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Geopolitical Risk and the Risk Spillover on the US Technology Firms: A Quantile Perspective

Abstract. *This article employs the quantile vector autoregression (QVAR) Connectedness method to investigate the impact of geopolitical risk on major US technology firms under various market conditions. The findings reveal that: 1) the overall Connectedness index peaks at 63.76% during market uptrends and reaches a low of 38.61% at the median state; 2) Microsoft and Nvidia act as net risk transmitters, whereas Apple and the geopolitical risk index serve as net risk receivers; and 3) during the COVID-19 period in 2020, Connectedness significantly increased across all quantile levels, while a differentiated pattern emerged during the Russia-Ukraine war in 2022. The main contributions of this study include: firstly, it is the first to examine the asymmetric risk linkages between geopolitical risk and US technology firms; secondly, it enriches existing theories through both static and dynamic association analyses; and thirdly, it offers valuable risk management insights for investors. These results have important implications for portfolio management and policy formulation.*

Keywords: *geopolitical risk, Quantile Vector Autoregression, technology firms, Connectedness Analysis.*

JEL Classification: G11, G15, C58, G32, F51.

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1. Introduction

In the 21st century's global political and economic landscape, geopolitical risk has manifested unprecedented complexity and uncertainty (Dalby, 2020; Lu et al., 2023). In recent years, from the Ukraine crisis to the heightened tensions between

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the United States and Iran, from the volatile situation between India and Pakistan to US–China trade frictions, geopolitical risk events have become increasingly frequent. These events have not only contributed to a slowdown in global economic growth, but also introduced substantial uncertainty in the prospects for global economic recovery. Simultaneously, as the globalisation of the technology industry deepens, US technology giants have come to play an increasingly important role in global markets. This reality underlines both the theoretical importance and the practical significance of studying the impact of geopolitical risk on US technology companies.

From a theoretical research perspective, the existing literature mainly concentrates on the following aspects: First, the conceptual definition and measurement methods of geopolitical risk. Scholars have defined geopolitical risk from various angles. For instance, Zeng et al. (2025b) define it as a trend of political and economic change that has the potential to undermine human well-being; the World Economic Forum in Davos characterises it from the perspective of systemic risk; and Dario and Iacoviello (2022) construct a more systematic measurement framework based on the dimensions of threat and behaviour. Second, studies on the macroeconomic impact of geopolitical risk have shown that such risk can inhibit investment and consumption by affecting the uncertainty perceptions of enterprises and households, thus influencing economic growth (Pata et al., 2023; Zeng et al., 2025a). Third, there is research on the transmission mechanisms of geopolitical risk in financial markets, including its effects on stock, commodity, and foreign exchange markets (Wang and Su, 2023; Wu et al 2025a).

In today’s complex international environment, US technology companies face multiple challenges. On the one hand, technology giants, represented by Apple, Google, and Microsoft, implement global strategies with business networks spanning the globe. For example, Apple operates more than 500 retail stores across 25 countries and regions, with a supply chain that involves multiple nations; Google’s cloud services cover major global markets; and Microsoft has branches in over 110 countries and regions. Such highly globalised business models render these firms particularly vulnerable to the shocks of geopolitical risk. On the other hand, recent years have witnessed emerging features of geopolitical risk, such as technological blockades, supply chain restructuring, and increasing concerns over data security, all of which pose new challenges to the global operating strategies of US technology companies. Notably, the impact of geopolitical risk on US technology firms is multidimensional: at the market access level, various forms of trade barriers and regulatory restrictions may lead to losses in market share and revenue (Bagwell et al., 2002); at the supply chain level, uncertainties in the supply of key resources – such as raw materials, components, and talent – arise (Tukamuhabwa et al., 2017); and at the level of innovation capacity, issues like technological blockades and intellectual property protection may affect firms’ long-term development potential (Woo et al., 2015; Wu et al., 2025b). These impacts may exhibit different characteristics under varying market conditions, warranting a more systematic research and analysis. Moreover, as global technological competition intensifies, the relationship between geopolitical risk and technological innovation becomes increasingly complex (Luo and Van Assche, 2023). Some countries have begun to closely link technological development with national security, leading to more prominent issues such as technology barriers and market access restrictions. This not only affects the global market layout of US technology companies but may also alter the overall pattern of global technological innovation. Additionally, in the era of the digital economy, the emergence of new geopolitical risk factors – such as data security and cyber sovereignty – further intensifies the challenges faced by technology companies (Adeyeri and Abroshan, 2024).

Therefore, an in-depth study of the impact of geopolitical risk on US technology firms is of great significance. Such research not only aids in understanding the transmission mechanism of geopolitical risk within the technology sector, but also provides theoretical guidance for firms in formulating risk management strategies. In particular, examining the asymmetric effects of geopolitical risk under different market conditions is of practical importance in enhancing firms' risk management capabilities. At the same time, this line of research contributes to a better understanding of the risk factors involved in the restructuring of global technology industry chains and offers valuable reference for policymaking.

