Quantitative Finance and Economics

QFE, 9(1): 76–99.
DOI: 10.3934/QFE.2025003
Received: 15 November 2024
Revised: 31 December 2024
Accepted: 07 February 2025
Published: 18 February 2025

https://www.aimspress.com/journal/QFE

Research article

Geopolitical risk transmission dynamics to commodity, stock, and energy markets

Mohammad Ashraful Ferdous Chowdhury[1], M. Kabir Hassan[2], Mohammad Abdullah[3,*] and Md Mofazzal Hossain[1]

[1] Department of Business Administration, Shahjalal University of Science & Technology, Sylhet, Bangladesh
[2] Department of Economics and Finance, College of Business Administration, University of New Orleans, New Orleans, USA
[3] Southampton Malaysia Business School, University of Southampton, Johor, Malaysia

* **Correspondence:** Email: M.Abdullah@soton.ac.uk.

Abstract: In this study, we examined the transmission of geopolitical risk (GPR) to the stock, commodity, and energy markets. Using daily data from 1994 to 2022, we applied transfer entropy and time-frequency quantile vector autoregression-based connectedness approaches to examine the risk transmission mechanism. The results for the transfer entropy showed that wheat and corn returns are sensitive to GPR in the short term, while silver returns are highly reactive to GPR overall. The food commodity, energy, and stock market returns are significantly impacted by GPR during economic events. The static analysis of the connectedness approach showed that in the lower and mid-quantiles, stocks, energy commodities, and agricultural commodities transmit shocks toward GPR.

Keywords: geopolitical risk; stock market; commodity market; energy market; transfer entropy; spillover

JEL Codes: F30, F50, G10, G14

1. Introduction

Geopolitical risk (GPR) has significantly impacted markets, including commodities and the stock market (Chowdhury et al., 2021), due to major geopolitical events over the last decades. These events, such as Gulf War II, 9/11, the Iraq War, the Global Financial Crisis, and the Russia-Ukraine War, have disrupted global food and commodity supply chains, impacted the global stock market, and affected the balance of the precious metal market. The Russia-Ukraine War, as a contemporary geopolitical event, has had a major impact on the crude oil and energy market due to its strategic importance (Wang et al., 2022), and stock prices of various indices have reacted heterogeneously to ongoing global geopolitical crises (Boungou & Yatié, 2022). There are several reasons for the strong connection between GPR and the commodity and stock markets, including the creation of supply imbalances on a global scale due to geopolitical uncertainty (Asadollah et al., 2024; Chowdhury et al., 2021; Umar et al., 2022; Wang et al., 2022).

GPR transmits information to financial markets via the information spillover mechanism. When major geopolitical events occur, news and information spread quickly through global media and communication channels (Umar et al., 2023). As a result, investors and market participants set their positions in response to perceived risks and opportunities. Therefore, changes in one market, such as the commodity or stock market, can impact others, resulting in a cascade of interconnected movements. During periods of geopolitical uncertainty, this information spillover promotes increased correlations among asset classes, which can lead to increased volatility and synchronized market responses. Because of the inter-connectedness of global markets, GPR can cause a significant fluctuation in the prices of commodities, financial instruments, as well as in financial markets (Nerlinger & Utz, 2022; Salisu et al., 2022). Theoretically, the efficient market hypothesis (EMH) (Fama, 1970) suggests that in the semi-strong form of efficiency, the financial markets quickly and accurately incorporate publicly available information into pricing. Additionally, the more efficient the markets are, the more they get connected (Wang, 2022), which implies that efficient markets process information quickly and thus transfer information to other markets. Market efficiency significantly contributes to processing information among markets, and the efficient groups, because of their strong mutual connections, become a net transmitter of information to their less efficient counterparts (Wang, 2022). However, political crises violate the efficient market hypothesis (Gaio et al., 2022) and thus increase asset price predictability amidst critical political and financial events. Therefore, the magnitude of information transmission from GPR to the markets unveils the efficiency of each market and suggests diversification opportunities in the portfolio.

There have been several linear and nonlinear studies that have examined the relationship between GPR and commodity markets, as well as stock and energy markets (Gong & Xu, 2022; Qin et al., 2020; Smales, 2021; Yilmazkuday, 2024). These researchers have examined how GPR transmits to the stock, energy, and commodity markets separately. Moreover, these researchers considered the Russia-Ukraine war as a case of contemporary geopolitical issue amongst all other historical geopolitical events. However, the pattern of GPR transmission to the global stock, commodity, and energy markets is yet to be jointly examined, considering the risk exposure. In addition to this, focusing on a specific geopolitical event can benefit the stakeholders in the short run while examining the historical dynamics and information transmission pattern among GPR and different asset classes can help to better understand the transmission mechanism in the short and long run. Our motivation for this study lies in answering two important but unanswered questions: How does GPR transmit to the stock, commodities, and energy market in the short and long run? How does GPR connect to the asset classes such as stock, commodity, and energy? Considering the theoretical linkage and empirical gap, we aim to examine the transmission of GPR to the stock, commodity, and energy markets.

For empirical analysis, we employ a novel complete ensemble empirical mode decomposition with adaptive noise (CEEMDAN) based Variable Lag (VL)-transfer entropy (Amornbunchornvej et al., 2021; Torres et al., 2011), which enables us to uncover how GPR transmits to the stock, commodity, and energy markets, along with different time frequencies. Using daily data, we uncover that the food market is the highest receiver of and transmitter to geopolitical risk index (GPRI), while the energy, commodity, and stock markets are crucially shaping the GPRI-assets-GPRI relationships. While the CEEMDAN-based VL-transfer entropy reveals how the GPRI is transmitted to the stock, commodity, and energy markets, the question remains unanswered regarding how GPRI is connected to the assets in different quantiles. The connectedness between GPRI and assets might vary across the assets and quantiles. Using the quantile connectedness model, we identify how the dynamics of GPRI increases risk and volatility spillover among stock, commodity, and energy assets across quantiles.

This study contributes to the literature in three ways. First, this is one of the first attempts to jointly examine the transmission mechanism of GPR to the stock, commodity, and energy markets over the last three decades. By delving into these assets, the research sheds light on the complex interplay between global political events and financial markets, offering valuable insights for investors and policymakers to better comprehend the impact of GPR on asset classes. Thus, we contribute to the growing body of GPR and finance literature by examining GPR transmission to the stock, commodity, and energy markets, considering short, medium, and long-term frequencies. Second, unlike other researcher, we employ a relatively novel CEEMDAN-based VL-transfer entropy and time-frequency quantile connectedness approach, which uncovers the risk transmission mechanism from GPR to stock commodity, and energy markets in the short term, medium-term, and long-term frequencies for every single geopolitical event of the sampled period. Thus, our study methodologically extends the previous studies on GPR and financial markets (Nerlinger & Utz, 2022; Salisu et al., 2022; Umar et al., 2023), by employing novel CEEMDAN-based VL-transfer entropy. Finally, our time-frequency analysis findings will assist investors, market participants, and academics in quantifying the contribution of net risk transmission from GPRI to other financial markets in terms of time and frequency. This aids in understanding asset responses to GPR by acknowledging heterogeneous effects across markets and empowering investors to make informed and tailored investment decisions.

The rest of the paper is structured as follows. Section 2 contains a literature review, and in Section 3, we outline data and methods. In Section 4, we depict the empirical findings. In Section 5, we highlight the policy implications, and we conclude the study in Section 6.

2. Literature review

An enormous body of empirical literature has outlined several interesting insights into how GPR is connected to the stock, commodity, energy, and precious metals markets individually. However, a few attempts have been made to examine the effect of GPR on the stock, commodity, and energy market as a whole. Although Coskun et al. (2023) attempted to examine the spillover connectedness among geopolitical oil price risk, clean energy, stock, and commodity market, they did not consider GPR in general. In this part of the study, our literature review splits into three major areas, namely commodity, stock, and energy markets.

To begin with the commodity market, the prices of global food and energy commodities have spiraled up in every major geopolitical event over the years. Because of the open market economic system, countries are more dependent on each other for international trade; moreover, recent geopolitical threats and attacks between Russia and Ukraine have shaken the global supply chain in an unexpectedly worse way than ever before (Wang et al., 2022), even more than the COVID-19 pandemic. The rise in GPR amplifies the global inflation through the supply imbalances in the global supply chain (Asadollah et al., 2024). Dahl et al. (2020) found that the information flow between crude oil and agricultural commodities becomes more intense during times of financial and economic instability, Chowdhury et al. (2021) studied the impact of GPR on food and other commodities and found GPR to be as crucial as the pandemic in negatively influencing the commodity, food, and stock markets, whereas another uncertainty imposes a similar impact on the markets. Moreover, GPR is capable of destabilizing the commodity market, especially the agricultural commodity market (Just & Exhaust, 2022).

With respect to the stock market, it is highly sensitive to geopolitical uncertainty, and GPR impacts the market return negatively (Caldara & Iacoviello, 2022; Hasan et al., 2024). The effects of conflicts vary among the markets based on the trading pattern and compositions, firm location, and industry belongingness (Ahmed et al., 2022; Yilmazkuday, 2024). Undoubtedly, the country that is closer to the event area and has a solid economic and financial tie with affected countries is exposed more quickly than others (Yousaf et al., 2022). Using effective transfer entropy and the maximum spanning tree method, Chen & Pantelous (2022) postulated that while the stocks of both the Chinese and U.S markets are exposed to explicit trade conflicts, the Chinese market is showing more sensitivity than its U.S. counterparts. Similarly, Das et al. (2023) documented that the return of Russian stocks are more exposed to the shock of GPR than other European firms. In addition to this, the GPR-induced uncertainty simultaneously impacts a market and shapes the interconnection among the markets (Evrim Mandaci et al., 2023). The significant negative impact of GPR on stock market volatility also causes oil price volatility to spill over the stock markets when the GPR intensifies oil returns in the short and long term (Smales, 2021), Obviously, the relationship between GPR to volatility and GPR to return varies among sectors. While some firms face negative shock from GPR to the assets value (Bougias et al., 2022), the return and volatility of defense companies are positively associated with GPR in the period of war (Zhang et al., 2022), and the investors capitalize from the excessive defense spending during the crisis period.

Energy markets' sensitivity to GPR is extremely intense and sensitive because of their particular influential role in world trade and industry and the lack of substitutes for major energy products and their producers. Interestingly, GPR is heterogeneously associated with energy markets (Qin et al., 2020), and rather than suppressing the market return, GPR amplifies the abnormal return and volatility in the energy market. Moreover, they documented that GPR negatively affects crude oil return and has a positive impact on crude oil volatility. However, Smales (2021) contradicts that GPR positively affects the oil market returns in the event of conflicts, which is also true for the renewable energy market (Umar et al., 2022). In terms of sectoral returns, the energy market benefits more from GPR with abnormal returns than the stock market (Nerlinger & Utz, 2022). In contrast to that, Yilmazkuday (2024) documents that GPR has no significant impact on energy prices. These findings could be interesting to examine if there is any heterogeneity between GPR and the energy market in the short and long terms.

