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Jiawei Xu
Nanjing University
Elie Bouri
Lebanese American University
Libing Fang
University of Pretoria
Rangan Gupta
University of Pretoria
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Department of Economics
University of Pretoria
0002, Pretoria
South Africa
Tel: +27 12 420 2413

US-China Tensions and Stock Market Co-movement between the US and China: Insights from a DCC-DAGARCH-MIDAS Model

Jiawei Xu[1], Elie Bouri[2,**], Libing Fang[1,*], Rangan Gupta[3]

1. School of Management and Engineering, Digital Finance Key Laboratory of Jiangsu Province, Nanjing University, 22 Hankou Road, Nanjing, Jiangsu 210093, China
2. School of Business, Lebanese American University, Lebanon.
3. Department of Economics, University of Pretoria, Private Bag X20, Hatfield 0028, South Africa.

Abstract

The US and China maintain deep economic ties, yet geopolitical tensions—especially during events such as the trade war—exert significant influence on their financial markets. This study examines how US-China tensions, as captured by the US-China Tension Index (UCT), affect the correlation between US and Chinese stock markets and stock market volatility using a DCC-DAGARCH-MIDAS model. Unlike prior studies that consider geopolitical risk and trade war shocks separately or give the same weight to positive and negative shocks of UCT, our approach jointly models asymmetric short-term volatility, macro-driven long-term variance, dynamic inter-market correlations, and assigns different weights to positive and negative shocks of UCT. The findings show that heightened tensions lead to stronger co-movements in return volatility, with effects becoming more immediate during the trade war. Beyond aggregate indices, we analyze the multi-tiered structure of the Chinese stock market, covering small and medium-sized enterprises (SMEs), blue-chip stocks, and technology-focused stocks. The results show that sensitivities vary across China's stock market indices, where SME index displays the most sensitive to UCT. These results provide practical insights for investors and policymakers aiming to manage risks in an increasingly geopolitically sensitive environment.

Keywords: US-China Tensions; Geopolitical Tensions; US and Chinese Stock Returns and Volatility; DCC-DA-GARCH-MIDAS

[*] Corresponding author: lbfang@nju.edu.cn (Libing Fang)
[**] Corresponding author: elie.elbouri@lau.edu.lb (Elie Bouri)

1. Introduction

The economies and stock markets of the United States and China hold the positions of the world's largest and the second largest respectively, attracting a considerable number of global investors. Spreading investments across the stock markets of various countries generally induces portfolio diversification, enabling investors to reduce portfolio volatility and achieve better risk-adjusted returns (Markowitz, 1952). Nevertheless, global risk shocks disturb and intensify the degree of stock market return co-movement among countries, challenging the diversification benefits. Notably, the recent geopolitical situation, exemplified by the Russia-Ukraine conflict and the Israel-Palestine conflict, has been increasingly tense and has exerted a significant influence on market co-movement (Bossman & Gubareva, 2023). In this regard, the US-China tension (UCT) has been an eminent risk factor, accentuated by the full-on trade clash under the first and second terms of the US President Donald Trump.

Existing literature has illustrated from various angles that geopolitical conflicts can enhance market co-movement, including suffering common economic shocks (Forbes & Rigobon, 2002), the influence of policy uncertainty on investors' risk preferences (Baele et al., 2010; Pastor & Veronesi, 2012), the disruption of trade and supply chain interdependence (Ramelli et al., 2021), and the significant fluctuations in exchange rates (Bruno & Shin, 2015). As for the relationship between China and the United States, the most high-profile geopolitical event in recent years has been the trade war. Due to the trade war, the linkage between the Chinese and American markets was intensified, which in turn gave rise to greater downside risks (Huynh & Burggraf, 2020; Shi et al., 2021; Song et al., 2023). Under such circumstances, the efficacy of diversifying investments in the stock markets of these two countries in terms of reducing the volatility of portfolios deteriorated.

Having said that, the trade conflict is only one manifestation of US-China tensions. The sources of US China tensions are multifaceted, including technology blockade, information security, South China Sea issue, and Taiwan issue. Therefore, merely focusing on the impact of the trade war is insufficient to comprehensively understand the impact of US-China conflicts on the market co-movement of these two main economies. To our best knowledge, there has been little research that analyzes the impact of US-China conflicts on the market co-movement between the two countries by depicting the changing degree of US-China tensions in the long term.

To address this research gap, we analyze the impact of the US-China Tensions on the dynamic correlations between the returns of the US and Chinese stock market indices. To this end, we use the US-China Tension (UCT) index of Rogers et al. (2024), which depicts the degree of geopolitical tensions between two rival countries, and apply the DCC-DAGARCH-MIDAS(Skew-t) model to capture the nuanced effects of US-China tensions on the correlation between US and Chinese stock markets. This model is ideal for this study as it innovatively integrates Dynamic Conditional Correlation (DCC), Double Asymmetric GARCH (DAGARCH), and Mixed Data Sampling (MIDAS)[1]. Importantly, given that in the real market, the impacts of positive and negative shocks of UCT are different, the DAGARCH model is more suitable than the GARCH model, allowing us to assign different weights to positive and negative shocks to understand the impact of shocks in different directions on stock market co-movement (Amendola et al., 2019). Interestingly, the DCC-DAGARCH-MIDAS(Skew-t) model provides a refined econometric structure that jointly models asymmetric short-term volatility, macroeconomically-driven long-term variance components, and dynamic cross-market correlations. This integrative structure is particularly well-suited for analyzing the transmission of geopolitical shocks, which often exhibit multi-frequency effects and nonlinear impacts on global financial markets. The DAGARCH component, equipped with skewed-t innovations, effectively models volatility clustering, heavy tails, and asymmetric market responses—features that are especially relevant during periods of geopolitical uncertainty when negative shocks tend to exert disproportionate influence. The MIDAS component incorporates low-frequency macroeconomic variables—such as economic policy uncertainty or geopolitical risk indices—into the conditional variance process, enabling the model to capture persistent shifts in risk dynamics that unfold over longer horizons but influence high-frequency financial data. Meanwhile, the DCC mechanism dynamically tracks changes in conditional correlations between the US and Chinese stock markets, allowing for a nuanced understanding of how cross-market dependencies evolve in response to external shocks. Collectively, these features not only enhance the model's statistical performance but also contribute substantively to the empirical investigation of geopolitical risk spillovers. By bridging high-frequency financial volatility with low-frequency macro-political developments, the DA

[1] Compared with the GARCH-MIDAS model that can only explores the impact of UCT on a single stock index, incorporating the DCC model enables us to study the influence of UCT on the correlations between the stock indices of the two countries (Engle, 2002).

model provides a novel and robust analytical lens—thereby constituting a key marginal contribution of this paper to the literature on geopolitical finance and market interconnectedness.

Embedding UCT as a low-frequency exogenous factor in the DCC-DAGARCH-MIDAS(Skew-t) model, we demonstrate that geopolitical tensions increase both individual stock market volatility and enhance the interdependence between US and Chinese stock market indices. The results underscore that US-China tensions have significant influence on long-term correlations between US and Chinese stock markets, especially during periods of heightened geopolitical tension and US-China trade war. Our analysis also shows a noticeable shift toward short-term market responses during heightened tensions, underlining the growing sensitivity of stock markets to geopolitical events. Beyond aggregate indices, we analyze the multi-tiered structure of China's stock market, including blue-chip stocks, high-growth small and medium-sized enterprises (SMEs), and the technology-focused STAR (formally known as the Shanghai Stock Exchange Science and Technology Innovation Board) Market. By including indices such as SSE 180 (blue chips), SME Index (growth-oriented SMEs), and STAR50 (technology-focused), our analysis offers a detailed view of UCT's impact on market segments, unlike the current research literature under the background of the trade war that mainly focuses on the market co-movement among different industries (Chen & Pantelous, 2022). Our findings indicate that UCT impacts differ across tiers: larger, institutionalized markets exhibit stable responses and somewhat resiliency, whereas SMEs and technology-focused segments are more sensitive and prone to geopolitical shifts.

Our study makes several notable contributions. Firstly, unlike existing literature that mostly relies on the trade war to study the US-China conflict's impact on financial markets, with trade conflict being only one type of geopolitical conflicts, we adopt the UCT index to more comprehensively depict the long-term changes in the US-China tense relationship. Secondly, we apply the DCC-DAGARCH-MIDAS(Skew-t) model which combines DCC, DAGARCH and MIDAS. Taking into account dynamic correlation clustering, asymmetric volatility, fat-tailed distribution, and long-term effects, this model empowers us to directly assess the impact of the US-China tense relationship on the co-movement of the stock markets of the two countries. Moreover, our paper analyzes the impact of the US-China tensions before and after the intensification of the trade war. After the escalation of the trade war, the co-movement between the two countries' markets responds more rapidly to the US-China tense relationship, extending the scarcity of discussions of this aspect in the existing literature. Thirdly, considering China's special national conditions, this paper also examines the impact of the US-China tense relationship on the co-movement between China's multi-tiered capital markets and the US market, offering more granulated and heterogeneous evidence in the context of newly introduced segments of the Chinese stock market.