However, there are several important gaps in the existing literature. First, there is insufficient research on the asymmetric impacts of geopolitical risk in different market environments. Specifically, the transmission mechanism and the intensity of impact of geopolitical risk may differ significantly between bull and bear markets – an issue that has not received adequate attention. Second, studies focusing on geopolitical risk in specific industries, particularly the high-tech industry, are relatively scarce. Although some studies have explored the overall impact of geopolitical risk on firms, technology companies – highly dependent on global supply chains and cross-border technological cooperation – may exhibit unique risk sensitivities and response mechanisms. Third, there is a lack of in-depth research on the cross-market spillover effects of geopolitical risk. In the context of globalisation, it is necessary to further explore how geopolitical risk influences firm value through multiple channels, such as supply chain networks and technological cooperation networks.

Methodologically, the current literature mainly relies on traditional econometric techniques – such as linear regression models, panel data analyses, and vector autoregression (VAR) models – to study the economic and financial effects of geopolitical risk. However, these methods have limitations in capturing the micro-level characteristics of risk transmission mechanisms, especially when analysing the highly globalised technology industry (Klement, 2021). Due to their unique industrial features – such as heavy reliance on global supply chains, cross-border technological cooperation, and data flows – technology companies often face geopolitical risks that exhibit pronounced nonlinearity and heterogeneity (Wu et al., 2024). In different market conditions, the strength and direction of risk transmission may change significantly, necessitating the use of more advanced econometric methods (e.g., quantile regression and network analysis) to characterise these complex dynamic relationships (Zhang et al., 2025). Hence, developing a research framework that can simultaneously capture the nonlinear characteristics of risk transmission and network effects is of great importance for a deeper understanding of the transmission mechanism of geopolitical risk in the technology sector (Chen et al., 2016).

To analyse the risk impact of geopolitical risk on US high-tech companies, this paper employs the Quantile Vector Autoregression (QVAR) Connectedness method (Ando et al., 2022). The selection of this method is based on several important considerations. First, while traditional VAR models can capture the dynamic relationships among variables, they are built on mean regression and cannot effectively characterise the nonlinear features and the impacts of extreme events that are common in financial markets. In contrast, the quantile VAR approach estimates the interrelationships among variables at different quantiles, allowing for a more comprehensive depiction of how geopolitical risk transmits under varying market conditions – particularly under extreme market scenarios where such nonlinear characteristics are pronounced. Second, the connectedness analysis framework provides a systematic approach to quantify and visualise the risk transmission network. By constructing a connectedness network based on quantile VAR, we can detail how geopolitical risk affects US technology firms through various channels, and how this impact varies under different market conditions. This method not only identifies the direction of risk transmission, but also quantifies its intensity, thereby offering an important tool for understanding the systemic nature of risk. Third, an additional advantage of the quantile VAR Connectedness method is its ability to capture the asymmetric characteristics of risk transmission. Under different market environments (e.g., bull versus bear markets), the impact of geopolitical risk on technology companies may differ significantly. By estimating connectedness measures at various quantiles, we can deeply analyse these asymmetric features and provide a basis for differentiated risk management strategies. Moreover, this approach allows for dynamic analysis of the time-varying features of the risk transmission network. This is particularly significant for understanding how the transmission mechanisms of geopolitical risk evolve before and after major events (such as COVID-19 and the Russia–Ukraine conflict). By employing a rolling window estimation, we can track the dynamic evolution of connectedness measures and identify structural changes in risk transmission patterns. Through this methodological framework, we aim to offer deeper insights into the relationship between geopolitical risk and US technology companies, particularly regarding the mechanisms of risk transmission under extreme market conditions. These findings will not only enrich the existing theoretical literature, but also provide important references for firms in risk management and for policymakers.

Using the quantile VAR Connectedness approach, this study examines the impact of geopolitical risk on major US technology firms and obtains the following key findings: (1) the overall Total Connectedness Index (TCI) reaches a peak of 63.76% at high quantiles (upward market phases) and falls to a low of 38.61% at the median state, indicating that market conditions significantly affect the intensity of risk transmission; (2) at the individual index level, Microsoft and Nvidia primarily function as net risk transmitters, whereas Apple and the Geopolitical Risk Database (GPRD) act as net risk receivers, with Alphabet shifting to a net risk receiver role under extreme market conditions; (3) during major events – such as the early stages of the COVID-19 outbreak in 2020 – connectedness across all quantile levels rises significantly, whereas during the Russia–Ukraine conflict in 2022, a divergence is observed: median-level connectedness declines while extreme quantile connectedness increases; (4) pairwise connectedness analysis reveals that the spillover effect between Microsoft and GPRD is most pronounced during bull and stable market periods, with Microsoft emerging as a key risk transmitter; and (5) robustness tests, using different rolling window lengths (150 days and 200 days), confirm the reliability of the research results. These findings not only deepen our understanding of the transmission mechanisms of geopolitical risk, but also provide important insights for investors' risk management and for policymaking.

The contributions of this paper are multifaceted. First, to the best of our knowledge, this study is the first to examine the asymmetric risk linkages between geopolitical risk and US high-tech companies. Previous research has rarely investigated the network of linkages between geopolitical risk and US high-tech firms. Second, by analysing both the static and time-varying connectedness among these different asset types, our study contributes to the theoretical literature and provides valuable resources for investors and regulators in addressing financial risk. Third, through pairwise network connectedness analysis, global investors can better hedge their investment positions and manage systemic risk by studying the interconnections among different markets. Our evaluation of the degree of interconnectedness across various quantiles indicates that GPRD and Apple are the primary risk receivers within the system, whereas Microsoft and Nvidia serve as the main sources of risk.