Based on the extensive body of empirical literature highlighting the connections between GPR and various financial markets, we hypothesize that GPR significantly influences commodity, stock, and energy markets. Specifically, we conjecture that there is information transmission and spillover from GPR to these markets. This hypothesis is grounded in prior research demonstrating the sensitivity of market returns and volatility to geopolitical events. For instance, Dahl et al. (2020) found increased information flow between crude oil and agricultural commodities during periods of financial instability. Similarly, Chowdhury et al. (2021) identified significant impacts of GPR on food and other commodity markets. Additionally, Caldara & Iacoviello (2022) observed negative effects of GPR on stock market returns, and Smales (2021) reported that geopolitical events can lead to increased volatility and abnormal returns in the energy market. Therefore, we propose the following hypothesis:

H1: There is information transmission and spillover from GPR to commodity, stock, and energy markets.

3. Data and methodology

3.1. Complete ensemble empirical mode decomposition with adaptive noise (CEEMDAN) based Variable Lag (VL)-transfer entropy

Following the semi-strong form efficiency of EMH, we employ CEEMDAN-based VL-transfer entropy combining the work of Torres et al. (2011) and Amornbunchornvej et al. (2021), which enables us to uncover the risk flow of GPR into the commodity and stock market. Transfer entropy describes the interaction of time series X and Y and detects the directionality of risk flow among the variables. However, Amornbunchornvej et al. (2021) demonstrated that the fixed-lag assumption limits the Granger causality test, which can be avoided by employing the variable-lag Granger causality test.

The CEEMDAN-VL-transfer entropy method offers significant improvements over the traditional EMD-VL approach by providing a more accurate and reliable decomposition of time series data (Dhifaoui et al., 2022). CEEMDAN enhances the EMD process by mitigating mode mixing and providing a more robust separation of intrinsic mode functions (IMFs), even in the presence of noise. This leads to a clearer and more precise identification of underlying patterns in the data. When combined with variable lag (VL) transfer entropy, CEEMDAN further refines the analysis by dynamically adjusting the lag based on data characteristics, thereby improving the detection of directional influence and information flow between time series (Amornbunchornvej et al., 2021; Torres et al., 2011). This advanced method ensures a more accurate capture of the complex, nonlinear relationships inherent in financial markets, making it superior to the traditional EMD-VL approach in uncovering risk flows and market dynamics.

3.2. Time-frequency quantile connectedness

The rationale behind employing the time-frequency quantile VAR (TF-QVAR)-based connectedness approach in this study is rooted in its ability to capture the quantile propagation mechanism of GPR into the commodity and stock market. TF-QVAR is proposed by Chatziantoniou et al. (2022) and builds upon the seminal work of (Diebold & Yilmaz, 2012, 2014), who introduced a generalized VAR framework using rolling-window dynamic analysis. A detailed methodology of time-frequency analysis is available from Chatziantoniou et al. (2022), and following their methodology, we set 1–5 days in the short term and 6 to infinity days in the long-term.

3.3. Data

We use the daily GPR index (Caldara & Iacoviello, 2022) to proxy the global GPR. The GPR index quantifies adverse geopolitical events and associated risks, providing insights into their evolution and economic implications since 1900. Furthermore, we select two indices from each category of energy commodity, agricultural commodity, precious metal commodity, global stock, and Baltic Dry Index for 9 indices for empirical analysis. By including these indices, we capture a broad spectrum of market reactions and interactions with GPR.

We aim to examine the effect of GPR across significant economic events. Therefore, we select data spanning from January 7, 1994, to October 31, 2022. This period encompasses numerous pivotal events that have had profound impacts on global markets. These events include the Asian Financial Crisis (1997), the Russian Financial Crisis (1998), the September 11 attacks (2001), the Gulf War II (2003), the Global Financial Crisis (2008), the European Debt Crisis (2010–2012), the COVID-19 pandemic (2020–2022), and the Russia-Ukraine War (2022). By including such a broad timeframe, we capture a diverse range of geopolitical and economic disruptions, enabling a comprehensive analysis of GPR's impact on stock, commodity, and energy markets. The list of selected indices and their data sources is presented in Table A.1.

We transform the variables into log first differences to consider changes in GPRI and return of the assets. Table 1 presents the summary statistics of all indices return series. The results show that the mean value of GPRI is −0.003, and the variance is 1449.845, suggesting significant variation in the series. The SKEW and KURT values of GPRI show that the data is positively skewed and fat-tailed, which is consistent with the variance. Among other indices, OIL has the highest mean return of 0.023, and BDI has the lowest mean return of 0.002. All indicators are negatively skewed, and most follow fat-tailed distributions, except GPRI, BDI, and WHEAT. Thereafter, we transform the original return series into short term long term and medium-term frequencies using CEEMDAN, which is illustrated in Figure 1.

Table 1. Summary statistics.

	Mean	Variance	Skewness	Ex.Kurtosis	JB	ERS
GPRI	−0.003	1449.845***	0.074***	1.809***	1031.947***	−12.921***
BDI	0.002	4.230***	0.454***	7.685***	18753.625***	−26.931***
OIL	0.023	6.176***	−1.354***	59.947***	1127703.849***	−9.084***
GAS	0.015	9.674***	−0.021	2.820***	2491.699***	−32.812***
WHEAT	0.011	3.158***	0.188***	2.768***	2444.628***	−37.658***
CORN	0.011	2.539***	−0.041	2.589***	2101.507***	−14.355***
GOLD	0.019	1.034***	−0.113***	7.297***	16690.036***	−30.496***
SILVER	0.018	3.416***	−0.755***	7.715***	19354.015***	−28.369***
MSCIW	0.019*	0.946***	−0.611***	11.080***	38915.481***	−17.626***
DJGI	0.018*	0.898***	−0.641***	10.502***	35051.808***	−21.430***

Note: ∗∗∗, ∗∗, and ∗ indicate significance at the 1%, 5%, and 10% level, respectively

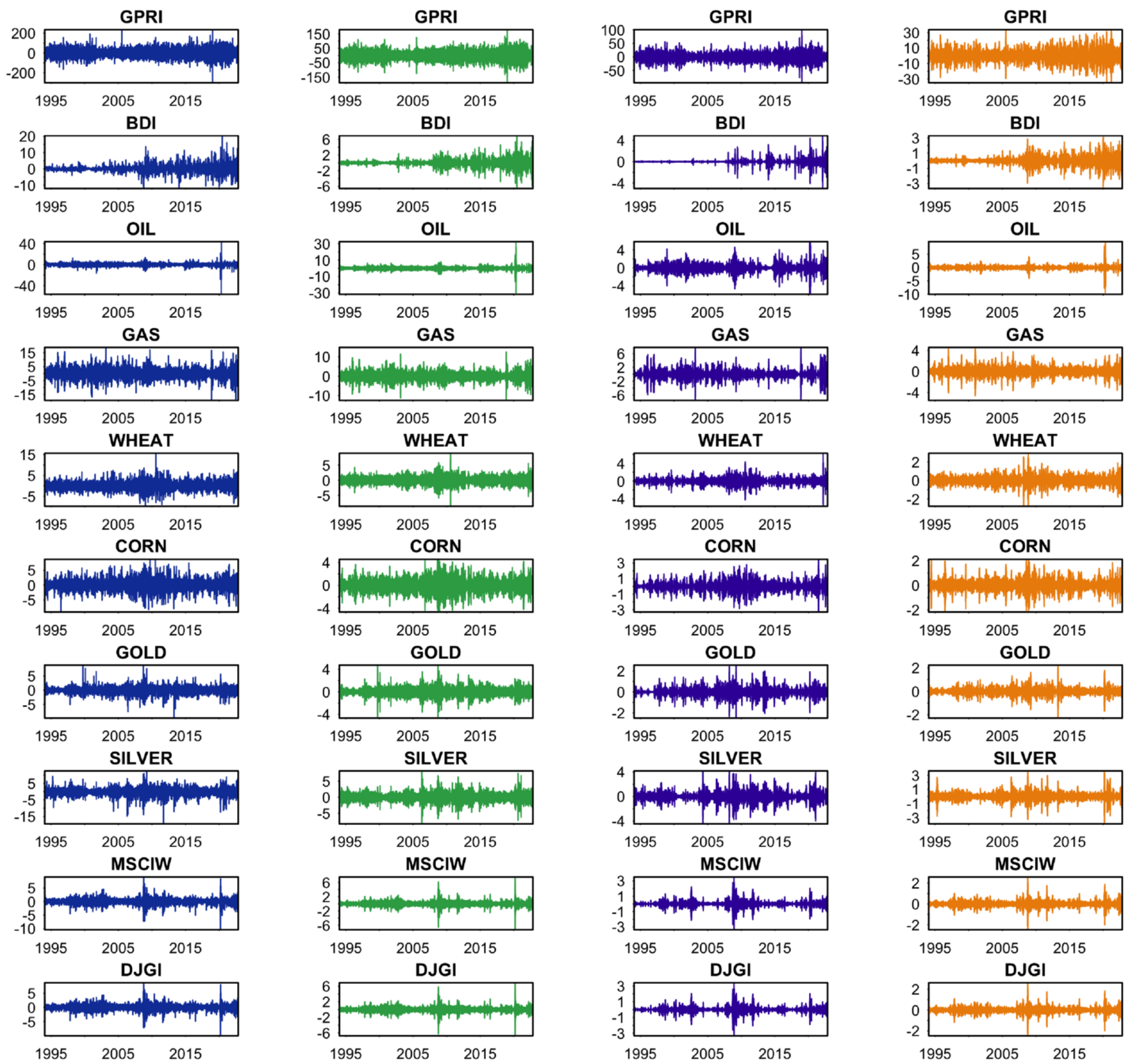

Figure 1. Dynamic fluctuation of the original time series and the extracted CEEMDAN components. Note: Red, green, purple, and orange color represent the original, short-term, medium-term, and long-term CEEMDAN components.

4. Empirical results and discussion

4.1. CEEMDAN-based VL-transfer entropy results

As we aim to examine the transmission of GPR throughout different global economic events, we develop eight panels for each event. The panels are: Panel A: Full Sample (1994-01-07 to 2022-31-10), Panel B: Asian and Russian Financial Crisis (1998-08-17 to 1998-11-17), Panel C: 9/11 (2001-09-11 to 2001-12-11), Panel D: Gulf War II (2003-01-01 to 2011-12-15), Panel E: Global Financial Crisis (2007-01-01 to 2008-12-20), Panel F: European debt crisis (2009-01-01 to 2010-12-20), Panel G: COVID-19 (2020-01-01 to 2021-12-20), and Panel H: Russia Ukraine War (2022-01-01 to 2022-10-31). Figure 2 presents the findings of Panel A: Full Sample (1994-01-07 to 2022-31-10). The results of the remaining panels' CEEMDAN-based VL-Transfer entropy results are presented in the subsequent figures, from Figure S.1 to Figure S.7.