Overall, this study enhances our understanding of how international political risks shape financial inter-linkages and offers a framework for analyzing geopolitical shocks in multi-tiered markets. Practically, within the contemporary global landscape characterized by the increasingly frequent occurrence of geopolitical conflicts, the insights offered in our analysis are valuable for investors and policymakers who are tasked with the challenging role of monitoring and managing interconnected markets in the midst of geopolitical uncertainty.

The rest of the paper proceeds as follows: Section 2 describes the methodology; Section 3 provides the data diagnostics; Section 4 presents the empirical results; and Section 5 concludes.

2. Methodology

We model the returns for the S&P500 COMPOSITE (S&P500), SHANGHAI SE A SHARE (SSE A Share) and SHANGHAI SHENZHEN (CSI300) stock market indices using two GARCH-type models, standard GARCH and Double Asymmetric GARCH (DAGARCH). As indicated in the introduction section, for the exogenous shocks from bilateral relationships in the interconnected global economy, we use the US-China Tension (UCT) index of Rogers et al. (2024).

Specifically, the impact of US-China tensions as exogenous shocks on the long-run volatility and dynamic correlation of S&P500 and SSE A-hares stock index returns, S&P500 and CSI300 stock index returns is examined in a multi-step approach. In the first step, we insert UCT into the long-run component of GARCH-MIDAS specification on the volatility of S&P500, SSE A Share and CSI300 stock index returns. We extend the conditional distribution to include nonzero skewness, excess kurtosis of innovation, and standard normal distribution. The results of this step show the impact of UCT on the long-run volatilities of stock index returns by assuming the index returns follow univariate time-varying processes. In the second step, we insert UCT into the long-run component of the DCC-MIDAS specification of the correlation of S&P500 and SSE A Share (CSI300) stock index returns.

We extend the asymmetric DCC-MIDAS to include the non-zero skewness, excess kurtosis of the innovation distribution, standard normal distribution, and asymmetric effect of innovation on short- and long-run correlations. The results of this step show the impact of UCT on the long-run correlations of different stock index returns by assuming the indices' returns follow bivariate time-varying processes.

2.1 GARCH-MIDAS with UCT

The standard univariate GARCH and its generalized specifications are used for modelling the conditional volatilities of the stock index returns. We follow the approach of Engle et al. (2013) to decompose the volatilities in GARCH specification into long- and short-run components and then link UCT to the long-run component. In practice, the short-run volatility component of the GARCH-MIDAS model is assumed to be temporarily shocked by innovations (in high frequency), while the long-run component is more likely to be related to fundamental/microeconomic factors that are usually low frequency, such as UCT in the present work. The specification for standard GARCH-MIDAS is,

$$r_t - \mu_t = \varepsilon_t \tag{1}$$

$$\varepsilon_t = \sigma_{t,\tau} z_t \tag{2}$$

$$\sigma_{t,\tau}^2 = m_\tau \times g_{t,\tau} \tag{3}$$

$$g_{t,\tau} = (1 - \alpha - \gamma/2 - \beta) + (\alpha + \gamma \cdot I_{r_{t-1,\tau<0}}) \frac{{\varepsilon_{t-1,\tau}}^2}{m_\tau} + \beta g_{t-1,\tau} \tag{4}$$

where r_t is the natural logarithmic rate of returns from stock index; the conditional mean is $\mu_t = E_{t-1}(r_t) = \mu - \rho r_{t-1}$ as the common specification; ε_t is the innovation standardized to be z_t by $\sigma_{t,\tau}$, the conditional standard deviation. In Eq. (2) and (3), we add subscript τ to $\sigma_{t,\tau}$, indicating ε_t as the innovation on week t of period τ, and $\sigma_{t,\tau}^2 = m_\tau \times g_{t,\tau}$ for its conditional volatility, where m_τ is thus the long-run component extracted from $\sigma_{t,\tau}^2$. α and β are the estimated coefficients. $\alpha \geq 0$, $\beta \geq 0$ and $\alpha + \beta < 1$ are used to ensure the nonnegativity and stationarity of the variance process.

When the conditional distribution is sstandard t-distribution or standard normal distribution, parameter γ disappears, and $I_{r_{t-1,\tau<0}}$ is an indicator function.

To introduce the effect of UCT ($X_{\tau-k}$) on m_τ, we follow Engle et al. (2013) and specify m_τ by smoothing the realized volatility or macroeconomic (exogenous) variable in the spirit of MIDAS regression:

$$\ln m_\tau = m + \theta \sum_{k=1}^{K} \varphi_k(w_1, w_2) X_{\tau-k} \tag{5}$$

Notably, $X_{\tau-k}$ is the innovation of UCT from the AR(1) regression as Engle et al. (2020) suggests, where *K* is the maximum lag. $\varphi_k(w_1, w_2)$ is a weight equation as:

$$\varphi_k(w_1, w_2) = \frac{\left(\frac{k}{K}\right)^{w_1-1}\left(1-\frac{k}{K}\right)^{w_2-1}}{\sum_{j=1}^{K}\left(\frac{j}{K}\right)^{w_1-1}\left(1-\frac{j}{K}\right)^{w_2-1}} \tag{6}$$

The Double Asymmetric GARCH-MIDAS (DAGM) model (Amendola et al. ,2019) is an extension of the GARCH-MIDAS family, which considers data at two different frequencies, combining the short-term dynamics and long-term trends of volatility. It introduces asymmetric effects to better describe the behaviour of volatility. The long-run component of the DAGM models is:

$$ln\, m_\tau = m + \theta^{+} \sum_{k=1}^{K} \varphi_k(w_1, w_2)^{+} X_{\tau-k} I_{X_{\tau-k\geq 0}} + \theta^{-} \sum_{k=1}^{K} \varphi_k(w_1, w_2)^{-} X_{\tau-k} I_{X_{\tau-k<0}} \tag{7}$$

To estimate the parameters in the various GARCH-MIDAS models given by Eq. (1) to (7), we use maximum likelihood estimation (MLE) as the literature (e.g., Engle et al., 2013; Amendola et al., 2021) does in common. However, different from the literature, we introduce Hansen's (1994) *skew-t* distribution as the conditional distribution of the standardized innovations to capture possible negative skewness as discussed by Hong and Stein (2003),

$$\text{Skew-t}(z_t|\lambda, \eta) = BC\left(1 + \frac{1}{\eta - 2}\left(\frac{Bz_t + A}{1 + \text{sgn}(\, z_t + \frac{A}{B})\lambda}\right)^2\right)^{-(\eta+1)/2}$$

where λ and η are the coefficient of skewness and degree of freedom, $\text{sgn}(x)$ is the sign function of *x*; and the constants A, B, and C are given by:

$$A = 4\lambda C\frac{\eta-2}{\eta-1},\ B = \sqrt{1 + 3\lambda^2 - A^2},\ C = \frac{\Gamma(\frac{(\eta+1)}{2})}{\sqrt{\pi(\eta-2)}\Gamma(\frac{\eta}{2})}$$

where $\lambda > 0$ and $\lambda < 0$ indicate that the distribution is positively and negatively skewed, respectively. The larger $|\lambda|$, the larger the skewness. The degree of freedom, η, captures the excess kurtosis, which is consistent with the tail heaviness.

When $\lambda = 0$, the *skew-t* distribution is symmetric and thus reduced to a standard *t* distribution. Therefore, we can easily compare the MLE results from *skew-t* with the standard *t* distribution. We implement the MLE procedure by extending the package 'rumidas' that is available from cran.r-project. It is an open source project maintained by Vincenzo Candila, one of the authors of Amendola et al. (2019, 2021).

2.2 DCC-MIDAS with UCT

To analyze the dynamic correlation between the S&P500 and SSE A Share, and between the S&P500 and CSI300, the DCC-DAGARCH-MIDAS (Skew-t) model is employed to examine the influence of UCT. The DCC-MIDAS model, used for mixed data sampling, builds on the DCC model by Engle (2002) and the DAGARCH-MIDAS model by Amendola et al. (2019). The DCC-MIDAS model primarily investigates how long-term components, derived through mixed data sampling, affect long-term fluctuations and dynamic correlations in financial time series. The DCC-DAGARCH-MIDAS model integrates Dynamic Conditional Correlation (DCC), Double Asymmetric GARCH (DAGARCH), and Mixed Data Sampling (MIDAS) to model dynamic correlations, asymmetric volatility, and long-term effects in financial time series. Its hierarchical structure and flexibility enable precise analysis of UCT's effects on US and Chinese stock markets across multiple dimensions.