The rest of this article is as follows. Section 2 provides the methodology of this work and data. Section 3 offers the empirical analysis, and Section 4 provide conclusions with policy implications.

2. Model specification

To estimate the connectedness of y_t at the quantile level τ, we first measure the N-dimensional QVAR(p) framework, and can be described,

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

Where, τ is between 0 and 1 and denotes the quantile we are studied; y_t and $y_{t-i}, (i = 1, \cdots, p)$ is an N-dimensional column vector; p is the lag length of the QVAR framework, c (τ) shows the N-dimensional intercept column vector; $B_i(\tau)$ denotes the N×N-dimensional element matrix; e_t(τ) shows the N-dimensional error column vector.

To observe the outcome of the element matrix $B_i(\tau)$ and the explanation parameter $c(\tau)$, it is defined that the error element $e(\tau)$ satisfies $Q_\tau(e_t(\tau) \mid y_{t-1}, \cdots, y_{t-p}) = 0$.

Under the above state, the regression framework of the dependent index y_t at the selected quantile τ is:

$$Q_\tau(y_t \mid y_{t-1}, \cdots, y_{t-p}) = c(\tau) + \sum_{i=1}^{p} \hat{B}_i(\tau) y_{t-i} \quad (2)$$

2.1 Connectedness Index

From the QVAR (p) function of Equation (1), it can be transfer into an infinite-order QVMA (∞) process:

$$y_t = \mu(\tau) + \sum_{s=0}^{\infty} A_s(\tau) e_{t-s}(\tau), t = 1, \cdots, T \quad (3)$$

Where $\mu(\tau) = (I_n - B_1(\tau) - \cdots - B_p(\tau))^{-1} c(\tau)$ and $A_s(\tau)$ indicate the QVMA element matrix according to the conditional the level of quantile τ, and:

$$A_s(\tau) = \begin{cases} 0, s < 0; I_n, s = 0 \\ B_1(\tau) A_{s-1}(\tau) + \cdots + B_p(\tau) A_{s-p}(\tau), s > 0 \end{cases} \quad (4)$$

Where, according to Diebold and Yilmaz (2012), we estimate the core of the Connectedness framework, the GFEVD (Koop et al., 1996; Pesaran and Shin, 1998). As GFEVD, in the H-step FEV of variable i, the proportion due to variable j is:

$$\theta_{ij}^{g}(H) = \frac{\sigma_{ij}^{-1} \sum_{h=0}^{H-1} (e_i A_h \Sigma e_j)^2}{\sum_{h=0}^{H-1} (e_i A_h \Sigma e_j)} \quad (5)$$

Where Σ is the variance matrix of $e_t(\tau)$; σ_{ij} is the jth diagonal parameter of the matrix Σ; e_i is a choose column vector with a amount of 1 for the ith parameter and 0 for the reminder of the parameters:

$$\tilde{\theta}_{ij}^{g}(H) = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{N} \theta_{ij}^{g}(H)} \quad (6)$$

$\tilde{\theta}_{ij}^{g}(H)$ estimates the level of connectedness from variable j to variable i under the forecast horizon H. The total Connectedness index (TCI), which estimates the degree total spillovers of all variables in the system, can be estimated as:

$$\mathrm{TCI}(\tau) = \frac{\sum_{i=1}^{N} \sum_{j=1, i \neq j}^{N} \tilde{\theta}_{ij}^{g}(H)}{\sum_{i=1}^{N} \sum_{j=1}^{N} \tilde{\theta}_{ij}^{g}(H)} \quad (7)$$

The directional Connectedness index (To), which estimates the total directional Connectedness from variable i to system is:

$$To_{ij}(\tau) = \frac{\sum_{j=1,j\neq j}^{N} \tilde{\theta}_{ji}^{g}(\tau)}{\sum_{j=1}^{N} \tilde{\theta}_{ji}^{g}(\tau)} \tag{8}$$

The directional Connectedness index (From), which estimates the total directional Connectedness to variable i from system is:

$$\mathrm{From}_{ij}(\tau) = \frac{\sum_{j=1,i\neq j}^{N} \tilde{\theta}_{ij}^{g}(\tau)}{\sum_{j=1}^{N} \tilde{\theta}_{ij}^{g}(\tau)} \tag{9}$$

The net Connectedness index (NET), which estimates the net directional Connectedness of variable i is:

$$\mathrm{Net}_{i}(\tau) = \mathrm{To}_{ij}(\tau) - \mathrm{From}_{ij}(\tau) \tag{10}$$

If $\mathrm{Net}_{i}(\tau) > 0(\mathrm{Net}_{i}(\tau) < 0)$, variable i is a net transmitter/receiver in the network system.