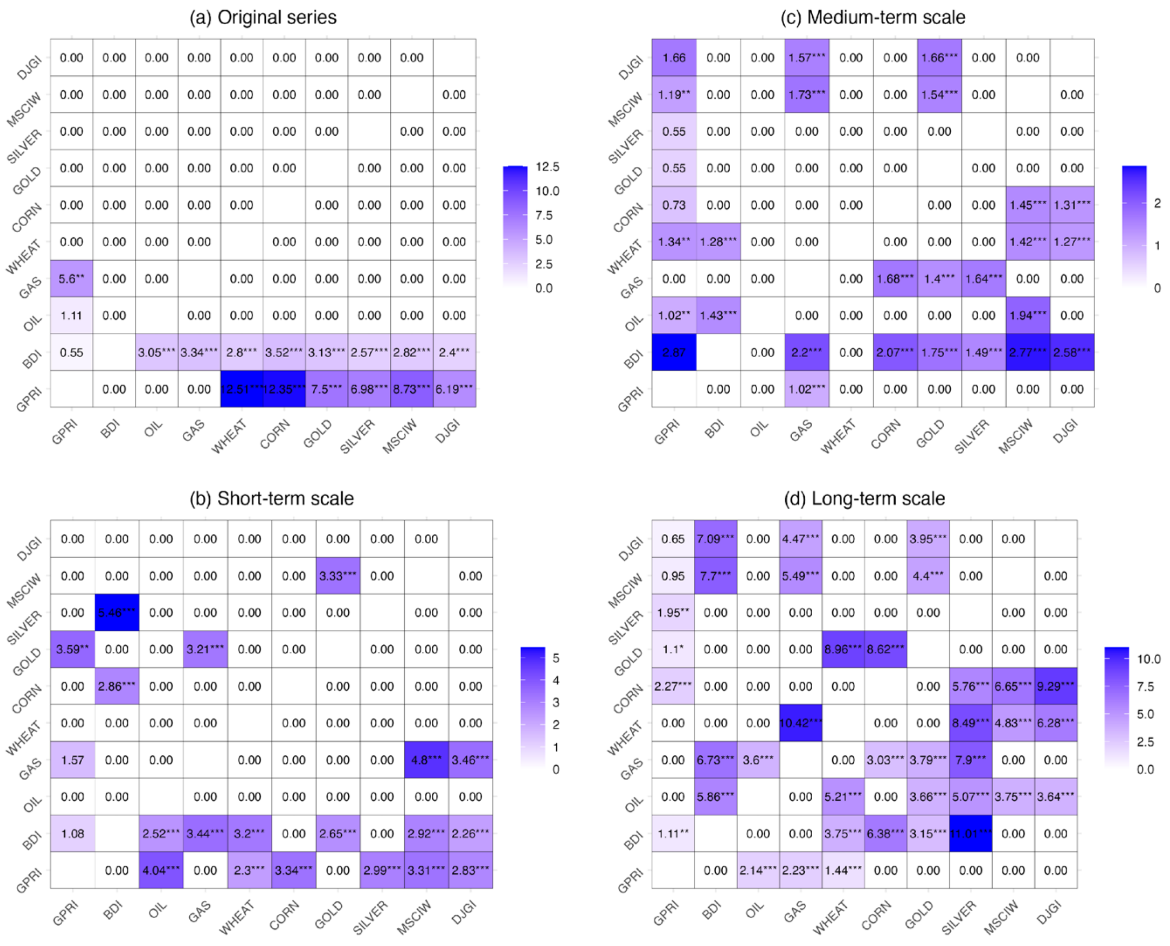

Figure 2. Full Sample (1994-01-07 to 2022-31-10). Note: The figure presents the Transfer-Entropy ratio of a, b, c, and d scales. ∗∗∗, ∗∗, and ∗ indicate significance at the 1%, 5%, and 10% levels, respectively.

The summary of transfer entropy results of bidirectional GPR transmission to the set of different assets for four series of events is presented in Table 2. The food market is the highest receiver of GPRI, while the precious metal market is the highest risk transmitter to GPRI. The energy, commodity, and stock markets also play a significant role in shaping the relationship between GPR and assets. This result is consistent with (Nicola et al., 2020), who showed how consumers' reactions to the market changed during the COVID-19 pandemic. Wheat and corn have the highest levels of GPR transmitted to them, whereas BDI received the strongest flow of GPR during Gulf War II. However, the risk flow varies widely across events. Wheat is the highest receiver of GPR in the full sample, but BDI and corn received the most risk during Gulf War II and the European Debt Crisis, respectively. Corn, surprisingly, experienced no significant impact from GPR during the COVID-19 pandemic despite the disturbance in the global supply chain during that period. Conversely, corn transmitted the strongest flow of risk to GPR during Gulf War II and the global financial crisis. Interestingly, there are several events, including 9/11, the European Debt Crisis, the COVID-19 pandemic, and the recent Russia-Ukraine War, where different asset pairs do not significantly transfer risks to each other. Additionally, at least one event in every scale is found when no significant risk transmission between GPR and assets is found.

Originally, wheat was the highest receiver of GPR, followed by corn among all events. This pattern of risk transmission can be attributed to the high sensitivity of the global food market to GPR. In the short-term series, Silver is the most affected asset by GPR among all events, highlighting the reactivity of the global precious metals market to geopolitical threats and tensions. Similarly, food, energy, and stock markets have also experienced significant risk transmission from GPRI during Gulf War II, GFC, and the COVID-19 pandemic. Interestingly, no immediate effect of GPRI is found during three profound crises- 9/11, the European Debt Crisis, and the Russian-Ukraine War. Moreover, it is worth noting that the effect of GPR on the energy market was weak during the COVID-19 pandemic, which can be interpreted as the low risk of geopolitical threat during that time. However, despite the strong and significant effect of GPR on the global stock market, no event is found to have any significant individual effect on a short-term scale. The short-term scale is crucial in igniting geopolitical tensions and threats. The pattern of risk transmission from assets to GPR is heterogeneous, and no asset has been found to transmit risk to the GPR during the Asian and Russian financial crisis, GFC, and COVID-19. Gold is the only asset that is found to have a significant impact on GPR in the full sample. Further, gold in 9/11, DJGI in the Gulf War II, corn in the European Debt Crisis, and oil and DJGI in the Russian-Ukraine War had the strongest effects on global geopolitical circumstances on the short-term scale.

In the medium term, oil experienced the highest transmission of GPR during the Russian-Ukraine War, which is also the highest transmission of GPR to any asset among all events, and this relationship between GPR and oil is also prevalent during Gulf War II. The risk transmission from oil market to GPR is also supported by Wang & Dong (2024). Additionally, the Gulf War II and the European Debt Crisis were two major events when the GPR transmitted risk to the maximum markets individually. Though GPRI significantly transmitted risk to the energy, commodity, and precious metals markets during Gulf War II, risk transmission during the European Debt Crisis was prevalent in the precious metals and stock market. The COVID-19 pandemic, however, experienced no GPRI transmission to the assets. Because the world was in lockdown, perhaps the low risk of war and geopolitical threats subsequently contributed to the zero-risk transmission in the medium term. Interestingly, only 9/11 and GFC experienced strong and significant risk transmission from assets to GPRI, even though the effect of gas during the European Debt Crisis was weak. Silver, as the top transmitter of risk flow to GPR, demonstrates that the precious metals market is equally important in receiving and transmitting risk flow to GPR in the medium term. Energy and commodity markets in the full sample, however, are the strongest transmitters of risk to GPRI, and the stock market is the weakest.

The relationship between the transmission of risk from GPR to assets is prevalent during all events in the long term, with the exception of the European Debt Crisis. In the long-term series, only the stock market is the strongest receiver of GPR. Although Silver has the strongest effect on GPR ignition among all events, only the global stock market was igniting GPR during the three most recent events (the European Debt Crisis, COVID-19, and Russia-Ukraine War), with the strongest effect during the European Debt Crisis, indicating that the stock market is not immediately reactive to GPR and contributes to the increase of GPR in the long term. However, almost all assets are important transmitters of risk to GPRI during all events.

Table 2. Results summary of bidirectional risk transmission.

Panel A: GPRI => Assets

Sample/ Event	Original Series	Short term	Medium-term	Long-term
Full Sample	WHEAT (12.51***)	OIL (4.04***)	GAS (1.02***)	OIL (2.14***)
	CORN (12.35***)	WHEAT (2.3***)		GAS (2.23***)
	GOLD (7.5***)	CORN (3.34***)		WHEAT (1.44***)
	SILVER (6.98***)	SILVER (2.99***)		
	MSCIW (8.73***)	MSCIW (3.31***)		
	DJGI (6.19***)	DJGI (2.83***)		
Asian and Russian Financial Crisis		BDI (1.28**)	GAS (1.27***)	BDI (11.07**)
				GAS (5.1***)
				WHEAT (2.13*)
9/11			GAS (0.5**)	BDI (4.06***)
			GOLD (0.78*)	
Gulf War II	BDI (9.94***)	BDI (4.17***)	OIL (1.01***)	WHEAT (1.95***)
	WHEAT (4.12***)	GAS (2.85***)	GAS (0.91***)	CORN (2.75***)
		WHEAT (1.84***)	WHEAT (0.98***)	SILVER (5.59***)
		CORN (2.3***)	GOLD (0.85***)	
		SILVER (1.81***)	SILVER (1.07***)	
Global Financial Crisis	GAS (1.01**)	BDI (0.8*)	BDI (2.4***)	BDI (0.97***)
		GAS (0.67**)		WHEAT (2.65***)
				GOLD (1.71**)
				MSCIW (1.55**)
				DJGI (1.44*)
European debt crisis	CORN (5.38***)		BDI (0.85***)	
	GOLD (2.24***)		GOLD (0.84**)	
			SILVER (0.71***)	
			MSCIW (1.54**)	
			DJGI (0.95***)	
COVID-19		OIL (1.75*)		BDI (1.08**)
		SILVER (4.38**)		OIL (0.95*)
				GAS (3.37**)
Russia Ukraine War	CORN (1.7***)		OIL (1.74***)	SILVER (0.76*)

Panel B: Assets => GPRI

Sample/ Event	Original Series	Short term	Medium-term	Long-term
Full Sample	GAS (5.6*)		OIL (1.02**)	BDI (1.11**)
		GOLD (3.59**)	WHEAT (1.34**)	CORN (2.27***)
			MSCIW (1.19*)	GOLD (1.1*)
				SILVER (1.95**)
Asian and Russian Financial Crisis	GAS (2.04***)			
9/11		BDI (1.49*)	OIL (1.85*)	GAS (1.09**)
		GOLD (1.47***)	SILVER (1.98**)	GOLD (1.4***)
				SILVER (1.82***)
				MSCIW (.77*)
				DJGI (9.77*)
Gulf War II	CORN (2.67***)	DJGI (1.42**)		
	GOLD (2.76**)			
Global Financial Crisis	CORN (1.97*)		WHEAT (1.66**)	
	MSCIW (2.33**)		CORN (0.8*)	
	DJGI (1.98*)		DJGI (1.22**)	
European debt crisis		CORN (1.14**)	GAS (0.87*)	MSCIW 1.75***)
				DJGI (1.26***)
COVID-19				MSCIW (1.34*)
				DJGI (1.62***)
Russia Ukraine War		BDI (1.65*)		DJGI (1.32**)
		OIL (1.32*)		
		DJGI (1.97**)		

Note: The table presents Transfer Entropy results, and only significant results are reported here. Please see Figures 1 to 9 for detailed results. Transfer Entropy ratios are in parenthesis. ∗∗∗, ∗∗ indicate significance at the 1% and 5% level, respectively.