Specifically, for each asset $i, j = 1,2$ to denote S&P500 and SSE A Share stock index returns, or S&P500 and CSI300 stock index returns. The univariate return series satisfies the DAGARCH-MIDAS process. The conditional correlation between them is:

$$\rho_{i,j,t} = \frac{q_{i,j,t}}{\sqrt{q_{i,i,t}}\sqrt{q_{j,j,t}}} \tag{8}$$

Following Colacito et al. (2011), the covariates directly affect the long-run component of stock index returns' dynamic correlation. That is, $q_{i,j,t}$ is given by:

$$q_{i,j,t} = \bar{\rho}_{i,j,\tau}(1 - a - b) + a\varepsilon_{i,t-1}\varepsilon_{j,t-1} + bq_{i,j,t-1} \tag{9}$$

where $\bar{\rho}_{i,j,\tau}$ is the long-run component of conditional correlation given by,

$$\bar{\rho}_{i,j,\tau} = \sum_{l=1}^{L} \varphi_l(w_1, w_2) C_{\tau-l} \tag{10}$$

where C_τ is the averaged conditional correlation of $\varepsilon_{i,t}$ and $\varepsilon_{j,t}$ in period τ. To capture the effect of UCT on the long-run correlation, we also introduce the effect directly into Eq. (10) following the spirit of Eq. (6). The difference is that a logistic transformation $\Lambda(x)$ is needed to make a valid definition of correlation:

$$\bar{\rho}_{i,j,\tau} = \Lambda(2x_\tau),$$

$$x_\tau = m_c + \theta^+ \sum_{l=1}^{L} \varphi_l(w_1, w_2)^+ X_{\tau-l} I_{X_{\tau-l \geq 0}} + \theta^- \sum_{l=1}^{L} \varphi_l(w_1, w_2)^- X_{\tau-l} I_{X_{\tau-l<0}} \tag{11}$$

where X_τ is the low-frequency part which is set to be UCT in our present work. The DAGARCH-MIDAS module integrates UCT into volatility modelling via the MIDAS weighting function, separating long-term (low-frequency) from short-term (high-frequency) volatility. As shown in Eq.(11), the DAGARCH component enhances GARCH by introducing asymmetry and dual-weight mechanisms, assigning different weights to positive and negative shocks to reflect the asymmetry typical in financial markets.

To address the fat-tailed and skewed characteristics of stock returns, especially during financial shocks, the Skew-t distribution is utilized to model asymmetric risks and extreme values, enhancing estimation accuracy. The bivariate skew-t distribution (biskew-t), proposed by Bauwens and Laurent (2005), is introduced to account for leptokurtosis and non-zero skewness in standardized innovations. The density function is expressed as:

$$\textit{biskew-t}\,(z|\nu, \lambda_1, \lambda_2) = C\left(\prod_{i=1}^{2} \frac{2b}{\lambda_i + \frac{1}{\lambda_i}}\right)\left(1 + \frac{{z^*}' z^*}{\nu - 2}\right)^{\frac{\nu+2}{2}}$$

where λ_1, λ_2 are the skewness parameters, ν is the degrees of freedom parameter, $z^* = \left(z_i^*, z_j^*\right)'$, $z_i^* = (b_i z_i + a_i)\lambda_i^{I_i}$, the indicator function $I_i = 1$ if $z_i < a_i/b_i$, otherwise, $I_i = -1$; and the constants a_i, b_i and C are:

$$a_i = \frac{\Gamma\left(\frac{v-1}{2}\right)\sqrt{v-2}}{\sqrt{\pi}\,\Gamma\left(\frac{v}{2}\right)}\left(\lambda_i - \frac{1}{\lambda_i}\right),\ b_i^2 = \left(\lambda_i + \frac{1}{\lambda_i} - 1\right) - a_i^2\ ,\ C = \frac{\Gamma\left(\frac{v+2}{2}\right)}{\pi(v-2)\Gamma\left(\frac{v}{2}\right)}$$

With the help of this density function, the log-likelihood function is directly equivalent to that of Cappiello et al. (2006), and thus MLE can be used to estimate the parameters. We implement the MLE by extending the package ‘dccmidas’ that is available from cran.r-project, an open source project maintained by Vincenzo Candila.

3 Data

We use weekly closing prices of the S&P500, SSE A Share, and CSI300 stock indices, collected from DataStream. The S&P500 tracks the stock market performance of leading firms in the US. SSE A Share and CSI300 are two leading benchmarks for the large Chinese stocks. For further analysis, we replace the SSE Composite Index and CSI300 index by the STAR 50 Index (representing the STAR Market), SSE 180 Index (large-cap blue-chip stocks), and SME Index (small and medium-sized enterprises) to assess if the results hold when considering technology stock sector, blue-chip Chinese stocks across key sectors such as finance, energy, and consumer goods, and small and medium-sized enterprises. The sample period for the S&P500 and SSE A Share spans from June 1993 to February 2024, including 1,605 weekly observations, whereas for the CSI300 stock index it spans from September 2005 to February 2024, including 962 weekly observations. We also employ the monthly UCT index of Rogers et al. (2024), extracted from https://www.policyuncertainty.com/US_China_Tension.html, over the period of June 1993 - February 2024, yielding 369 monthly observations. Panel A of Table 1 provides summary statistics for the logarithmic returns of the US and Chinese stock indices. Panel B of Table 1 provides the descriptive statistics for UCT index.

Table 1: Descriptive statistics

	Panel A: US and Chinese stock indices						Panel B: UCT	
	S&P500 stock index returns		SSE A Share stock index returns		CSI300 stock index returns		UCT	
	Raw	GARCH	Raw	GARCH	Raw	GARCH	Raw	AR1
mean	0.180%	2.163%	0.173%	3.679%	0.178%	3.312%	100.000	100.150
std	0.023	0.009	0.044	0.026	0.035	0.012	42.547	36.570
min	-18.341%	1.384%	-23.582%	1.440%	-14.781%	1.681%	37.983	46.94
Q(25%)	-0.921%	1.671%	-1.663%	2.289%	-1.513%	2.431%	67.988	67.987
Median	0.312%	1.913%	0.134%	2.925%	0.253%	2.932%	90.908	92.034
Q(75%)	1.452%	2.354%	1.772%	4.240%	1.991%	3.893%	120.809	118.508
max	17.968%	10.908%	70.362%	10.914%	17.283%	8.214%	349.946	314.770
Skew	-0.851	3.976	3.060	4.4539	-0.0444	1.337	1.552	1.547
Kurt	10.100	24.259	46.443	31.1248	2.263	1.728	4.440	4.357

JB-stats	7.172E3	4.423E4	1.502E5	7.102E4	3.142E3	4.161E2	4.462E2	4.431E2
Sample Period	Jun. 1993-Feb. 2024 (weekly #Obs.: 1605)				Sep. 2005-Feb. 2024 (weekly #Obs.: 962)		Jun. 1993-Feb. 2024 (monthly #Obs.: 369)	

Note: We report the descriptive statistics of the raw returns of US and China stock index, and their innovations filtered by GARCH(1,1). AR1 denotes the first-order autoregression. Raw return is used to clearly distinguish original return series from model-filtered innovations. It highlights that the reported statistics refer to unprocessed market data, ensuring clarity when comparing with GARCH-filtered results and aiding interpretation of market characteristics before any adjustment.

Figure 1 shows the dynamics of US and China stock indices and the UCT index. To make the data comparable, we scale each series to [0,1]. The Pearson correlation coefficient between UCT and the S&P500, SSE A Share, and CSI300 indices is 0.7440, 0.6388, and 0.5082, respectively. The Pearson correlation coefficients between UCT and the returns of S&P500, SSE A Share, and CSI300 are: -0.0018, -0.0410, and -0.0908, respectively. These contrasting correlations reflect the difference in variable type: while the UCT index is positively correlated with the levels of stock indices—possibly due to shared macro trends over time—it is negatively correlated with stock returns, indicating that rising geopolitical tensions are often accompanied by contemporaneous market declines. This highlights the importance of distinguishing between price levels and return dynamics when evaluating the impact of geopolitical risk on financial markets.