The empirical analysis in this study utilises daily stock price data from major technology companies – including Tesla, Nvidia, Microsoft, Amazon, Apple, and Alphabet – as well as the GPRD index. The sample period extends from January 5, 2015, to March 7, 2024, covering approximately eight years of market activity. This time frame captures several significant market events, including the COVID-19 pandemic and its aftermath, thereby providing a rich context for examining the relationship between these technology giants and economic policy uncertainty. The company stock price data are sourced from Datastream, while the GPRD data are obtained from the Economic Policy Uncertainty (EPU) website (https://www.policyuncertainty.com/), which maintains an index measuring policy-related economic uncertainty based on newspaper reports. By combining financial market data with the economic uncertainty indicator, this study is able to comprehensively assess how policy uncertainty has influenced the performance of leading technology firms during the sample period.

3. Results and discussion

According to the descriptive statistics reported in Table 1, starting with the mean values, the GPRD exhibits the highest average return at 1.142, followed by NVIDIA at 0.119 and Microsoft at 0.082. Notably, Apple, Amazon, Alphabet, and Tesla all show negative average returns, indicating that these companies performed relatively poorly over the sample period. In terms of volatility, the variance indicator reveals that Alphabet and Amazon display the highest volatility, with variances of 47.64 and 47.498 respectively, suggesting that these companies experienced the largest fluctuations in stock returns. In contrast, the variance of GPRD is only 0.297, indicating a relatively stable behaviour.

Table 1. Descriptive Statistics

	GPRD	MSFT	APPLE	AMAZON	ALPHABET	TESLA	NVIDIA
Mean	1.142	0.082	0.016	-0.058	-0.084	-0.008	0.119
Variance	0.297	3.164	12.453	47.498	47.64	29.616	18.702
Skewness	2.252	-0.168	-27.442	-39.136	-40.768	-14.064	-16.337
Kurtosis	10.125	8.138	1049.502	1687.581	1781.866	354.430	528.454
JB	10524.708***	5685.863***	94662017.482***	244616320.432***	272697644.397***	10834545.635***	24026698.060***
ERS	-8.276***	-11.349***	-8.663***	-16.408***	-16.099***	-9.087***	-13.583***

Source: Authors' processing.

Regarding distributional characteristics, the skewness statistics reveal an interesting pattern. GPRD shows a significant positive skew (2.252), indicating a long right tail and a higher frequency of extreme positive returns. Conversely, the other technology companies exhibit marked negative skewness, particularly Alphabet (–40.768) and Amazon (–39.136), suggesting that their return distributions are characterised by a higher likelihood of extreme negative returns. The kurtosis analysis indicates that all variables possess kurtosis values significantly exceeding those of a normal distribution (which has a kurtosis of 3). In particular, the kurtosis of Alphabet and Amazon reaches as high as 1781.866 and 1687.581 respectively, signifying that these series have pronounced peakedness and fat tails – implying that the probability of extreme events is far higher than that expected under a normal distribution. The Jarque-Bera test results (JB statistics) indicate that the null hypothesis of normality is strongly rejected at the 1% significance level for all series, which is consistent with the observed high kurtosis and significant skewness. Finally, the results of the ERS test are significantly negative at the 1% level for all series, confirming the stationarity of all the time series and thus providing a reliable basis for subsequent modelling analyses.

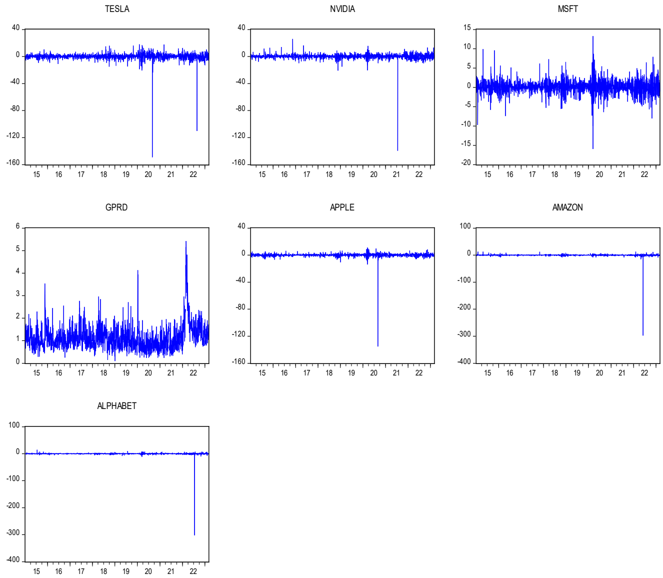


Figure 1. Dynamic of variable
Source: Authors' own creation.