4.2. Time-frequency QVAR results

4.2.1. Static analysis results

We begin our analysis of connectedness by examining static connectedness across lower, middle, and upper quantiles (τ= 0.05, 0.50, and 0.95). The lower quantile reflects a declining market trend, the middle quantile represents normal market conditions, and the upper quantile indicates an upward trend. Table 3 displays the results for the lower quantile (τ= 0.05) static connectedness. The diagonal elements show own-variance shocks, while the off-diagonal elements illustrate the connectedness between variables. The table 3 also includes total connectedness measures and both short-term and long-term connectedness (in parentheses). For instance, MSCIW has the highest own-variance shocks (11.63%), with 6.95% in the short term and 4.68% in the long term. The NET row highlights net directional spillovers, where negative values indicate a net receiver of shocks, and positive values indicate a net transmitter. WHEAT (−7.43%) is the largest receiver of shocks in the network, with −2.75% in the short term and −4.69% in the long term. The total connectedness index (TCI) value of 89.73% shows significant spillover within the network at the lower quantile.

Table 3. Lower quantile averaged connectedness results (τ =0.05).

	GPRI	BDI	OIL	GAS	WHEAT	CORN	GOLD	SILVER	MSCIW	DJGI	FROM
GPRI	9.77 (7.37, 2.40)	10.07 (7.35, 2.72)	9.85 (7.18, 2.67)	9.52 (7.03, 2.49)	9.34 (7.04, 2.30)	9.55 (6.98, 2.56)	10.04 (7.09, 2.95)	10.05 (7.27, 2.79)	11.23 (7.75, 3.49)	10.57 (7.06, 3.51)	90.23 (64.75, 25.47)
BDI	9.14 (5.49, 3.65)	10.46 (5.97, 4.49)	9.82 (5.76, 4.06)	9.43 (5.53, 3.90)	9.08 (5.53, 3.55)	9.44 (5.55, 3.89)	10.18 (5.73, 4.46)	10.09 (5.83, 4.26)	11.45 (6.20, 5.25)	10.91 (5.60, 5.31)	89.54 (51.22, 38.32)
OIL	9.36 (6.36, 3.01)	10.13 (6.68, 3.45)	10.1 (6.69, 3.41)	9.51 (6.35, 3.15)	9.22 (6.33, 2.89)	9.5 (6.30, 3.20)	10.07 (6.46, 3.61)	10.04 (6.54, 3.50)	11.36 (7.07, 4.29)	10.71 (6.41, 4.30)	89.9 (58.49, 31.41)
GAS	9.34 (6.39, 2.95)	10.09 (6.71, 3.38)	9.9 (6.59, 3.31)	9.78 (6.59, 3.19)	9.26 (6.41, 2.85)	9.5 (6.35, 3.15)	10.09 (6.50, 3.59)	10.06 (6.65, 3.41)	11.32 (7.08, 4.24)	10.65 (6.39, 4.25)	90.22 (59.08, 31.14)
WHEAT	9.35 (6.44, 2.91)	10.06 (6.71, 3.36)	9.85 (6.58, 3.27)	9.52 (6.41, 3.11)	9.48 (6.59, 2.89)	9.6 (6.43, 3.17)	10.11 (6.52, 3.59)	10.06 (6.64, 3.42)	11.3 (7.14, 4.16)	10.66 (6.46, 4.20)	90.52 (59.34, 31.18)
CORN	9.35 (6.32, 3.03)	10.14 (6.64, 3.50)	9.83 (6.47, 3.36)	9.49 (6.32, 3.17)	9.34 (6.38, 2.97)	9.78 (6.46, 3.32)	10.09 (6.40, 3.69)	10.08 (6.56, 3.52)	11.28 (6.99, 4.29)	10.62 (6.31, 4.31)	90.22 (58.38, 31.84)
GOLD	9.32 (6.38, 2.94)	10.05 (6.68, 3.37)	9.83 (6.55, 3.28)	9.56 (6.42, 3.14)	9.23 (6.36, 2.88)	9.47 (6.35, 3.12)	10.36 (6.69, 3.67)	10.11 (6.71, 3.40)	11.35 (7.09, 4.27)	10.71 (6.42, 4.29)	89.64 (58.95, 30.68)
SILVER	9.33 (6.38, 2.95)	10.12 (6.71, 3.40)	9.87 (6.58, 3.29)	9.43 (6.34, 3.09)	9.2 (6.33, 2.87)	9.56 (6.37, 3.19)	10.12 (6.54, 3.58)	10.31 (6.81, 3.50)	11.32 (7.04, 4.27)	10.75 (6.43, 4.32)	89.69 (58.73, 30.96)
MSCIW	9.26 (6.08, 3.18)	10.07 (6.42, 3.65)	9.86 (6.31, 3.55)	9.44 (6.07, 3.37)	9.2 (6.12, 3.08)	9.45 (6.12, 3.33)	10.07 (6.24, 3.83)	10.01 (6.36, 3.65)	11.63 (6.95, 4.68)	11.01 (6.30, 4.71)	88.37 (56.02, 32.35)
DJGI	9.26 (6.04, 3.22)	10.03 (6.33, 3.70)	9.82 (6.25, 3.57)	9.46 (6.05, 3.41)	9.2 (6.10, 3.11)	9.45 (6.06, 3.39)	10.05 (6.19, 3.86)	10 (6.31, 3.69)	11.66 (6.91, 4.75)	11.07 (6.28, 4.79)	88.93 (56.22, 32.71)
TO	83.72 (55.87, 27.85)	90.77 (60.23, 30.54)	88.63 (58.29, 30.35)	85.35 (56.52, 28.83)	83.08 (56.59, 26.49)	85.51 (56.52, 29.00)	90.83 (57.66, 33.18)	90.49 (58.87, 31.63)	102.28 (63.28, 39.01)	96.58 (57.38, 39.20)	897.26 (581.19, 316.07)
Inc.Own	93.49 (63.24, 30.25)	101.22 (66.20, 35.03)	98.73 (64.97, 33.76)	95.13 (63.11, 32.01)	92.57 (63.18, 29.38)	95.29 (62.98, 32.31)	101.2 (64.35, 36.85)	100.8 (65.68, 35.12)	113.91 (70.23, 43.69)	107.65 (63.65, 43.99)	TCI
Net	−6.51 (−8.88 , 2.38)	1.22 (9.01, −7.78)	−1.27 (−0.21, −1.06)	−4.87 (−2.56, −2.31)	−7.43 (−2.75, −4.69)	−4.71 (−1.87, −2.84)	1.2 (−1.29, 2.49)	0.8 (0.14, 0.66)	13.91 (7.26, 6.66)	7.65 (1.16, 6.49)	89.73 (58.12, 31.61)

Notes: The results are derived from a GFEVD with 100 steps ahead and a 504-day rolling-window QVAR model with a lag length of 6 (AIC). The values in parentheses represent the short-term and long-term frequency connectedness measures, respectively.

Table 4. Mid quantile averaged connectedness results (τ =0.50).