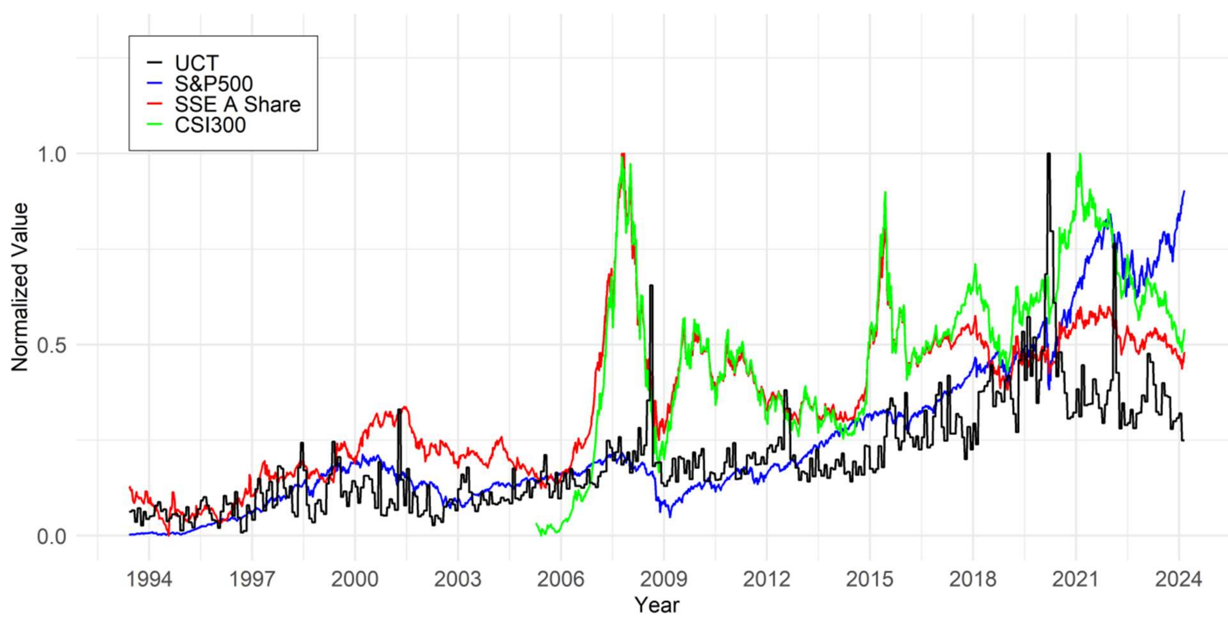


Figure 1: The dynamics of US and China stock indices with UCT

4 The effect of UCT on long-run volatility and correlation

We first present the long-run volatilities of the US and China stock indices and their relationship with the UCT based on the GARCH-MIDAS model with various specifications of structure and conditional distribution. We then show the relation of UCT to the long-run correlations between US and China stock index returns based on various DCC-MIDAS specifications.

4.1 The effect of UCT on the long-run volatility of US and China stock indices

Tables 2, 3 and 4 present the estimated results of the impact of the UCT on the US and China stock index long-run volatilities based on the GARCH-MIDAS model, and the DAGARCH-MIDAS with the conditional distribution of standard-t , skew-t and standard-n . We see that the estimated coefficients of α and β are all significantly positive, and $\alpha + \beta$ is near to one for both stock returns. That is, the short-run volatility component for all specifications is mean-reverting. For the returns of all three stock indices, the DAGARCH-MIDAS model (with skew-t distribution) performs the best (based on LLF, AIC and BIC), with the main parameters being significant.

Table 2 shows that when using the DAGARCH model to distinguish the effects in different directions (positive and negative), the θ values are significant, which indicates that a positive innovation leads to smaller conditional volatility in the next period whereas a negative innovation leads to bigger conditional volatility. This result clearly demonstrates that the deterioration of US-China relations inevitably intensifies the volatility of the S&P 500 index returns, which is a phenomenon that can be readily comprehended. Firstly, given that the US and China represent the two largest economies globally, an intensification of the tense relations between the two nations has the potential to escalate geopolitical risk, which in turn, amplifies market uncertainty and subsequently elevates stock market volatility (Caldara & Iacoviello, 2022). Secondly, the tense relation exerts a significant influence on investor sentiment and risk aversion. Accordingly, the worsening of US-China relations prompts flight-to-safety behavior, leading to an increase in stock market volatility (Baker & Wurgler, 2006). Thirdly, a substantial number of S&P 500 firms, especially in the technology and industrial sectors, exhibit a large dependence on China in terms of supply chains and to a lesser extent revenues. Consequently, their earnings are highly susceptible to geopolitical shocks involving the US –China relations (Ramelli & Wagner, 2020). Finally, the US China tense relationship tends to exacerbate policy uncertainty. Heightened policy uncertainty disrupts monetary and fiscal expectations, thereby contributing to market instability (Pastor & Veronesi, 2012).

Table 2: Conditional volatility of S&P500 with UCT

Coef	GARCH-MIDAS			DAGARCH-MIDAS		
	Std-t	Skew-t	Std-n	Std-t	Skew-t	Std-n
α	0.117***	0.001	0.146***	0.112***	0.187***	0.120***
	(0.045)	(0.001)	(0.057)	(0.043)	(0.073)	(0.047)
β	0.846***	0.776***	0.784***	0.850***	0.718***	0.804***
	(0.328)	(0.301)	(0.304)	(0.330)	(0.279)	(0.312)
γ		0.320***			0.190***	
		(0.124)			(0.074)	
m	-7.646***	-7.459***	-7.586***	-7.820***	-0.859**	-8.095***
	(2.968)	(2.896)	(2.945)	(3.036)	(0.438)	(3.143)
θ	0.003	-0.003	0.001			
	(0.002)	(0.002)	(0.001)			
$\theta_{\_}$				0.013	-0.178***	0.028**
				(0.008)	(0.069)	(0.014)
$\theta_{\_neg}$				-0.010	0.196***	-0.000432
				(0.006)	(0.076)	
w_2	1.036*	1.002*	1.668***			
	(0.611)	(0.591)	(0.648)			
w_{2_pos}				1.812**	1.002***	1.796**
				(0.925)	(0.389)	(0.916)
w_{2_neg}				1.362*	1.026***	1.110**
				(0.803)	(0.398)	(0.566)
LLF	-4921.41	**-3954.073**	-4563.482	-4921.142	**-3970.631**	-4958.582
AIC	9857.82	**7922.15**	9138.58	9857.28	**7955.88**	9933.78
BIC	9879.38	**7942.28**	9155.31	9878.84	**7976.93**	9957.7
Sample Period	1993-06-03/2024-02-29(#Obs.:1605)					

Note: α and β are the coefficients of the volatility equation (4) which capture the clustering effect stylized fact in volatility, while γ captures the asymmetric effect; m is constant in the long-run volatility component equation (5) while θ captures the effect of long-run variable (e.g., UCT). Different from equation (5), equation (7) uses $\theta_{\_}$ and $\theta_{\_neg}$ for the effect of positive and negative shock from the long-run variable. We follow Engle et al. (2008) and Colacito et al. (2011) and set $w_1 = 1$ in equation (6) and (11). Therefore, w_2 reflects the influence of UCT on long-term correlation in equation (6), while w_{2_pos} and w_{2_neg} captures the asymmetric effect in the long-run component in equation (11).

Table 3: Conditional volatility of SSE A Share with UCT

Coef	GARCH-MIDAS			DAGARCH-MIDAS		
	Std-t	Skew-t	Std-n	Std-t	Skew-t	Std-n
α	0.178***	0.145***	0.210***	0.149***	0.148***	0.191**
	(0.069)	(0.056)	(0.082)	(0.058)	(0.057)	(0.097)
β	0.821***	0.838***	0.782***	0.842***	0.834***	0.802***
	(0.319)	(0.325)	(0.304)	(0.327)	(0.324)	(0.311)
γ		0.015			0.016	
		(0.009)			(0.010)	
m	-0.460***	-5.588***	-5.160***	-5.605***	-5.595***	-5.339***
	(0.179)	(2.169)	(2.003)	(2.176)	(2.172)	(2.073)
θ	0.023**	0.003	0.002			
	(0.012)	(0.002)	(0.001)			
$\theta_{\_}$				0.005**	0.000	0.007
				(0.003)	(0.000)	(0.004)
$\theta_{\_neg}$				0.001	0.004	-0.012
				(0.001)	(0.002)	(0.007)
w_2	1.012**	13.564***	10.145			
	(0.516)	(5.266)	(6.168)			
w_{2_pos}				21.349	1.009	16.044
				(12.979)	(0.613)	(9.754)
w_{2_neg}				8.447	6.814	1.335*
				(5.135)	(4.143)	(0.787)
LLF	-4101.912	**-3203.111**	-4188.963	-4193.222	**-3197.021**	-4196.832
AIC	8230.588	**6438.362**	8388.558	8402.449	**6415.425**	8415.055
BIC	8262.873	**6465.266**	8436.986	8445.496	**6453.091**	8452.721
Sample Period	1993-06-03/2024-02-29(Obs.:1605)					

Note: α and β are the coefficients of the volatility equation (4) which capture the clustering effect stylized fact in volatility, while γ captures the asymmetric effect; m is constant in the long-run volatility component equation (5) while θ captures the effect of long-run variable (e.g., UCT). Different from equation (5), equation (7) uses $\theta_{\_}$ □□□ $\theta_{\_neg}$ for the effect of positive and negative shock from the long-run variable. We follow Engle et al. (2008) and Colacito et al. (2011) and set $w_1 = 1$ in equation (6) and (11). Therefore, w_2 reflects the influence of UCT on long-term correlation in equation (6), while w_{2_pos} and w_{2_neg} captures the asymmetric effect in the long-run component in equation (11).