Based on the time series data shown in Figure 1, one can observe the volatility characteristics and the occurrences of extreme events for each index from 2015 to 2023. In terms of overall trends, with the exception of Microsoft (MSFT) and the geopolitical risk index (GPRD), the stock price fluctuations of the other major technology companies exhibit pronounced extreme values. These extreme values are primarily concentrated during two significant historical periods: the outbreak of the COVID-19 global pandemic in 2020 and the period following the outbreak of the Russia–Ukraine conflict in 2022. This indicates that major global events have had a profound impact on the technology stock market. A closer analysis of the performance of individual companies reveals that Tesla's time series exhibits the most severe fluctuations, with multiple significant negative extremes observed during the period, particularly in 2020 and 2022. NVIDIA's trend also displays noticeable volatility, though its extreme fluctuations are relatively milder compared to Tesla's. Apple's stock price, while also experiencing extreme values, tends to exhibit relatively more stable fluctuations overall. It is noteworthy that Alphabet's time series shows a significant downward jump toward the end of the sample period, which may be related to specific company events or changes in market conditions. Similarly, Amazon's trend presents analogous features, with marked downward extremes during certain periods. In contrast, Microsoft's stock price trend is relatively stable, with a lower frequency and magnitude of extreme values, potentially reflecting the robustness of its business model and its capacity to withstand risks. Although the GPRD also exhibits volatility, its pattern differs from that of the technology stocks, displaying unique time series characteristics. In particular, following the outbreak of the Russia-Ukraine conflict in 2022, the index shows a distinct upward trend.

These observations suggest that major global events exert heterogeneous impacts on the technology sector. Differences in business models, market positioning, and risk management capabilities among various companies lead to divergent market reactions. This also implies that, in portfolio management, it is crucial to fully consider the differentiated effects of extreme events on different assets, as well as the potential impacts of external factors such as geopolitical risk.

Table 2. Static connectedness across quantile

	TESLA	NVIDIA	MSFT	AMAZON	APPLE	ALPHABET	GPRD	FROM
Panel A. Extreme upper quantile (q=0.95)								
TESLA	27.09	14.37	18.10	13.70	6.79	6.48	13.48	72.91
NVIDIA	13.21	29.42	19.24	14.80	4.85	5.27	13.22	70.58
MSFT	14.36	16.60	27.48	16.45	4.66	6.12	14.32	72.52
AMAZON	13.59	14.78	20.71	26.20	5.46	6.47	12.81	73.80
APPLE	8.26	4.86	4.21	5.27	57.53	12.01	7.86	42.47
ALPHABET	6.54	4.62	4.17	4.50	12.32	59.84	8.00	40.16
GPRD	14.14	16.16	18.08	13.87	5.69	5.94	26.12	73.88
TO	70.10	71.39	84.51	68.59	39.75	42.28	69.69	446.32
NET	-2.81	0.81	11.99	-5.21	-2.72	2.12	-4.19	TCI=63.76%
NPDC	3.00	3.00	4.00	3.00	3.00	3.00	2.00	
Panel B. Intermediate quantile (q=0.5)								
TESLA	71.74	5.08	6.48	5.25	7.01	3.61	0.83	28.26
NVIDIA	3.29	64.90	10.15	5.75	7.53	7.47	0.90	35.10
MSFT	2.33	8.88	47.22	14.47	11.04	15.50	0.55	52.78
AMAZON	3.36	6.40	16.52	55.25	7.51	10.42	0.54	44.75
APPLE	5.09	7.92	14.61	8.45	54.31	8.85	0.76	45.69
ALPHABET	2.28	7.84	16.23	10.28	7.79	54.98	0.60	45.02
GPRD	3.85	3.14	3.28	3.43	2.53	2.44	81.33	18.67
TO	20.21	39.26	67.27	47.63	43.41	48.29	4.18	270.27
NET	-8.05	4.17	14.50	2.88	-2.28	3.27	-14.48	TCI=38.61%
NPDC	1.00	5.00	6.00	3.00	2.00	4.00	0.00	
Panel C. Extreme lower quantile (q=0.05)								
TESLA	62.10	5.60	5.63	4.86	8.39	6.59	6.82	37.90
NVIDIA	4.99	59.86	12.62	8.42	4.19	3.84	6.08	40.14
MSFT	4.82	12.30	51.16	17.65	3.75	3.43	6.90	48.84
AMAZON	4.24	8.32	18.18	54.91	4.37	3.99	6.00	45.09
APPLE	13.35	5.12	11.51	8.66	32.31	17.10	11.95	67.69
ALPHABET	12.69	5.24	7.67	9.12	17.65	34.98	12.65	65.02
GPRD	6.53	5.97	6.90	6.28	14.75	15.01	44.54	55.46
TO	46.62	42.55	62.52	55.00	53.10	49.95	50.39	360.13
NET	8.72	2.42	13.68	9.91	-14.59	-15.07	-5.07	TCI=51.45%
NPDC	2.00	3.00	6.00	5.00	2.00	1.00	2.00	

Source: R studio.

Based on the quantile VAR Connectedness analysis results presented in Table 2, we can gain a deeper understanding of the dynamic relationship between geopolitical risk and US technology firms. In this study, a 100-day rolling window is used with a lag order of 1 and a forecast horizon of 10 steps, and extreme quantiles are set at 0.05 and 0.95 to capture the risk transmission characteristics at different quantile levels. Regarding the net spillover effects, different firms exhibit significant heterogeneity across various market environments. Specifically, Microsoft (MSFT) and Nvidia (NVIDIA) act as net risk transmitters, indicating that their volatility is more likely to be transmitted to other entities. In contrast, Apple and the geopolitical risk index (GPRD) consistently serve as net risk receivers across all quantile levels, suggesting that these entities are more vulnerable to systemic shocks. It is particularly noteworthy that Alphabet behaves as a net risk receiver under extreme market conditions (whether in bull or bear markets), reflecting its sensitivity to such environments, while Tesla and Amazon tend to receive net spillover effects from the system in extreme market states.