	GPRI	BDI	OIL	GAS	WHEAT	CORN	GOLD	SILVER	MSCIW	DJGI	FROM
GPRI	80.5 (78.87, 1.64)	1.63 (1.54, 0.10)	2.17 (2.10, 0.08)	2.36 (2.29, 0.07)	1.94 (1.87, 0.06)	1.9 (1.84, 0.06)	2.53 (2.47, 0.06)	2.6 (2.52, 0.08)	2.18 (2.08, 0.10)	2.19 (2.08, 0.11)	19.5 (18.79, 0.71)
BDI	1.4 (0.49, 0.91)	86.01 (22.79, 63.22)	1.51 (0.48, 1.03)	1.39 (0.43, 0.96)	1.23 (0.42, 0.81)	1.22 (0.40, 0.83)	1.58 (0.53, 1.05)	1.44 (0.48, 0.96)	2.06 (0.59, 1.47)	2.16 (0.55, 1.61)	13.99 (4.37, 9.62)
OIL	1.36 (1.19, 0.17)	1.35 (0.97, 0.38)	66.36 (55.62, 10.74)	5.17 (4.26, 0.91)	2.54 (2.08, 0.46)	2.94 (2.43, 0.50)	3.59 (2.98, 0.61)	4.19 (3.42, 0.77)	6.16 (4.96, 1.20)	6.33 (5.06, 1.28)	33.64 (27.36, 6.28)
GAS	1.94 (1.77, 0.17)	1.82 (1.20, 0.62)	6.37 (5.41, 0.96)	77.38 (62.90, 14.48)	1.86 (1.52, 0.34)	2.15 (1.65, 0.49)	2.24 (1.90, 0.34)	2.02 (1.63, 0.39)	2.11 (1.62, 0.49)	2.12 (1.59, 0.53)	22.62 (18.28, 4.34)
WHEAT	1.66 (1.49, 0.17)	1.61 (1.18, 0.43)	2.98 (2.55, 0.43)	1.75 (1.36, 0.38)	60.35 (49.75, 10.59)	21.93 (17.96, 3.97)	2.25 (1.92, 0.33)	2.6 (2.27, 0.32)	2.42 (1.93, 0.49)	2.47 (1.99, 0.48)	39.65 (32.65, 7.00)
CORN	1.55 (1.35, 0.21)	1.48 (0.98, 0.50)	3.28 (2.73, 0.54)	1.85 (1.43, 0.42)	21.84 (17.78, 4.06)	60.73 (48.63, 12.11)	2.4 (1.90, 0.50)	2.73 (2.25, 0.48)	2.06 (1.61, 0.45)	2.07 (1.65, 0.43)	39.27 (31.67, 7.59)
GOLD	1.01 (0.90, 0.11)	1.21 (0.78, 0.43)	3.03 (2.58, 0.45)	1.27 (1.03, 0.24)	1.69 (1.42, 0.27)	1.81 (1.47, 0.34)	56.55 (47.09, 9.46)	28.41 (23.57, 4.84)	2.43 (1.98, 0.45)	2.58 (2.07, 0.51)	43.45 (35.82, 7.63)
SILVER	1.02 (0.89, 0.12)	1.19 (0.75, 0.44)	3.37 (2.68, 0.69)	1.13 (0.92, 0.21)	2 (1.68, 0.32)	2.21 (1.72, 0.48)	27.86 (23.43, 4.43)	54.94 (45.63, 9.31)	2.98 (2.32, 0.67)	3.3 (2.51, 0.79)	45.06 (36.92, 8.14)
MSCIW	0.94 (0.79, 0.14)	1.14 (0.68, 0.46)	4.34 (3.30, 1.04)	1.07 (0.75, 0.32)	1.41 (1.12, 0.29)	1.46 (1.11, 0.35)	1.91 (1.52, 0.39)	2.51 (1.98, 0.53)	43.66 (33.66, 10.00)	41.57 (32.08, 9.49)	56.34 (43.33, 13.01)
DJGI	0.97 (0.83, 0.14)	1.15 (0.68, 0.48)	4.4 (3.28, 1.12)	1.1 (0.78, 0.31)	1.46 (1.15, 0.31)	1.52 (1.15, 0.37)	1.93 (1.52, 0.42)	2.67 (2.08, 0.59)	41.58 (31.33, 10.25)	43.22 (32.88, 10.34)	56.78 (42.80, 13.98)
TO	11.83 (9.70, 2.13)	12.59 (8.77, 3.83)	31.44 (25.12, 6.33)	17.07 (13.25, 3.82)	35.97 (29.06, 6.92)	37.14 (29.73, 7.41)	46.29 (38.17, 8.12)	49.17 (40.21, 8.97)	63.98 (48.42, 15.56)	64.8 (49.58, 15.23)	370.3 (292.00 , 78.31)
Inc.Own	92.34 (88.57, 3.77)	98.6 (31.55, 67.05)	97.81 (80.74, 17.07)	94.45 (76.15, 18.30)	96.32 (78.81, 17.51)	97.88 (78.36, 19.52)	102.84 (85.26, 17.58)	104.11 (85.84, 18.28)	107.64 (82.08, 25.56)	108.02 (82.46, 25.56)	TCI
Net	−7.66 (−9.09, 1.43)	−1.4 (4.40, −5.80)	−2.19 (−2.24, 0.05)	−5.55 (−5.03, −0.52)	−3.68 (−3.60, −0.09)	−2.12 (−1.94, −0.18)	2.84 (2.36, 0.49)	4.11 (3.29, 0.82)	7.64 (5.08, 2.55)	8.02 (6.78, 1.24)	37.03 (29.20, 7.83)

Notes: The results are derived from a GFEVD with 100 steps ahead and a 504-day rolling-window QVAR model with a lag length of 6 (AIC). The values in parentheses represent the short-term and long-term frequency connectedness measures, respectively.

Table 5. Upper quantile averaged connectedness results (τ =0.95).

	GPRI	BDI	OIL	GAS	WHEAT	CORN	GOLD	SILVER	MSCIW	DJGI	FROM
GPRI	10.7 (8.58, 2.12)	10.63 (7.79, 2.85)	9.31 (7.53, 1.77)	10.44 (8.04, 2.40)	10.41 (7.94, 2.46)	9.63 (7.67, 1.96)	9.82 (7.76, 2.06)	9.45 (7.31, 2.14)	9.94 (8.11, 1.83)	9.67 (7.82, 1.85)	89.3 (69.97, 19.33)
BDI	9.64 (5.40, 4.24)	12.21 (5.75, 6.47)	9.07 (5.22, 3.84)	10.46 (5.73, 4.73)	10.65 (5.67, 4.98)	9.59 (5.37, 4.23)	9.83 (5.41, 4.42)	9.84 (5.18, 4.66)	9.44 (5.67, 3.78)	9.26 (5.39, 3.86)	87.79 (49.03, 38.75)
OIL	9.78 (7.09, 2.69)	10.95 (7.22, 3.73)	9.87 (7.38, 2.49)	10.56 (7.46, 3.09)	10.49 (7.31, 3.18)	9.6 (7.02, 2.58)	9.86 (7.14, 2.72)	9.57 (6.72, 2.85)	9.79 (7.38, 2.40)	9.53 (7.09, 2.44)	90.13 (64.43, 25.70)
GAS	9.81 (6.81, 3.00)	10.99 (6.87, 4.12)	9.33 (6.65, 2.68)	11.15 (7.55, 3.60)	10.52 (7.00, 3.52)	9.59 (6.69, 2.89)	9.87 (6.77, 3.10)	9.58 (6.42, 3.16)	9.71 (7.05, 2.66)	9.45 (6.75, 2.71)	88.85 (61.02, 27.83)
WHEAT	9.78 (6.91, 2.87)	10.94 (6.96, 3.98)	9.23 (6.70, 2.53)	10.4 (7.13, 3.27)	11.11 (7.58, 3.53)	9.81 (6.98, 2.83)	9.84 (6.93, 2.91)	9.63 (6.58, 3.05)	9.76 (7.20, 2.56)	9.49 (6.88, 2.61)	88.89 (62.28, 26.61)
CORN	9.8 (6.95, 2.85)	10.9 (7.02, 3.88)	9.29 (6.78, 2.51)	10.43 (7.20, 3.23)	10.72 (7.30, 3.42)	10.27 (7.36, 2.91)	9.85 (6.94, 2.91)	9.57 (6.61, 2.96)	9.71 (7.22, 2.49)	9.45 (6.91, 2.54)	89.73 (62.94, 26.79)
GOLD	9.83 (7.02, 2.81)	10.9 (7.10, 3.80)	9.32 (6.82, 2.50)	10.41 (7.25, 3.16)	10.46 (7.18, 3.27)	9.62 (6.90, 2.72)	10.33 (7.30, 3.03)	9.8 (6.79, 3.01)	9.81 (7.31, 2.50)	9.53 (6.99, 2.54)	89.67 (63.35, 26.31)
SILVER	9.79 (6.95, 2.85)	10.93 (7.01, 3.92)	9.24 (6.75, 2.49)	10.41 (7.19, 3.21)	10.5 (7.17, 3.33)	9.61 (6.87, 2.74)	10.09 (7.16, 2.93)	10.13 (7.01, 3.12)	9.78 (7.27, 2.51)	9.52 (6.96, 2.56)	89.87 (63.33, 26.54)
MSCIW	9.78 (7.12, 2.66)	10.81 (7.20, 3.61)	9.25 (6.91, 2.34)	10.4 (7.38, 3.02)	10.43 (7.31, 3.12)	9.56 (7.02, 2.54)	9.8 (7.11, 2.69)	9.5 (6.75, 2.75)	10.43 (7.94, 2.49)	10.03 (7.53, 2.50)	89.57 (64.33, 25.24)
DJGI	9.78 (7.13, 2.65)	10.8 (7.21, 3.60)	9.26 (6.92, 2.34)	10.4 (7.39, 3.01)	10.46 (7.36, 3.10)	9.61 (7.05, 2.56)	9.81 (7.16, 2.66)	9.51 (6.77, 2.74)	10.3 (7.84, 2.45)	10.07 (7.58, 2.49)	89.93 (64.81, 25.12)
TO	88 (61.38, 26.62)	97.86 (64.38, 33.49)	83.29 (60.28, 23.02)	93.9 (64.77, 29.13)	94.63 (64.23, 30.40)	86.62 (61.56, 25.06)	88.77 (62.38, 26.39)	86.46 (59.13, 27.33)	88.25 (65.06, 23.18)	85.92 (62.32, 23.60)	893.72 (625.50, 268.22)
Inc.Own	98.7 (69.96, 28.74)	110.08 (70.12, 39.95)	93.17 (67.66, 25.50)	105.05 (72.32, 32.73)	105.75 (71.82, 33.93)	96.89 (68.92, 27.97)	99.1 (69.68, 29.42)	96.59 (66.14, 30.45)	98.68 (73.01, 25.67)	95.99 (69.90, 26.09)	TCI
Net	−1.3 (−8.59, 7.29)	10.08 (15.34, −5.26)	−6.83 (−4.15, −2.69)	5.05 (3.75, 1.30)	5.75 (1.96, 3.79)	−3.11 (−1.39, −1.72)	−0.9 (−0.97, 0.08)	−3.41 (−4.19, 0.78)	−1.32 (0.73, −2.05)	−4.01 (−2.49, −1.52)	89.37 (62.55, 26.82)

Notes: The results are derived from a GFEVD with 100 steps ahead and a 504-day rolling-window QVAR model with a lag length of 6 (AIC). The values in parentheses represent the short-term and long-term frequency connectedness measures, respectively.

To better understand the shock transmission mechanism, the results are illustrated in Figure 3 using a network connectedness plot. Based on the plot, MSCIW is identified as the main transmitter of shocks, indicating its significant role in influencing other assets. Moreover, WHEAT is shown to be the major receiver of shocks, suggesting its vulnerability to external influences. Furthermore, when examining the results in terms of short-term and long-term frequencies, it is observed that the short term GPRI appears as the main receiver of shocks. This implies that GPRI is more responsive to immediate changes and fluctuations within the network. Moreover, this result implies that when GPR suddenly rise or fall, GPRI suffers a significant impact and becomes more vulnerable to external shocks. The GPRI's response to the short-term dynamics can be attributed to the fact that geopolitical events and risks frequently have immediate consequences on various aspects of the global economy and financial markets.

The results of the mid-quantile are presented in Table 4. The TCI value indicates a 37.03% connectedness within the network, with 29.20% attributed to the short-term and 7.83% to the long-term, suggesting a lower level of dependency in the network under normal market conditions. Moreover, the result shows that BDI has the highest own variance shock of 86%, with 22.79% in the short term and 63.22% in the long term. The NET row result shows that GPRI (−7.66%) is the main receiver of shocks and DJGI (8.02%) is the main transmitter of shocks. The result of the network connectedness plot in Figure 4 of the quantile shows similar results. The figures show DJGI and MSCIW are the major transmitters of shocks, and most of the shocks are transmitted towards BDI, CORN, WHEAT, GAS, and OIL. In the short term, GPRI is the main receiver of shocks, which is similar to our lower quantile findings. Interestingly, in the long term, the GPRI primarily transmits significant shocks towards the BDI, and other financial markets such as stocks, energy, and commodity markets also transmit shocks towards the BDI, revealing noteworthy dynamics within the network.