Table 4: Conditional volatility of CSI300 with UCT

Coef	GARCH-MIDAS			DAGARCH-MIDAS		
	Std-t	Skew-t	Std-n	Std-t	Skew-t	Std-n
α	0.098***	0.113***	0.102***	0.094***	0.233***	0.095***
	(0.038)	(0.044)	(0.040)	(0.036)	(0.090)	(0.037)
β	0.883***	0.889***	0.879***	0.889***	0.697***	0.889***
	(0.343)	(0.345)	(0.341)	(0.345)	(0.271)	(0.345)

γ		-0.00096			0.135*	
					(0.080)	
m	-6.902***	-6.982***	-6.891***	-7.073***	-0.739	-7.115***
	(2.680)	(2.711)	(2.675)	(2.746)	(0.449)	(2.762)
θ	0.003	0.003	0.002			
	(0.002)	(0.002)	(0.001)			
$\theta_{\_}$				0.008**	-0.157***	0.008*
				(0.004)	(0.061)	(0.005)
$\theta_{\_neg}$				-0.009	0.132***	-0.011
				(0.005)	(0.051)	(0.007)
w_2	7.445***	9.741	11.634***			
	(2.890)	(5.922)	(4.517)			
w_{2_pos}				17.290	1.001***	18.563
				(10.512)	(0.389)	(11.286)
w_{2_neg}				1.474**	1.006**	1.539***
				(0.752)	(0.513)	(0.597)
LLF	-2542.251	-1986.842	-2542.392	-2542.592	**-1987.472**	-2541.583
AIC	5100.51	3989.683	5100.796	5101.191	**3990.94**	5099.166
BIC	5129.724	4014.028	5144.618	5135.274	**4025.023**	5138.118
Sample Period	2005-09-29/2024-02-29(#Obs:962)					

Note: α and β are the coefficients of the volatility equation (4) which capture the clustering effect stylized fact in volatility, while γ captures the asymmetric effect; m is constant in the long-run volatility component equation (5) while θ captures the effect of long-run variable (e.g., UCT). Different from equation (5), equation (7) uses $\theta_{\_}$ □□□ $\theta_{\_neg}$ for the effect of positive and negative shock from the long-run variable. We follow Engle et al. (2008) and Colacito et al. (2011) and set $w_1 = 1$ in equation (6) and (11). Therefore,w_2 reflects the influence of UCT on long-term correlation in equation (6), while w_{2_pos} and w_{2_neg} captures the asymmetric effect in the long-run component in equation (11).

4.2 The effect of UCT on the long-run correlation between US and China stock indices

In this section, we first analyze the impact of UCT on the long-term correlation between US and Chinese stock index returns. Furthermore, the sample period is divided using the US-China trade war as a demarcation point to explore UCT's impact on the correlations between Chinese and US stock indices. To account for the multi-tiered structure of China's capital market, the STAR Market Index, the large-cap blue-chip index, and the SME Index are also included in the analysis.

4.2.1 The effect of UCT on the long-run correlation between US and China stock indices

We analyze the impact of UCT on the long-term correlation between US and Chinese stock indices. We include four lagged values of UCT into the MIDAS regression for the long-run correlation, i.e., L = 4 in Eq. (11). As shown in Table 5, the parameters β and w_2 are significant. The DCC-DAGARCH-MIDAS (skew-t) model performs best for both S&P500 and SSE A Share, S&P500 and CSI300. α and β describe the dynamics of short-term correlation between assets, while w_2 reflects the influence of UCT on long-term correlation. In the DCC model, the sum of α and β approaches 1, indicating that the quasi-correlations are mean-reverted. A larger β suggests stronger persistence in the correlation between the returns of the two stock indices. It reflects that the correlation tends to stabilize over time. w_2 controls the relationship between low-frequency variable (UCT) and long-term correlation. Table 5 also shows that the low-frequency variable (i.e. monthly UCT) has a significantly positive impact on the long-term correlation between high-frequency (i.e. daily) stock index returns, which implies that US-China Tension raises the correlation of returns between the two stock markets, and this can be attributed to several economic mechanisms.

First, a rising UCT represents heightened geopolitical risk, which amplifies global market uncertainty and leads to stronger co-movement across markets during crises, as noted by Forbes & Rigobon (2002). Second, UCT-driven policy uncertainty affects both the US and Chinese economies through trade disruptions, supply chain risks, and monetary policy adjustments, which is consistent with Pastor and Veronesi (2012). Third, global investor sentiment becomes more synchronized during periods of geopolitical tension, resulting in correlated capital flows and risk repricing, as discussed by Baele et al. (2010). Fourth, UCT-induced shocks to multinational corporations, such as US firms reliant on Chinese supply chains and Chinese exporters that are dependent on US demand, generate shared economic impacts that increase the market stock linkage between the US and China (Ramelli & Wagner, 2020). Finally, the US dollar's role as a global financial intermediary amplifies these dynamics, as its fluctuations affect liquidity and risk pricing in both markets, aligning with Bruno &Shin (2015). These factors collectively explain why rising UCT strengthens the correlation between US and Chinese equity markets.

Table 5: Estimated results of DCC-MIDAS for US and China stock indices with the effect of UCT

Coef.	DCC-GARCH-MIDAS			DCC-DAGARCH-MIDAS		
	Std-t	Skew-t	Std-n	Std-t	Skew-t	Std-n
Panel A:S&P500 & SSE A Share						
α	0.003	0.004	0.004	0.003	0.006	0.006
	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)	(0.004)
β	0.993***	0.993***	0.993***	0.993***	0.992***	0.992***
	(0.386)	(0.386)	(0.386)	(0.386)	(0.385)	(0.385)
w_2	8.052***	9.313***	7.873***	7.527	7.178***	2.338
	(3.126)	(3.616)	(3.056)	(4.576)	(2.787)	(1.421)
LLF	-3228.251	-3201.862	-3200.333	-3207.801	**-3193.981**	-3206.472
AIC	6472.502	6419.720	6416.658	6431.592	**6403.958**	6428.934
BIC	6488.645	6453.863	6432.801	6447.735	**6420.101**	6445.077
Sample Period	1993-06-03/2024-02-29(#Obs.:1605)					
Panel B:S&P500&CSI300						
α	0.006	0.142*	0.012	0.011	0.022	0.013
	(0.004)	(0.084)	(0.007)	(0.007)	(0.013)	(0.008)
β	0.992***	0.856***	0.986***	0.988***	0.977***	0.986***
	(0.385)	(0.332)	(0.383)	(0.384)	(0.379)	(0.383)
w_2	2.184***	2.644	2.218	3.806**	4.800***	2.401
	(0.848)	(1.607)	(1.348)	(1.942)	(1.863)	(1.460)
LLF	-1937.601	-1903.862	-1926.883	-1943.182	**-1006.903**	-1905.843
AIC	3891.208	3823.724	3869.762	3902.36	**2029.804**	3827.682
BIC	3905.815	3838.331	3884.369	3916.967	**2044.411**	3824.289
Sample Period	2005-09-29/2024-02-29(#Obs.:962)					

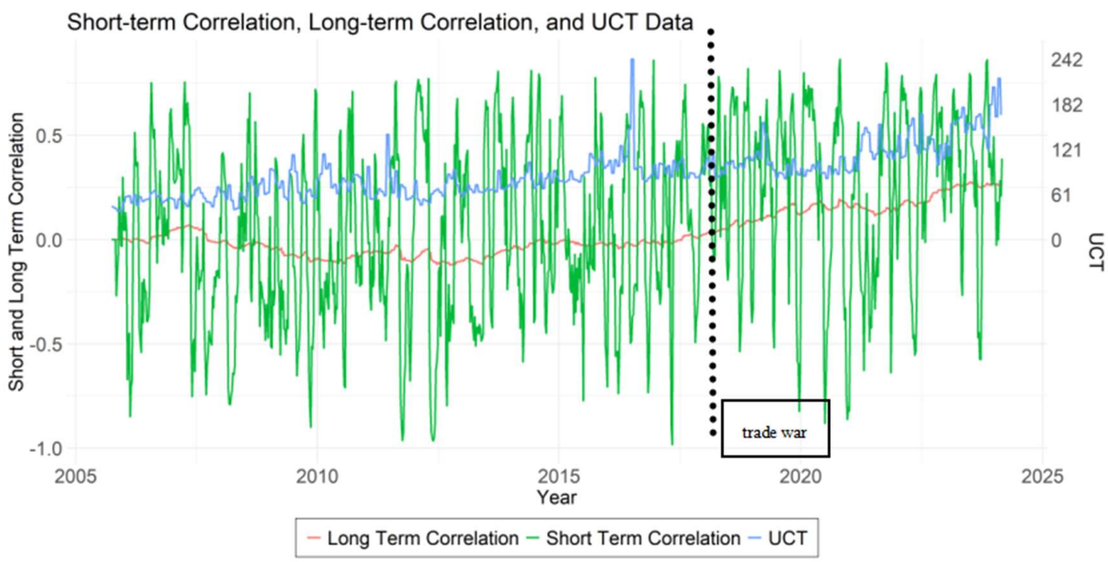
Note: α and β are the coefficients of the volatility equation (4) which capture the clustering effect stylized fact in volatility. We follow Engle et al. (2008) and Colacito et al. (2011) and set $w_1 = 1$ in equation (6) and (11). Therefore, w_2 reflects the influence of UCT on long-term correlation in equation (6).