With respect to the Total Connectedness Index (TCI), its value increases from 51.45% at the lower quantile (q = 0.05) to 63.76% at the upper quantile (q = 0.95), which carries important implications. A higher TCI indicates that market participants are more interconnected and that risk transmission is more pronounced at the upper quantile. This asymmetry may stem from behavioural differences among market participants under different market conditions. Further analysis of the time-series characteristics of the dynamic TCI reveals several key patterns. First, the TCI fluctuates between 40% and 100% throughout the sample period, demonstrating persistent mutual influence among market participants. Second, the TCI at the median state (q = 0.5), recorded at 38.61%, is significantly lower than that in extreme market conditions, confirming the nonlinear nature of risk transmission. Particular attention should be paid to the changes in Connectedness during major events. During the early stages of the COVID-19 outbreak in 2020, the TCI increased significantly across all quantile levels, reflecting the broad diffusion of systemic risk. However, during the Russia–Ukraine conflict in 2022, the market exhibited an intriguing divergence: only the median quantile Connectedness declined, while the Connectedness at extreme quantiles showed a significant upward trend. This phenomenon indicates that changes in market conditions can substantially affect both the intensity and the direction of risk spillovers. The study also finds that the peaks in total spillover effects often coincide with periods of declining stock prices for the majority of the sample firms. This phenomenon can be explained by the herd behaviour observed in behavioural finance, wherein investors, driven by loss aversion, tend to follow the crowd during periods of market stress, thereby significantly increasing inter-market connectedness (Aslam et al., 2021). This finding has important practical implications for understanding risk management in extreme market environments.

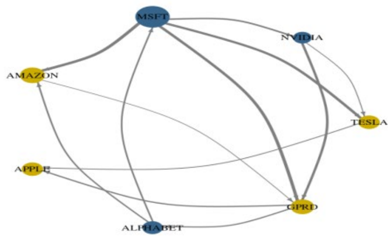
Figure 2. Dynamic Total Connectedness
Source: R studio.

Based on the dynamic total connectedness analysis results shown in Figure 2, we can gain an in-depth understanding of the dynamic relationships between geopolitical risk and US technology firms under different market conditions. The study reveals several key features and patterns. First, regarding the overall level of connectedness, the total connectedness reaches its highest level at 63.76% when the market is in an upward or upper-tail state, whereas it drops to a minimum of 38.61% when the market is at the median state. Over the entire sample period, the total connectedness index fluctuates between 40% and 100%, a significant range that reflects the highly dynamic nature of market interconnectedness. Notably, the connectedness observed during median market conditions is generally lower than that in extreme market states, confirming the nonlinear characteristics of risk transmission. Second, during periods of major events, the market exhibits unique dynamic features in connectedness. In the early stages of the COVID-19 outbreak in 2020, the total connectedness across all quantile levels experienced a significant increase, with the dynamic TCI under median market conditions rising from its usual level of around 20% to nearly 90%. This comprehensive increase in connectedness reflects the widespread diffusion of systemic risk during the crisis. However, during the Russia–Ukraine conflict in 2022, the market displayed a clear divergence: the connectedness at the median quantile declined, while the connectedness at the extreme quantiles showed a marked upward trend. This differentiated performance suggests that changes in market conditions can substantially affect both the intensity and the transmission pathways of risk spillovers.

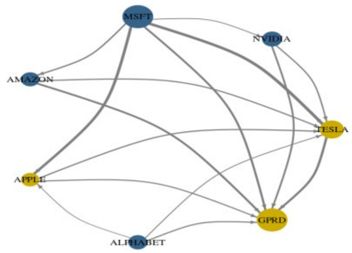
Finally, an examination of the dynamic characteristics across quantiles reveals that the extreme quantiles (the 5th and 95th percentiles) exhibit higher levels of interdependence. This finding is consistent with the results of Hanif et al. (2023), which support the hypothesis of increased risk correlation under extreme market conditions. In particular, during the early stages of the COVID-19 outbreak in 2020, the TCI across different quantile levels reached similar extreme values, a phenomenon that echoes the findings of Zeng et al. (2023). This indicates that as the market transitions from normal to extreme states – whether in bull or bear markets – not only does individual risk spillover increase, but the impact of systemic shocks is also amplified. Most notably, the peaks in the total spillover effects tend to coincide with periods of declining stock prices for the majority of the sample firms. This phenomenon can be explained by herd behaviour in behavioural finance: during periods of market stress, investors, driven by loss aversion, exhibit herd behaviour that leads to a significant increase in interconnectedness among markets. This finding has important implications for understanding the mechanisms of risk transmission under market stress.

Table 3. Networks of paired connectedness under different market conditions

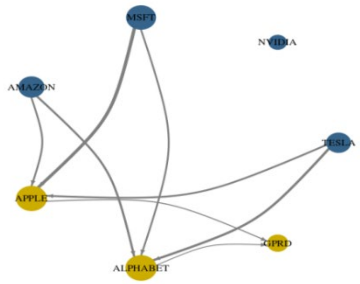
Panel A. Extreme upper quantile (q=0.95)



Panel B. Intermediate quantile (q=0.5)



Panel C. Extreme lower quantile (q=0.05)



Source: R studio.