Table 5 displays the findings of the upper quantile. The TCI value indicates 89.37% connectedness within the network, with 62.55% attributed to the short term and 26.82% to the long term. This suggests that there is a considerable level of dependency in the network under extreme upward market conditions. Additionally, the results show that BDI has the highest own variance shock of 12.21%, with 5.75% occurring in the short-term and 6.47% in the long-term. In terms of net directional spillover, OIL (−6.83%) is identified as the main receiver of shocks, and BDI (10.08%) is the main transmitter of shocks. The network connectedness plot in Figure 5, representing the upper quantile result, also supports these findings. The plot illustrates that BDI, GAS, and WHEAT are the major transmitters of shocks within the network, with a significant portion of these shocks being transmitted towards OIL, GPRI, and MSCIW. In the short term, GPRI continues to be the main receiver of shocks, which is consistent with the findings from the lower and mid-quantile analyses. This observation implies that rising food and energy prices are linked to increased GPR. Geopolitical events and risks, particularly those related to food and energy, can have a significant impact on commodity markets. Conflicts or disruptions in major oil-producing regions, for example, can disrupt global oil supply, leading to price increases. Similarly, geopolitical tensions can impact agricultural commodity production, distribution, and trade, resulting in higher food prices. The transmission of shocks from OIL, WHEAT, and CORN to GPRI indicates that these commodities are geopolitically sensitive. Supply disruptions, trade barriers, political instability in key producing regions, and geopolitical factors influencing market sentiment and investor behavior can be attributed to this sensitivity. Interestingly, GPRI is the main transmitter of shocks in the long term, revealing important dynamics between GPR and the stock, energy, and commodity markets. When the GPRI rises, it indicates an increased level of GPR, which has a long-term impact on these markets. This suggests that changes in geopolitical conditions can have long-term consequences for investor sentiment, market behavior, and stock, energy, and commodity pricing. GRPs create uncertainty and destabilize market conditions by affecting global supply chains, trade relationships, and investor confidence. The long-term impact of GPRI on these markets suggests that GPR are not only transient but can have long-term consequences. These findings are consistent with earlier studies (Nerlinger & Utz, 2022; Salisu et al., 2022; Z. Umar et al., 2023), which demonstrate the adverse effect of geopolitical tension on different financial markets.

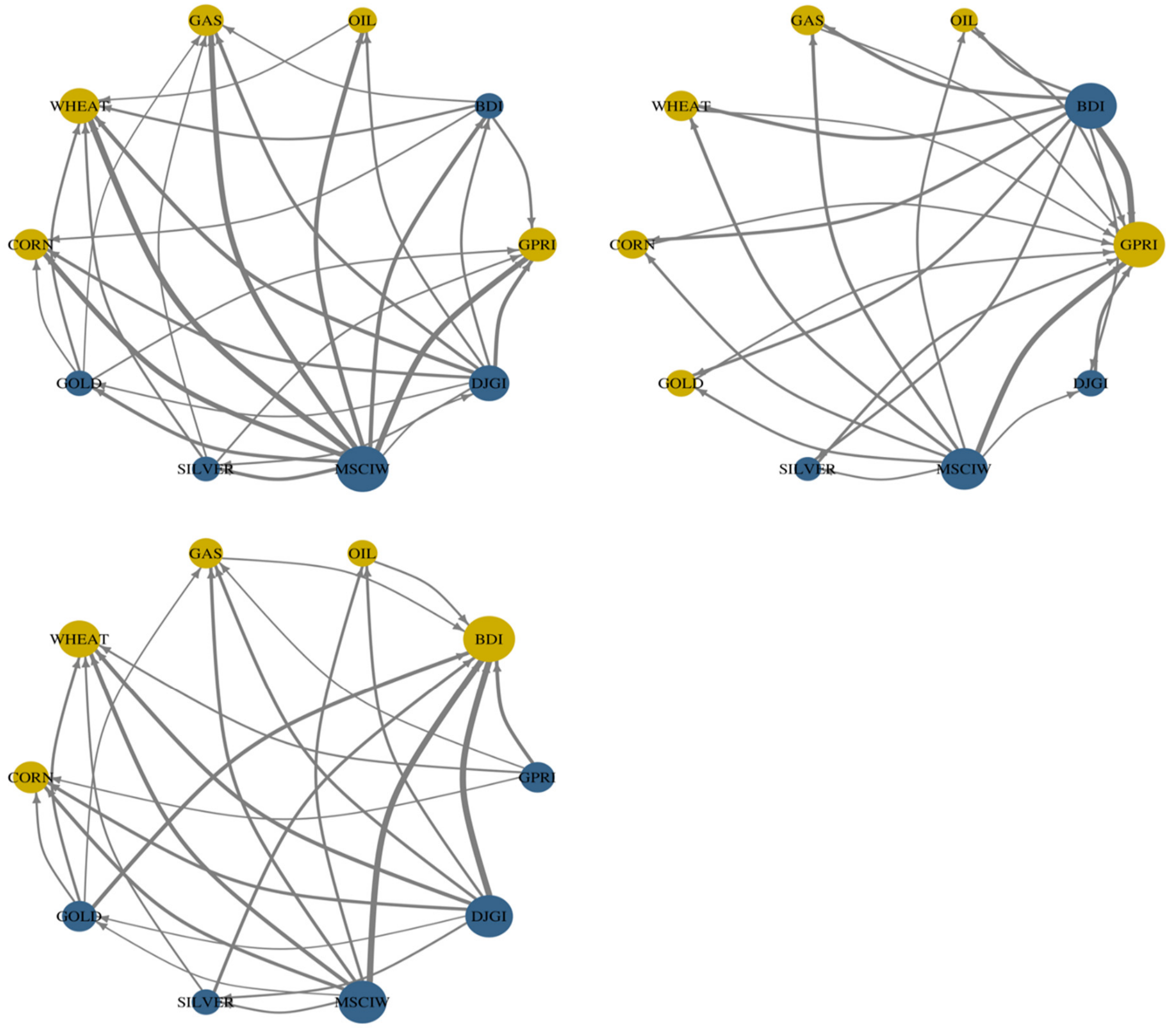

Figure 3. Lower quantile network plot (τ =0.05),

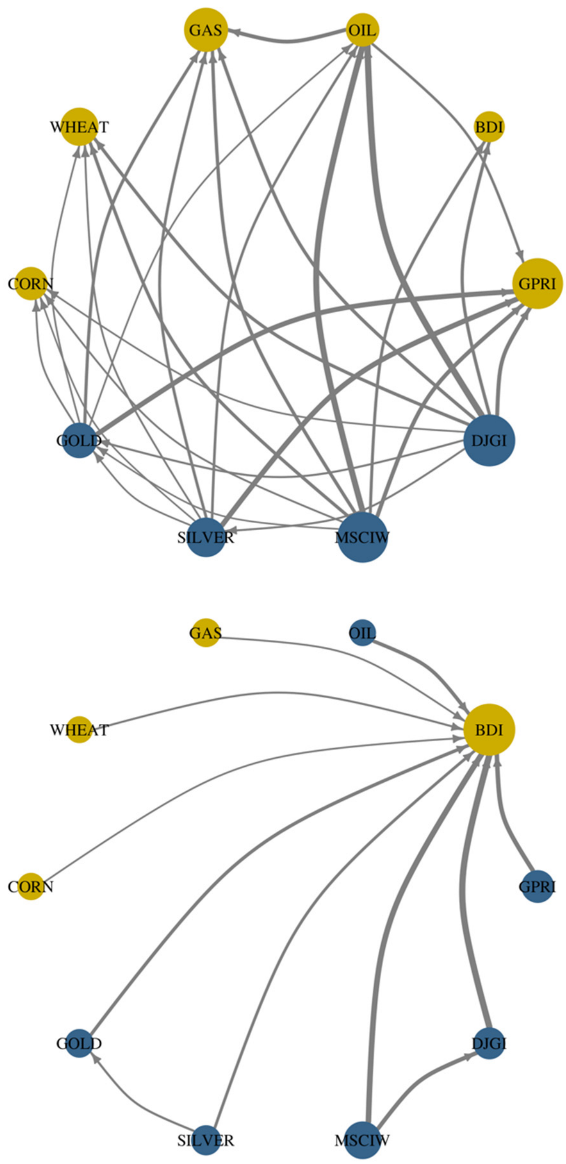

Figure 4. Mid quantile network plot (τ =0.50).

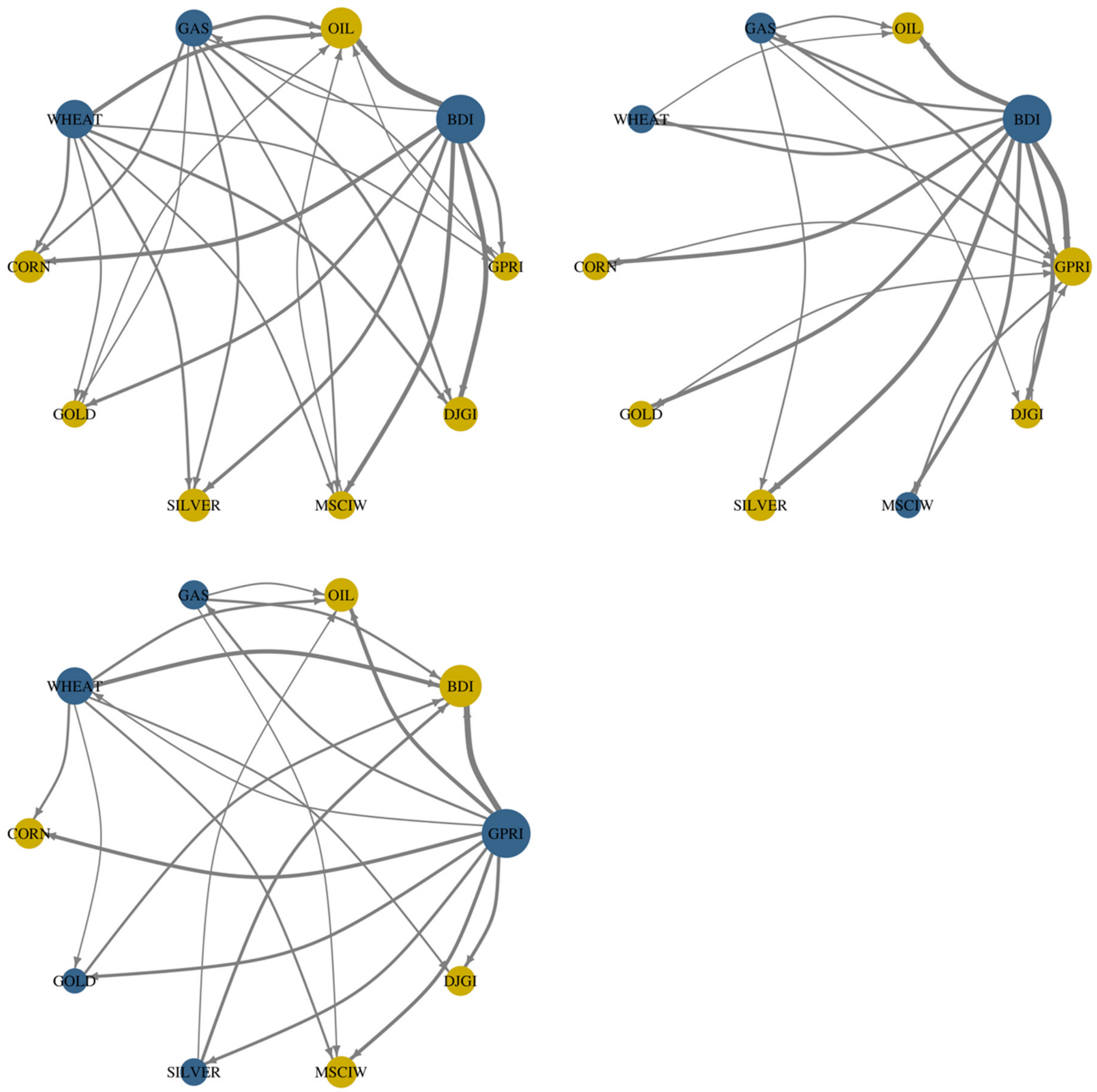

Figure 5. Upper quantile network plot (τ =0.95).