4.2.2 Subsample Analysis Based on the Division of the US-China Trade War

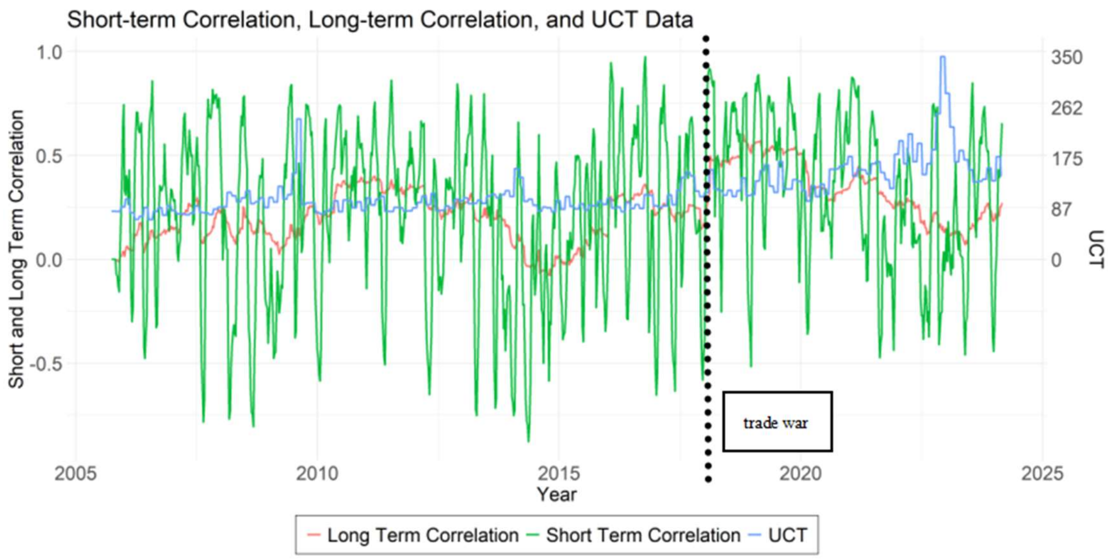
Here, we consider the US-China Trade war instead of the US-China Tension index. The US-China trade war can amplify the impact of the US-China Tension (UCT) index on the long-term correlation between CSI300 and S&P500 returns based on the following several mechanisms. First, the trade war exacerbates shared economic shocks, such as disrupted supply chains and reduced trade flows, increasing market co-movement (Forbes & Rigobon, 2002). Second, heightened policy uncertainty during the trade war affects risk pricing in both markets, consistent with Pastor & Veronesi (2012). Third, multinational corporations, such as US tech firms reliant on Chinese supply chains and Chinese exporters dependent on US markets, experience similar profitability shocks, aligning with Ramelli & Wagner (2020). Fourth, currency fluctuations act as a transmission channel, where trade tensions drive synchronized movements in the US dollar and Chinese yuan, amplifying stock market correlations (Bruno & Shin, 2015). Finally, the trade war intensifies global systemic risk, leading to tail risk contagion across markets (Longin & Solnik, 2001). These mechanisms collectively explain why UCT's influence on long-term stock market correlations strengthens during the trade war.

To investigate the impact of UCT on long-term volatility and dynamic correlations of stock market indices in China and the US, the sample is split into two subsamples: pre-trade war (Subsample 1) and post-trade war (Subsample 2), using the onset of the US-China trade war on March 22, 2018 as the dividing point. Subsample regression analysis is then performed. Based on prior model comparisons, the DCC-DAGARCH-MIDAS (Skew-t) model, identified as the best performing approach, is employed for fitting. We plot the short-term and long-term dynamic correlations between the U.S and China stock index returns, as well as the fluctuations of the UCT index, as shown in Figures 2(a) and 2(b). The red line represents the long-term dynamic correlation, the green line represents the short-term dynamic correlation, and the blue line displays the fluctuations of the UCT. Figure 2(b) shows that after the onset of the US-China trade war (marked by the dashed line), UCT drove a significant increase in the long-term correlation of returns between China (CSI300) and the US stock market indices.

Table 6 displays the subsample regression results for SP500 & SSE A Share and SP500 &CSI300. The fitted parameter w_2 for both indices are statistically significant before and after the trade war, with notable differences in magnitude. To clarify the implications of this parameter, smoothing functions for SSE A Share and CSI300 indices are plotted in Figures 3(a) and 3(b), respectively. The figures indicate that before the trade war, UCT influenced the correlation between Chinese and US stock indices over a longer lag period (up to three lags), demonstrating the strong explanatory power of long-term UCT. After the trade war began, heightened US-China tensions induced higher instability in the dynamic correlations, which are primarily influenced by the most recent lag of UCT. This suggests that during the trade war period, UCT from distant lags lost its explanatory power for current correlations between Chinese and US stock indices. This phenomenon reflects a shift in market response towards short-term dynamics under heightened tension. In other words, escalating US-China tensions made the correlation between stock indices more immediately reactive to UCT shocks. During the trade war—a period of high uncertainty—UCT, as an indicator of US-China tension, directly shaped investors' risk perceptions. The trade war serves as a significant indication of the escalation of the Sino-US confrontation. Following the outbreak of the trade war, a new phase of even more strained Sino-US relations has emerged. In an environment of highly uncertain policies, frequent information shocks have occurred, and investors have attached more attention to short-term information (Shi et al., 2021; Tang & Wan, 2022). According to the noise trading theory, under high uncertainty, investors prioritize the most recent information for decision-making (Da et al., 2015; Delong et al., 1990).



(a) The short-term and long-term dynamic correlation between S&P 500 and SSE A Share, and the fluctuation of the UCT index



(b) The short-term and long-term dynamic correlation between S&P 500 and Shenzhen, and the fluctuation of the UCT index

Figure 2: The short-term and long-term dynamic correlation between S&P 500 and SSE A share, and the fluctuation of the UCT index

Meanwhile, previous studies have demonstrated that during periods of heightened policy uncertainty, the effects of short-term information shocks is also magnified (Baker et al., 2016; Bloom, 2009). Therefore, under the combined influence, investors in both countries have become more sensitive to the events of the deterioration of Sino-US relations.

Table 6: Subsample Estimated results of DCC-DAGARCH-MIDAS for US stock index and China stock index (SSE A Share or CSI300) with the effect of UCT

Coef.	DCC-DAGARCH-MIDAS(Skew-t)		
	Panel A: S&P500&SSE A Share		
Sample Period	Sub-sample1(Before trade war) 1993-06-03/2018-03-22 (#Obs.:1295)	Sub-sample2(Post trade war) 2018-03-29/2024-02-29 (#Obs:310)	Full-sample 1993-06-03/2024-02-29 (#Obs.:1605)
α	0.007 (0.004)	0.001 (0.001)	0.006 (0.004)

β	0.992*** (0.385)	0.946*** (0.367)	0.992*** (0.385)
w_2	2.083*** (0.809)	4.328** (2.208)	7.178*** (2.787)
LLF	-2604.382	-628.029	-3193.981
AIC	5214.764	1262.058	6403.958
BIC	5230.263	1273.268	6420.101

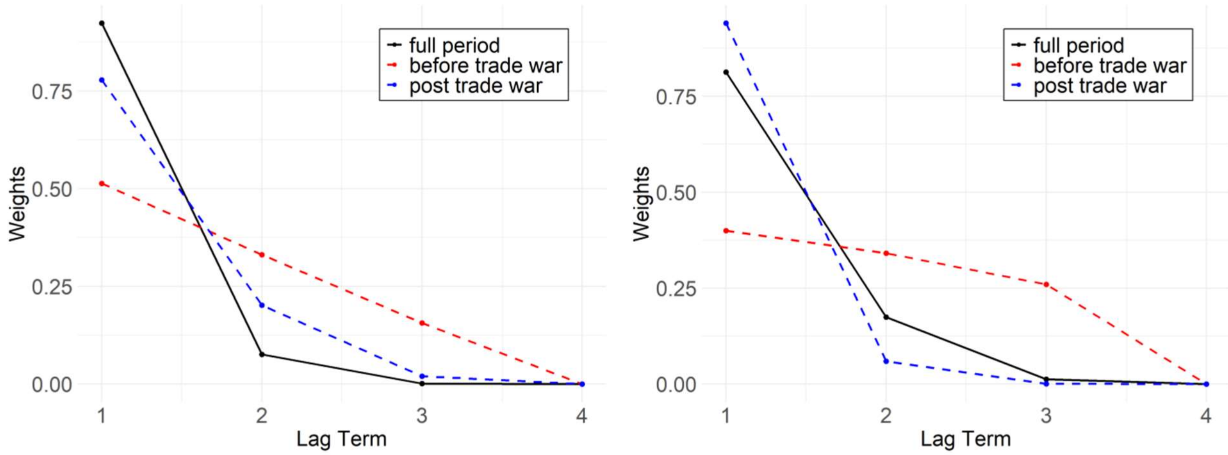
Panel B: S&P500&CSI300

Sample Period	Sub-sample1(Before trade war) 2005-09-29/2018-03-22 (#Obs.: 652)	Sub-sample2(Post trade war) 2018-03-29/2024-02-29 (#Obs.:310)	Full-sample 2005-09-29/2024-02-29 (#Obs.:962)
α	0.017 (0.010)	0.001 (0.001)	0.022 (0.013)
β	0.982*** (0.381)	0.945*** (0.367)	0.977*** (0.379)
w_2	1.394*** (0.541)	7.828*** (3.039)	4.800*** (1.863)
LLF	-1328.881	-628.825	-1006.903
AIC	2663.762	1263.65	2029.804
BIC	2677.202	1274.86	2044.411

Note: α and β are the coefficients of the volatility equation (4) which capture the clustering effect stylized fact in volatility. We follow Engle et al. (2008) and Colacito et al. (2011) and set $w_1 = 1$ in equation (6) and (11). Therefore w_2 reflects the influence of UCT on long-term correlation.

