions do not spread uniformly throughout the financial system; rather, they affect different parts of the financial system with varying intensities and in different directions, depending on market conditions. During periods of high uncertainty and stress, the link between the US and Chinese stock markets has been found to tighten significantly, spillover effects are amplified, and market segments exhibit different sensitivities to these shocks. The fact that Chinese stock markets respond more sensitively to tension shocks than US markets suggests that geopolitical risks can exacerbate financial vulnerabilities.

The study's findings also reveal that the impacts of US-China geopolitical tensions on financial markets cannot be fully understood through static, average-based approaches. This study makes a significant contribution to the literature by demonstrating that tensions reshape market linkages over time and that this impact is sensitive to the direction of shocks and market conditions. In this context, the study demonstrates that geopolitical risks are not merely temporary fluctuations but have become persistent factors affecting the structure of financial markets. Furthermore, it highlights the need for investors to monitor geopolitical risks dynamically in portfolio management and for policymakers to consider geopolitical shocks in financial stability assessments systematically. In particular, the greater sensitivity of Chinese stock markets to stress shocks suggests that geopolitical risks can exacerbate financial vulnerabilities and accelerate market instability. For China, this highlights the importance of macroprudential policies and transparent communication strategies to enhance the resilience of financial markets to external shocks. For the US, findings indicate that geopolitical tensions can trigger volatility and risk contagion in global markets, potentially leading to the international spread of financial shocks. Therefore, for both countries, the implications of trade, technology, and security policies for both the real economy and financial stability should be considered.

The study has three primary limitations. First, reliance on monthly data allows identification of long-term structural trends but masks short-term intraday volatility spikes important for high-frequency trading analysis. Second, the UCT index is derived principally from US media sources, which may reflect a Western-centric perception of risk rather than the sentiment of Chinese investors. Third, our empirical design focuses on equity indices. While this successfully isolates the impact of geopolitical risk on general corporate profitability expectations, it does not capture the full extent of systemic financial spillovers across the broader financial system. Expanding the Asymmetric TVP-VAR framework to include exchange rates, bond markets, or commodities poses a significant methodological challenge due to the dimensionality; decomposing numerous variables into positive and negative series would lead to severe over-parameterization. Future studies could address these gaps by utilizing high-frequency data and incorporating Chinese-language text mining to provide a more balanced view of how geopolitical narratives drive global financial networks, and extending similar approaches to different country groups, sectors, alternative geopolitical risk indicators, or employing methodologies suited for high-dimensional network structures to map the transmission of the US-China tension across broader asset classes.

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