4.2.2. Dynamic analysis results

The previous analysis is static and does not capture the time-varying spillover effects. To address this, we turn to dynamic connectedness, which accounts for the changing nature of spillover across GPR, stock, commodity, and energy markets. Figure 6 presents both static and dynamic total connectedness indices across quantiles. The static results show that the mid-quantile connectedness is lower than in the extreme quantiles, highlighting the greater impact of extreme market conditions. Similarly, the dynamic connectedness reveals that short-term spillovers are higher than long-term ones. This implies that market participants react faster to new information and short-term fluctuations, resulting in greater short-term spillover effects. This implies that changes in GPRI have an immediate impact on market dynamics, which are influenced by factors like market sentiment and investor reactions. The lower long-term spillover, on the other hand, indicates that the effects of market shocks and events gradually fade over time. Market participants gradually adjust their strategies and incorporate new information, lowering the long-term impact of previous events on market interconnectedness. Long-term spillover effects are shaped by factors such as structural changes, policy adjustments, and long-term trends. Understanding the dynamics of both short-term and long-term spillovers is critical for determining the timing and duration of market effects caused by GPRI.

The dynamic TCI also shows an upsurge in spillover during different economic events such as the Asian and Russian Financial Crisis, Nine-elven, Gulf War II, Global Financial Crisis, European debt crisis, COVID-19, and Russia-Ukraine war (Alam et al., 2023). During these economic events, the transmission of shocks between GPR, stock, commodity, and energy markets increases. This suggests that during times of increased economic uncertainty and instability, the interconnectedness between these markets becomes more pronounced and impactful. These events frequently have far-reaching consequences, disrupting global financial systems, influencing market sentiment, and increasing volatility and interconnectedness among market segments. During these significant economic events, the dynamic TCI analysis provides empirical evidence of increased spillover effects. This result is consistent with a study by Smales (2021), who also documented a similar dynamic nature of TCI for oil and GPR.

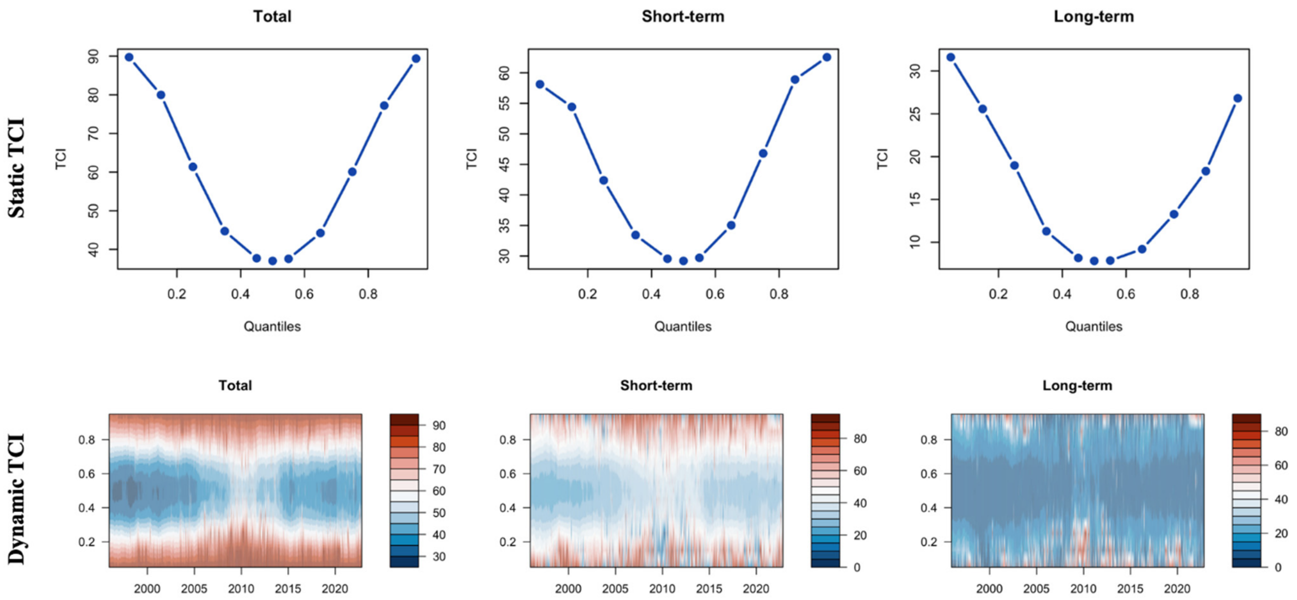

Figure 6. Static and dynamic total connectedness index across quantiles. Notes: The results are derived from a GFEVD with 100 steps ahead and a 504-day rolling-window QVAR model with a lag length of 6 (AIC).

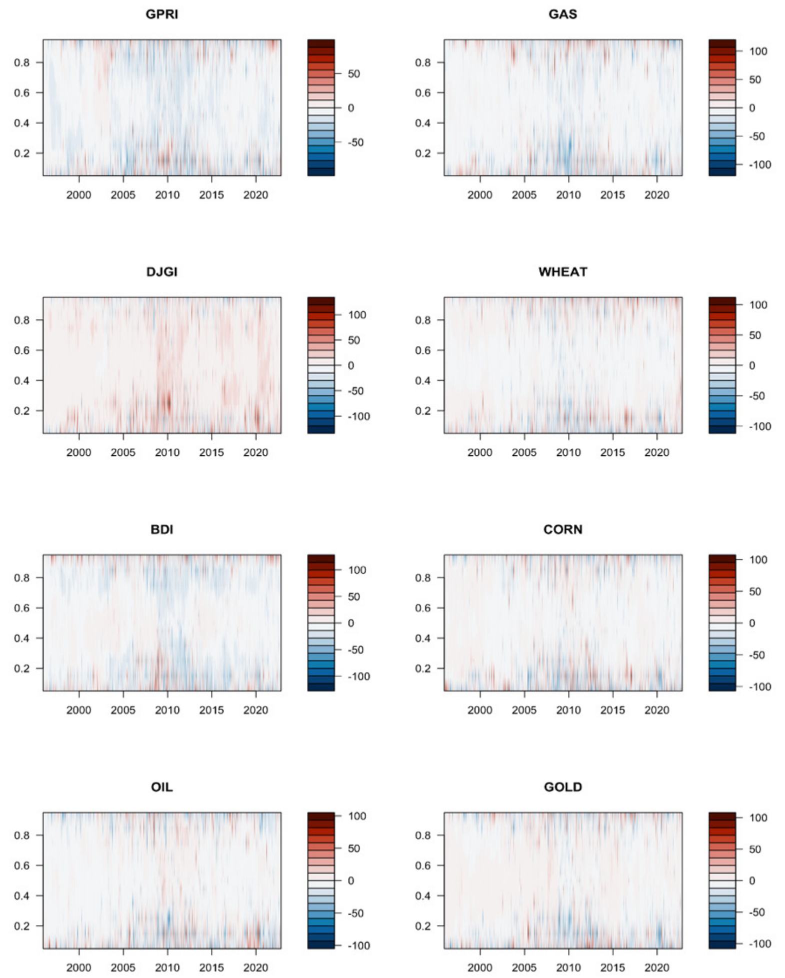

Figure 7. Net total directional connectedness across quantiles (Total). Notes: The results are derived from a GFEVD with 100 steps ahead and a 504-day rolling-window QVAR model with a lag length of 6 (AIC).

Figures 7, S.8, and S.9 illustrate the net directional connectedness of the total, short-term, and long-term results. The positive values (shown in red) in the figures indicate the transmitter of shocks, whereas the negative values (shown in blue) indicate the receiver of shocks. The results show interesting dynamics in the GPRI spillover patterns in both the short and long term. GPRI consistently acts as a receiver of shocks in the mid-quantiles in the short term. This means that under normal market conditions, GPRI is more sensitive to shocks caused by other variables in the network. However, there are times when GPRI acts as a shock transmitter during specific economic events. This implies that during these events, GPRI becomes a source of spillover and influences other network variables. In contrast, GPRI tends to be a shock transmitter across extreme quantiles in the long run. This suggests that, over a longer time horizon, changes in GPRI have a long-term impact on other network variables. The GPRI's enduring influence suggests that GPR has long-term implications for the interconnectedness of the stock, commodity, and energy markets. These findings emphasize the importance of taking the time dimension into account when examining the role of GPRI and its impact on market dynamics. The contrasting behavior of GPRI as a receiver and a transmitter in the short and long term highlights the complexities of spillover effects and their underlying drivers. Short-term market reactions to specific events or changes in market sentiment may influence short-term dynamics, whereas long-term dynamics may be influenced by structural factors, long-term trends, or policy developments that shape the overall risk environment.

5. Policy implications

Our findings have significant policy implications for a variety of stakeholders, including policymakers, regulators, and risk managers. To begin, policymakers must acknowledge the significant impact of GPR on market interconnectedness and risk transmission. This emphasizes the importance of closely monitoring geopolitical developments and the potential consequences for stock, commodity, and energy markets. Policymakers can develop proactive measures to mitigate risks and maintain market stability by understanding the dynamic nature of these effects. They can also consider incorporating GPR factors into their policy decisions and risk management frameworks.