4.2.3 The Dynamic Correlations in China's Multi-Tiered Capital Market

To extend the analysis of UCT's impact on dynamic correlations, we consider the multi-tiered structure of China's capital market. Instead of the SSE A Share Index and CSI300 index, we use the STAR 50 Index (representing the STAR Market), SSE 180 Index (large-cap blue-chip stocks), and SME Index (small and medium-sized enterprises). The STAR 50 Index represents the STAR Market on the Shanghai Stock Exchange. It comprises 50 leading tech innovation firms with high market capitalization and liquidity, reflecting the performance of China's technology sector. The SSE 180 Index includes 180 large-cap, highly liquid companies listed on the Shanghai Stock Exchange, representing mature blue-chip Chinese stocks across sectors like finance, energy, and consumer goods. The SME Index primarily consists of SMEs with high growth potential, listed on the Shenzhen Stock Exchange.



(a) SSE A Share Beta Smoothing Function

(b) CSI300 Beta Smoothing Function

Figure 3: Beta Smoothing Function of SSE A & CSI300

In line with the previous analysis, we apply the DCC-DAGARCH-MIDAS (Skew-t) model with a lag order of 4, and the results are summarized in Table 7. The correlation model shows that the sum of estimated coefficients α and β is close to 1, indicating mean-reversion in the correlation between Chinese and US indices. The w_2 for SSE 180 and SME indices are significant, demonstrating that UCT substantially affects the dynamic correlation between Chinese and US indices, with the strongest influence at a one-period lag.

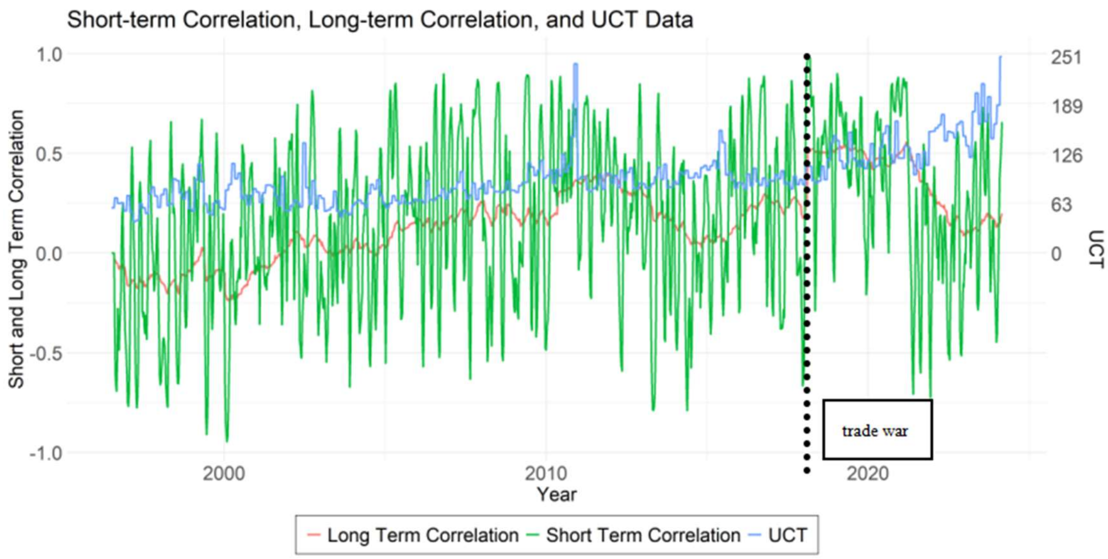
Table 7: Estimated results of DCC-DAGARCH-MIDAS for US and China stock indices with the effect of UCT

Coef.	DCC-DAGARCH-MIDAS(Skew-t)		
	STAR50	SSE180	SME
	Panel A:Univariate Model		
α	0.001 (0.001)	0.128*** (0.050)	0.118*** (0.046)
β	0.906*** (0.352)	0.870*** (0.338)	0.864*** (0.335)
γ	0.174** (0.089)	-0.004 (0.002)	-0.009 (0.005)

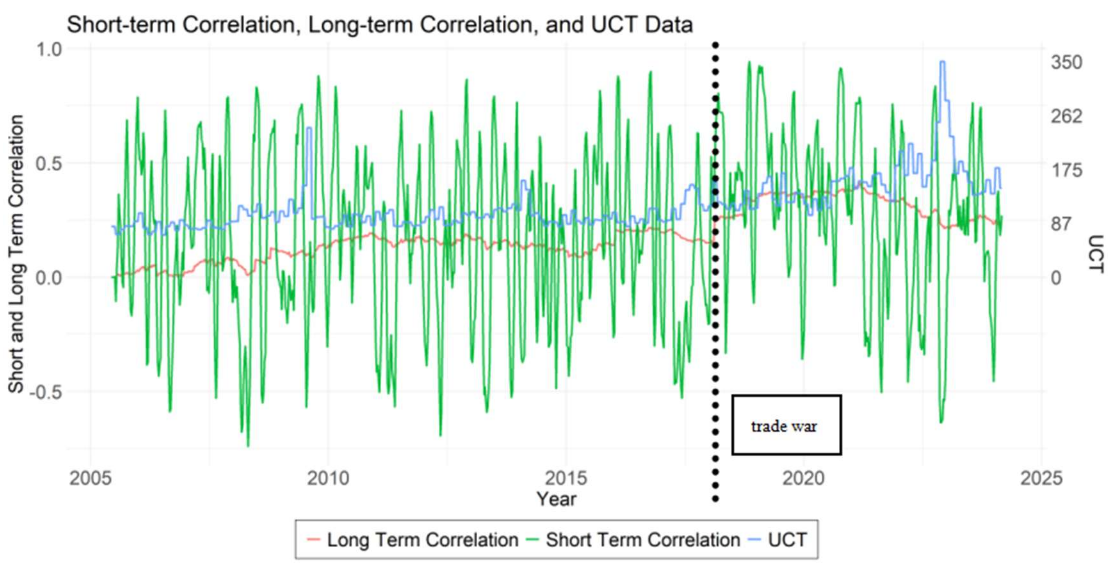
m	3.215*** (1.248)	4.168*** (1.618)	2.686*** (1.043)
$\theta_{\_}$	0.013 (0.008)	-0.001 (0.001)	0.005 (0.003)
$\theta_{\_neg}$	0.011 (0.007)	0.001 (0.001)	-0.002 (0.001)
w_{2_pos}	1.002 (0.609)	1.107 (0.673)	1.111 (0.675)
w_{2_neg}	1.660 (1.009)	11.940 (7.259)	1.979** (1.010)
Panel B:Correlation Model			
α	0.001 (0.001)	0.017 (0.010)	0.007 (0.004)
β	0.990*** (0.384)	0.980*** (0.380)	0.992*** (0.385)
w_2	1.617 (0.983)	2.396*** (0.930)	2.488*** (0.966)
LLF	-360.609	-2755.244	-1979.448
AIC	727.218	5516.488	3964.896
BIC	736.934	5532.314	3979.553
Sample Period	2020-07-23/2024-02-29 (#Obs:189)	1996-07-04/2024-02-29 (#Obs:1444)	2005-06-09/2024-02-29 (#Obs:978)

Note: α and β are the coefficients of the volatility equation (4) which capture the clustering effect stylized fact in volatility, while γ captures the asymmetric effect; m is constant in the long-run volatility component equation (5) while θ captures the effect of long-run variable (e.g., UCT). Different from equation (5), equation (7) uses $\theta_{\_}$ □□□ $\theta_{\_neg}$ for the effect of positive and negative shock from the long-run variable. We follow Engle et al. (2008) and Colacito et al. (2011) and set $w_1 = 1$ in equation (6) and (11). Therefore, w_2 reflects the influence of UCT on long-term correlation in equation (6), while w_{2_pos} and w_{2_neg} captures the asymmetric effect in the long-run component in equation (11).