Table 3 visually illustrates the dynamic Connectedness structure between major US technology companies and geopolitical risk through a network visualisation approach. Based on the quantile Connectedness model framework, we systematically evaluate this Connectedness structure from two dimensions: pairwise Connectedness and network pairwise Connectedness. While pairwise Connectedness reflects the strength and direction of risk transmission between market participants, network pairwise Connectedness identifies the core risk transmitters and receivers within the network by calculating the net value of bidirectional spillover effects.

Under different market conditions, the risk transmission network exhibits pronounced structural differences. First, during upward market phases and under normal market conditions, the Geopolitical Risk Uncertainty Index (GPRD) primarily acts as a net receiver of risk. This is clearly observable in the network diagram, where the arrow directions point toward GPRD. This suggests that when market risk is relatively low, geopolitical risk is more influenced by the volatility of technology firms. Second, in terms of individual firm roles, MSFT and NVIDIA mostly serve as net risk transmitters under most market conditions; however, they display marked differences. Microsoft consistently maintains a significant role as a risk transmitter across various market environments, whereas Nvidia's risk transmission role is notably diminished during market downturns (lower quantiles). This reflects that the roles of different firms in risk transmission may vary with market conditions. Third, with regard to the transition of firm roles, Alphabet switches to a net risk receiver during market downturns (lower quantiles), in stark contrast to its behaviour under stable and upward market conditions. At the same time, Apple receives a considerably higher net spillover under extreme negative market conditions compared to other market states, indicating a marked increase in its risk sensitivity during downturns. In terms of pairwise Connectedness, the spillover effect between Microsoft and GPRD is particularly pronounced during upward and stable market periods, with Microsoft primarily acting as the net conduit of geopolitical risk during these times. A similar pattern is observed for Tesla and Amazon: under median market conditions, Tesla is mainly subjected to a strong spillover effect from Microsoft, while during upward market phases (high quantiles), Amazon receives significant spillover from Microsoft. Notably, Apple sends net risk spillovers to GPRD under median and downward market conditions, whereas this relationship reverses during upward markets, with GPRD transmitting net risk to Apple. These dynamic changes confirm the significant influence of market conditions on the direction of risk transmission.

4. Conclusions

This study provides an in-depth examination of the quantile association between geopolitical uncertainty and major US technology companies. The sample period spans from January 5, 2015, to March 7, 2024, and utilises daily data from six influential technology giants (MATANA: Microsoft, Amazon, Tesla, Alphabet, Nvidia, and Apple). By applying a quantile Connectedness analysis framework, the nonlinear characteristics of risk transmission are revealed.

Empirical findings indicate that the risk spillover effect exhibits pronounced excess volatility in the tails of the distribution, a phenomenon that surpasses traditional frameworks based on mean and median analyses. Specifically, both positive and negative extreme shocks display an enhanced conditional association with shock magnitude – this is particularly evident during the early stages of the COVID-19 outbreak in 2020, when the dynamic total Connectedness across different quantiles converged notably. In particular, at the upper tail of the distribution, corresponding to extreme market conditions, higher levels of Connectedness are observed. In terms of individual firm roles, Apple consistently acts as a net receiver of volatility spillovers across all quantile levels, whereas Microsoft and Nvidia maintain their roles as net transmitters under various market conditions. This stable role distribution provides important insights for portfolio management.

The study also carries significant policy implications. The results underscore the importance of addressing extreme risk spillover effects, especially in the context of the interaction between geopolitical risk and technology companies. Traditional policy-making tends to overly rely on analyses of average shocks within the system – an approach that may be effective in normal market environments but could lead to inadequate or inappropriate responses during extreme events. Policymakers need to establish more comprehensive monitoring and early warning mechanisms that focus on the nonlinear transmission of risk under varying market conditions.

For investors, the study's findings offer crucial guidance for optimising investment decisions. The research indicates that traditional investment strategies may require adjustments in the face of extreme market events. Specifically, during periods of market stress, investors should pay more attention to the dynamic characteristics of risk spillovers and adjust their portfolios based on the flow and magnitude of spillover returns. For instance, when certain firms are identified as net risk transmitters (such as Microsoft and Nvidia), investors may need to adjust their exposure to these stocks; conversely, for firms acting as net risk receivers (such as Apple and the GPRD), a more cautious investment strategy might be warranted under extreme market conditions. Moreover, the experience during the COVID-19 period suggests that investors should establish a more flexible risk management framework – one that can promptly respond to abrupt changes in market conditions. This might involve setting dynamic risk limits, adopting more sophisticated hedging strategies, and adjusting the rebalancing frequency of portfolios across different market environments. Additionally, investors should pay particular attention to the interaction between geopolitical risk and technology stocks, fully considering this nonlinear risk transmission effect when constructing their portfolios.

Future research directions include expanding the scope of analysis to incorporate a quantile system of Connectedness for both traditional and unconventional assets, in order to more comprehensively understand the impact of extreme market conditions on return and volatility spillovers. Furthermore, extending the in-sample analysis to out-of-sample examinations – through parameter re-estimation and forecasting – can help validate the model's goodness-of-fit across various market scenarios.