Second, regulators can use our findings to improve their risk assessment and monitoring frameworks. Regulators can identify potential systemic risks and develop appropriate regulatory measures by recognizing the interconnectedness of GPR and other markets. This can include implementing stress testing methodologies that take into account shock transmission across market segments as well as the impact of geopolitical events. The findings emphasize the importance of incorporating GPR into risk management strategies for risk managers. Risk managers can better assess and manage the potential impacts of geopolitical events on their portfolios by understanding the short-term and long-term spillover patterns. This may entail diversifying investments, implementing hedging strategies, and assessing exposure to GPR factors on a regular basis.

6. Conclusions

This study reveals the complex risk transmission and spillover between GPR, stock, energy, food, and precious metals using the CEEMDAN -VL transfer entropy and TF-QVAR-based connectedness approach. The results of transfer entropy show that different assets are influenced by GPRI in different ways during various events. Wheat and corn are sensitive to GPRI in the short term, while Silver is highly reactive to GPRI overall. The food, energy, and stock markets are significantly impacted by GPRI during events like Gulf War II, the Global Financial Crisis, and the COVID-19 pandemic. However, some events, such as 9/11 and the European Debt Crisis, showed no immediate effect of GPRI. The stock market is the strongest receiver of GPRI in the long term, and most assets play a role in transmitting risk to GPRI across events. The static analysis of TF-QVAR reveals that in the lower and mid-quantile stocks, energy commodities and agricultural commodities tend to transmit shocks to GPR. On the other hand, in the upper quantile, GPR transmits shocks to other markets. In the dynamic TF-QVAR results, it is observed that in the short term, the GPRI tends to act as a receiver of shocks; however, it acts as a transmitter in the long term. This suggests that the relationship between shocks and GPRI is dynamic, with GPRI playing different roles depending on the time horizon.

While we uncover the transmission and spillover effects between GPR and the stock, energy, food, and precious metals markets, our study has limitations. Specifically, we do not explore the transmission mechanisms for digital assets such as cryptocurrencies and NFTs. Researchers could address this gap by examining how GPR impact these emerging asset classes, providing a more comprehensive understanding of GPR's influence across a broader spectrum of financial markets.

Author contributions

Mohammad Ashraful Ferdous Chowdhury: supervision, methodology, project administration, writing - original draft; M. Kabir Hassan: conceptualization, data curation, validation, writing - original draft; Mohammad Abdullah: formal analysis, investigation, software, visualization, writing - original draft.; Md Mofazzal Hossain: conceptualization, data curation, validation, writing - original draft.

Use of AI tools declaration

The authors declare they have not used Artificial Intelligence (AI) tools in the creation of this article.

Acknowledgments

Authors received no funding for the preparation and publication of this paper.

Conflict of interest

All authors declare no conflicts of interest in this paper.

References

Ahmed S, Hasan MM, Kamal MR (2023) Russia–Ukraine crisis: The effects on the European stock market. *Eur Financ Manag* 29: 1078–1118. https://doi.org/10.1111/eufm.12386

Alam M, Chowdhury MAF, Abdullah M, et al. (2023) Volatility spillover and connectedness among REITs, NFTs, cryptocurrencies and other assets: Portfolio implications. *Invest Anal J* 52: 83–105 https://doi.org/10.1080/10293523.2023.2179161

Amornbunchornvej C, Zheleva E, Berger-Wolf T (2021) Variable-Lag Granger Causality and Transfer Entropy for Time Series Analysis. *ACM Trans Knowl Discov Data* 15: 1–30. https://doi.org/10.1145/3441452

Asadollah O, Carmy LS, Hoque MR, et al. (2024) Geopolitical risk, supply chains, and global inflation. *World Econ* 47: 3450–3486. https://doi.org/10.1111/TWEC.13585

Bougias A, Episcopos A, Leledakis GN (2022) Valuation of European firms during the Russia–Ukraine war. *Econ Lett* 218: 110750. https://doi.org/10.1016/j.econlet.2022.110750

Boungou W, Yatié A (2022) The impact of the Ukraine–Russia war on world stock market returns. *Econ Lett* 215: 110516. https://doi.org/10.1016/j.econlet.2022.110516

Caldara D, Iacoviello M (2022) Measuring Geopolitical Risk. *Am Econ Rev* 112: 1194–1225. https://doi.org/10.1257/aer.20191823

Chatziantoniou I, Abakah EJA, Gabauer D, et al. (2022) Quantile time–frequency price connectedness between green bond, green equity, sustainable investments and clean energy markets. *J Clean Prod* 361: 132088. https://doi.org/10.1016/j.jclepro.2022.132088

Chen Y, Pantelous AA (2022) The U.S.-China trade conflict impacts on the Chinese and U.S. stock markets: A network-based approach. *Fin Res Lett* 46: 102486. https://doi.org/10.1016/j.frl.2021.102486

Chowdhury MAF, Meo MS, Aloui C (2021) How world uncertainties and global pandemics destabilized food, energy and stock markets? Fresh evidence from quantile on quantile regressions. *Int Rev Finac Anal* 76: 101759. https://doi.org/10.1016/j.irfa.2021.101759

Coskun M, Khan N, Saleem A, et al. (2023) Spillover connectedness nexus geopolitical oil price risk, clean energy stocks, global stock, and commodity markets. *J Clean Prod* 429: 139583. https://doi.org/10.1016/J.JCLEPRO.2023.139583

Dahl RE, Oglend A, Yahya M (2020) Dynamics of volatility spillover in commodity markets: Linking crude oil to agriculture. *J Commod Mark* 20: 100111. https://doi.org/10.1016/j.jcomm.2019.100111

Das BC, Hasan F, Sutradhar SR, et al. (2023) Ukraine–Russia Conflict and Stock Markets Reactions in Europe. *Glob J Flex Syst Manag* 24: 395–407. https://doi.org/10.1007/s40171-023-00345-0

Dhifaoui Z, Khalfaoui R, Abedin MZ, et al. (2022) Quantifying information transfer among clean energy, carbon, oil, and precious metals: A novel transfer entropy-based approach. *Fin Res Lett* 49: 103138. https://doi.org/10.1016/j.frl.2022.103138

Diebold FX, Yilmaz K (2012) Better to give than to receive: Predictive directional measurement of volatility spillovers. *Int J Forecast* 28: 57–66. https://doi.org/10.1016/J.IJFORECAST.2011.02.006

Diebold FX, Yilmaz K (2014) On the network topology of variance decompositions: Measuring the connectedness of financial firms. *J Econom* 182: 119–134. https://doi.org/10.1016/j.jeconom.2014.04.012

Evrim Mandaci P, Azimli A, Mandaci N (2023) The impact of geopolitical risks on connectedness among natural resource commodities: A quantile vector autoregressive approach. *Resour Policy* 85: 103957. https://doi.org/10.1016/j.resourpol.2023.103957

Fama EF (1970) Efficient Capital Markets: A Review of Theory and Empirical Work. *J Financ* 25: 383–417. https://doi.org/10.2307/2325486

Gaio LE, Stefanelli NO, Pimenta T, et al. (2022) The impact of the Russia-Ukraine conflict on market efficiency: Evidence for the developed stock market. *Fin Res Lett* 50: 103302. https://doi.org/10.1016/j.frl.2022.103302

Gong X, Xu J (2022) Geopolitical risk and dynamic connectedness between commodity markets. *Energy Econ* 110: 106028. https://doi.org/10.1016/j.eneco.2022.106028

Hasan F, Al-Okaily M, Choudhury T, et al. (2024) A comparative analysis between FinTech and traditional stock markets: using Russia and Ukraine war data. *J Electron Commer Res* 24: 629–654. https://doi.org/10.1007/s10660-023-09734-0

Just M, Echaust K (2022) Dynamic spillover transmission in agricultural commodity markets: What has changed after the COVID-19 threat? *Econ Lett* 217: 110671. https://doi.org/10.1016/j.econlet.2022.110671

Nerlinger M, Utz S (2022) The impact of the Russia-Ukraine conflict on energy firms: A capital market perspective. *Fin Res Lett* 50: 103243. https://doi.org/10.1016/j.frl.2022.103243

Nicola M, Alsafi Z, Sohrabi C, et al. (2020) The socio-economic implications of the coronavirus pandemic (COVID-19): A review. *Int J Surg* 78: 185–193. https://doi.org/10.1016/J.IJSU.2020.04.018

Qin Y, Hong K, Chen J, et al. (2020) Asymmetric effects of geopolitical risks on energy returns and volatility under different market conditions. *Energy Econ* 90: 104851. https://doi.org/10.1016/j.eneco.2020.104851

Salisu AA, Lasisi L, Tchankam JP (2022) Historical geopolitical risk and the behaviour of stock returns in advanced economies. *Eur J Fin* 28: 889–906. https://doi.org/10.1080/1351847X.2021.1968467

Smales LA (2021) Geopolitical risk and volatility spillovers in oil and stock markets. *Q Rev Econ Financ* 80: 358–366. https://doi.org/10.1016/j.qref.2021.03.008

Torres ME, Colominas MA, Schlotthauer G, et al. (2011) A complete ensemble empirical mode decomposition with adaptive noise, *2011 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, 4144–4147. https://doi.org/10.1109/ICASSP.2011.5947265

Umar M, Riaz Y, Yousaf I (2022) Impact of Russian-Ukraine war on clean energy, conventional energy, and metal markets: Evidence from event study approach. *Resour Policy* 79: 102966. https://doi.org/10.1016/j.resourpol.2022.102966

Umar Z, Bossman A, Choi SY, et al. (2023) Information flow dynamics between geopolitical risk and major asset returns. *PLoS One* 18: e0294959. https://doi.org/10.1371/journal.pone.0284811

Wang X (2022) Efficient markets are more connected: An entropy-based analysis of the energy, industrial metal and financial markets. *Energy Econ* 111: 106067. https://doi.org/10.1016/j.eneco.2022.106067

Wang Y, Bouri E, Fareed Z, et al. (2022) Geopolitical risk and the systemic risk in the commodity markets under the war in Ukraine. *Fin Res Lett* 49: 103066. https://doi.org/10.1016/j.frl.2022.103066

Wang Z, Dong Z (2024) Volatility spillover effects among geopolitical risks and international and Chinese crude oil markets--A study utilizing time-varying networks. *Resour Policy* 96: 105225. https://doi.org/10.1016/j.resourpol.2024.105225

Yilmazkuday H (2024) Geopolitical risk and stock prices. *Eur J Political Econ* 83: 102553. https://doi.org/10.1016/J.EJPOLECO.2024.102553

Yousaf I, Patel R, Yarovaya L (2022) The reaction of G20+ stock markets to the Russia–Ukraine conflict "black-swan" event: Evidence from event study approach. *J Behav Exp Financ* 35: 100723. https://doi.org/10.1016/j.jbef.2022.100723

Zhang Z, Bouri E, Klein T, et al. (2022) Geopolitical risk and the returns and volatility of global defense companies: A new race to arms? *Int Rev Finac Anal* 83: 102327. https://doi.org/10.1016/j.irfa.2022.102327