Following the previous regression analysis, subsamples are divided at the onset of the US-China trade war (March 22, 2018). The results are presented in Figures 4(a) and 4(b) and Table 8. The STAR 50 Index is excluded from the subsample analysis due to its data availability starting only in 2020. Figures 4(a) and 4(b) demonstrate that, similar to the CSI300, the US-China trade war (marked by the dashed line) significantly increases the long-term correlation in index returns between China and the US, driven by UCT. This indicates that the trade war substantially strengthened the correlation between the SSE 180 (blue-chip index) and the S&P 500, as well as between the SME Index and the S&P 500.



(a) The dynamic correlation between S&P 500 and SSE 180, and the fluctuation of the UCT index



(b) The dynamic correlation S&P 500 and SME, and the fluctuation of the UCT index

Figure 4: The short term and long term dynamic correlation between S&P 500 and blue chip or SME, and the fluctuation of the UCT index

Table 8 summarizes the subsample regression results. The w_2 for the SSE 180 index are significant before and after the trade war. In contrast, the w_2 values for the SME Index are insignificant before the trade war but become significant afterward. This suggests that the US-China trade war induced a significant effect of UCT on the dynamic correlation between the SME Index and the S&P 500. The differing responses of the SME and SSE 180 indices to the trade war may arise from differences in investor composition and scale effects. The blue-chip market, with more institutional investors and larger market capitalization, shows a relatively stable response to UCT. In contrast, the SME market, dominated by retail investors and smaller in scale, is less resilient to risks and more sensitive to policy and international changes. During the post-trade war, short-term UCT shocks significantly altered dynamic correlations, highlighting SMEs' heightened sensitivity to policy and international uncertainties. This could be attributed to the fact that numerous SMEs primarily concentrate on exports and assume significant positions within the global supply chain. Once the trade war broke out, the Sino-US conflict predominantly manifests in the form of a trade conflict. Tariff barriers and export restrictions directly undermined the profitability of Chinese SMEs and simultaneously impacted American enterprises' ability to obtain products from China, thereby giving rise to a substantial elevation in the sensitivity of the linkage between the SME Board market and the US market with respect to the UCT (Ramelli et al., 2021). Moreover, these firms frequently encounter more stringent financing constraints. The trade war magnified the role of US dollar liquidity as a global transmission channel. Specifically, the fluctuations of the US dollar driven by the UCT led to an increase in capital outflows and risk premiums for SMEs (Bruno & Shin, 2015). Smoothing coefficients for SSE 180 and SME indices (Figures 5(a) and 5(b)) show that before the trade war, the correlation between Chinese and US indices was influenced by UCT over three prior periods. After the trade war, UCT primarily influenced correlations during the most recent period, reflecting the time-varying impact of UCT under changing US-China relations. This result aligns with the findings for SSE A Share and CSI300 indices. This phenomenon reflects a shift toward short-term market responses during periods of heightened tension. As US-China tensions escalated, stock market correlations showed a stronger reaction to the most recent UCT shock, indicating a shift toward more immediate and short-horizon.

Table 8: Subsample Estimated results of DCC-DAGARCH-MIDAS for US and China stock indices (SSE180 and SME) with the effect of UCT

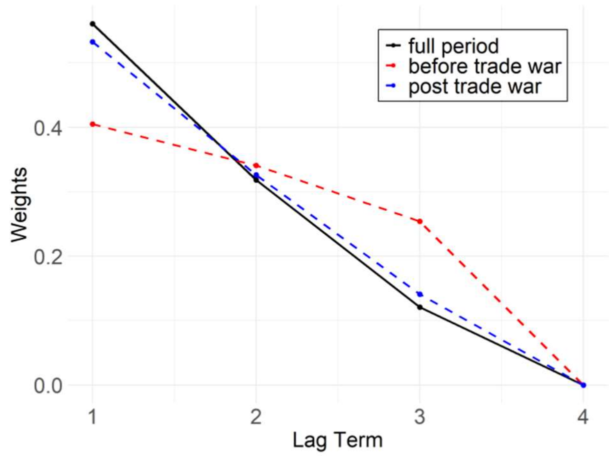
Coef.	DCC-DAGARCH-MIDAS(Skew-t)		
	Panel A:S&P500&SSE180		
Sample	Sub-sample1(Before trade war)	Sub-sample2(Post trade war)	Full-sample
Period	1993-07-04/2018-03-22	2018-03-29/2024-02-29	1996-07-04/2024-02-29

	(Obs.:1134)	(Obs.:310)	(Obs.: 1444)
α	0.015 (0.009)	0.032 (0.019)	0.017 (0.010)
β	0.984 (0.598)	0.956*** (0.371)	0.980*** (0.380)
w_2	1.425*** (0.553)	2.210*** (0.858)	2.396*** (0.930)
LLF	-2185.782	-623.962	-2755.244
AIC	4377.562	1253.921	5516.488
BIC	4392.661	1265.132	5532.314

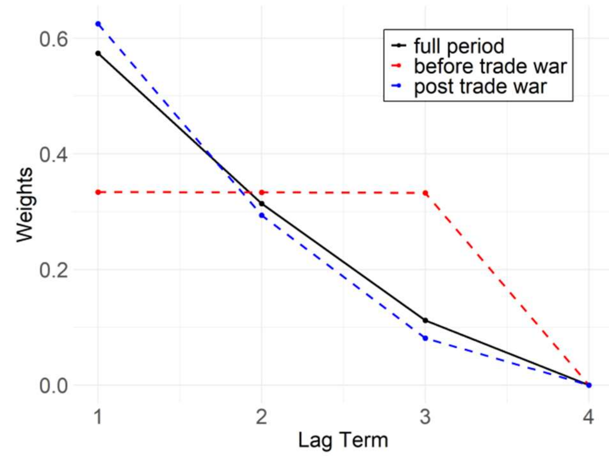
Panel B:S&P500&SME

Sample Period	Sub-sample1(Before trade war) 2005-06-09/2018-03-22 (#Obs.: 668)	Sub-sample2(Post trade war) 2018-03-29/2024-02-29 (#Obs.:310)	Full-sample 2005-06-09/2024-02-29 (#Obs.:978)
α	0.001 (0.001)	0.021 (0.013)	0.007 (0.004)
β	0.995*** (0.386)	0.974*** (0.378)	0.992*** (0.385)
w_2	1.004 (0.610)	2.860*** (1.110)	2.488*** (0.966)
LLF	-1365.905	-635.237	-1979.448
AIC	2737.810	1276.474	3964.896
BIC	2751.323	1287.684	3979.553

Note: α and β are the coefficients of the volatility equation (4) which capture the clustering effect stylized fact in volatility. We follow Engle et al. (2008) and Colacito et al. (2011) and set $w_1 = 1$ in equation (6) and (11). Therefore, w_2 reflects the influence of UCT on long-term correlation in equation (6).



(a) SSE180 Beta Smoothing Function



(b) SME Beta Smoothing Function

Figure 5: Beta Smoothing Function of SSE180 and SME

5 Conclusion

This study analyzes how US-China tensions, represented by the US-China Tension (UCT) index, affect long-term correlations and volatilities of stock indices in both countries using the DCC-DAGARCH-MIDAS (Skew-t) model, which provides a refined econometric structure that jointly models asymmetric short-term volatility, macroeconomically-driven long-term variance components, and dynamic cross-market correlations.

The key findings are as follows: Firstly, UCT exerts a significant and positive influence on the long-term correlations between US and Chinese stock indices, especially during the trade war, leading to stronger and more persistent correlations. Secondly, in periods of heightened geopolitical uncertainty, correlations become highly sensitive to short-term UCT shocks, aligning with the noise trading theory. Thirdly, in China's multi-tiered capital market, blue-chip indices such as SSE 180 respond relatively in a stable way, while SME and technology indices such as the SME Index and STAR50 are more vulnerable to geopolitical risks due to differences in investor composition and market scale. Finally, the subsample analysis based on the trade war indicates a significant change in the dynamics of correlation, with UCT's impact being more apparent through recent lags after the war, reflecting an increased market sensitivity.

These findings emphasize geopolitical tensions as key drivers of market behavior in US and China, stressing the importance of robust risk management and offer valuable insights for both investors and policymakers. Investors are advised to dynamically adjust global portfolios in response to rising US-China tensions, as such, tensions significantly increase cross-market correlations and reduce diversification benefits. Special attention should be given to short-term UCT shocks, which trigger immediate market responses. Within China's capital market, allocating more to stable blue-chip indices while cautiously approaching SME and tech sectors can help manage risk. Ultimately, incorporating geopolitical risk into investment strategies is essential for maintaining resilience and capturing potential rebound opportunities as tensions subside. As for policymakers, they should closely monitor the impact of geopolitical tensions on financial markets and formulate appropriate policies to maintain market stability, such as providing support and guidance to SMEs to enhance their resilience to external shocks.

In conclusion, integrating an advanced econometric approach with detailed market analysis, this study enhances our understanding of how geopolitical risks affect the volatility of financial markets and their dynamic correlation.

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