References

[1] Adeyeri, A., Abroshan, H. (2024), *Geopolitical ramifications of cybersecurity threats: State responses and international cooperations in the digital warfare era. Information, 15*(11), 682.

[2] Ando, T., Greenwood-Nimmo, M., Shin, Y. (2022), *Quantile connectedness: Modeling tail behavior in the topology of financial networks. Management Science,* 68(4), 2401-2431.

[3] Bagwell, K., Mavroidis, P.C., Staiger, R.W. (2002), *It's a question of market access. American Journal of International Law,* 96(1), 56-76.

[4] Caldara, D., Iacoviello, M. (2022), *Measuring geopolitical risk. American Economic Review,* 112(4), 1194-1225.

[5] Chen, N., Liu, X., Yao, D.D. (2016), *An optimization view of financial systemic risk modeling: Network effect and market liquidity effect. Operations Research,* 64(5), 1089-1108.

[6] Dalby, S. (2020), *Anthropocene geopolitics: Globalization, security, sustainability*. University of Ottawa Press, Ottawa, Canada.

[7] Diebold, F.X., Yilmaz, K. (2012), *Better to give than to receive: Predictive directional measurement of volatility spillovers. International Journal of forecasting,* 28(1), 57-66.

[8] Hanif, W., Teplova, T., Rodina, V., Alomari, M., Mensi, W. (2023), *Volatility spillovers and frequency dependence between oil price shocks and green stock markets. Resources Policy,* 85, 103860.

[9] Klement, J. (2021), *Geo-economics: The interplay between geopolitics, economics, and investments. CFA Institute Research Foundation,* https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3836915#.

[10] Koop, G., Pesaran, M.H., Potter, S.M. (1996), *Impulse response analysis in nonlinear multivariate models. Journal of econometrics*, 74(1), 119-147.

[11] Luo, Y., Van Assche, A. (2023), *The rise of techno-geopolitical uncertainty: Implications of the United States CHIPS and Science Act. Journal of international business studies*, 54(1), 1423-1440.

[12] Lu, R., Xu, W., Zeng, H., Zhou, X. (2023), *Volatility connectedness among the Indian equity and major commodity markets under the COVID-19 scenario. Economic Analysis and Policy*, 78, 1465-1481.

[13] Pata, U.K., Alola, A.A., Erdogan, S., Kartal, M.T. (2023), *The influence of income, economic policy uncertainty, geopolitical risk, and urbanization on renewable energy investments in G7 countries. Energy Economics,* 128, 107172.

[14] Pesaran, H.H., Shin, Y. (1998), *Generalized impulse response analysis in linear multivariate models. Economics letters*, 58(1), 17-29.

[15] Tukamuhabwa, B., Stevenson, M., Busby, J. (2017), *Supply chain resilience in a developing country context: A case study on the interconnectedness of threats, strategies and outcomes. Supply Chain Management: An International Journal,* 22(6), 486-505.

[16] Wang, M., Su, Y. (2023), *How Russian-Ukrainian geopolitical risks affect Chinese commodity and financial markets? Finance Research Letters,* 56, 104179.

[17] Woo, S., Jang, P., Kim, Y. (2015), *Effects of intellectual property rights and patented knowledge in innovation and industry value added: A multinational empirical analysis of different industries. Technovation,* 43, 49-63.

[18] Wu, R., Li, M., Liu, F., Zeng, H., Cong, X. (2024), *Adjustment strategies and chaos in duopoly supply chains: The impacts of carbon trading markets and emission reduction policies. International Review of Economics & Finance*, 95, 103482.

[19] Wu, R., Zeng, H., Abedin, M. Z., Ahmed, A. D. (2025a), *The impact of extreme climate on tourism sector international stock markets: A quantile and time-frequency perspective. Tourism Economics,* 13548166241311633.

[20] Wu, R., Zeng, H., Yan, J., Işık, C. (2025b), *Introducing the environmental governance policy uncertainty (EGPU) for China. Journal of Environmental Management*, 386, 125748.

[21] Zeng, H., Abedin, M.Z., Ahmed, A.D., Lucey, B. (2025a), *Quantile and Time–Frequency Risk Spillover Between Climate Policy Uncertainty and Grains Commodity Markets. Journal of Futures Markets*, 45(6), 659-682.

[22] Zeng, H., Benkraiem, R., Abedin, M.Z., Hajek, P. (2025b), *Transitioning to Sustainability: Dynamic Spillovers Between Sustainability Indices and Chinese Stock Market. European Financial Management*, https://doi.org/10.1111/eufm.12560.

[23] Zeng, H., Lu, R., Ahmed, A.D. (2023), *Return connectedness and multiscale spillovers across clean energy indices and grain commodity markets around COVID-19 crisis. Journal of Environmental Management,* 340, 117912.

[24] Zhang, X., Li, G., Wu, R., Zeng, H., Ma, S. (2025), *Impact of Carbon Emissions, Green Energy, Artificial Intelligence and High-Tech Policy Uncertainty on China's Financial Market. Finance Research Letters*, 107599.