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The risk transmission mechanism between Geopolitical risks and the international agricultural product market: an analysis based on the cross-quantilogram and TVP-VAR-BK Models

Xinghan Ren[1✉], Tianning Wang[2], Zekai Liu[3] & Haoqi Xu[4,5]

Geopolitical risk (GPR) is a critical volatility driver in agricultural futures markets. This paper innovatively integrates the cross-quantilogram approach and TVP-VAR-BK model to construct a two-dimensional framework of "extreme shock - systematic transmission" and use daily data from January 2001 to July 2024 for analysis. Results demonstrate asymmetric responses: grains show immediate sensitivity driven by financialization, while energy-intensive commodities exhibit lagged cost-transmission effects. Core crops (corn, wheat) function as systemic risk transmitters, contrasting with vulnerable receivers. Risk spillovers concentrate predominantly in ultra-short horizons, with crises triggering connectedness surges where GPR transitions to a net receiver. Findings advocate hierarchical mitigation strategies through differentiated reserves and international coordination mechanisms.

[1] Xi'an Jiaotong-Liverpool University, Suzhou, China. [2] Hohai University, Nanjing, China. [3] Fuzhou University, Fuzhou, China. [4] London School of Economics and Political Science, London, UK. [5] University of Liverpool, Liverpool, UK. ✉email: 1542683383@qq.com

Introduction

Since the turn of the millennium, although the world has largely maintained a peaceful and stable environment, major geopolitical events have occurred frequently. These include inter-state conflicts (such as the ongoing Russo-Ukrainian War and Israeli-Palestinian conflict) and internal political crises (the Syrian civil war). These events have not only intensified international geopolitical risks but also exerted extensive and profound impacts globally. Geopolitical risk refers to risks related to events such as wars, terrorist acts, and political tensions that affect the normal peaceful progress of international relations (Gong and Xu, 2022). The sharp rise in geopolitical risks in recent years presents new opportunities to study their impacts on international markets. Existing research has primarily focused on the effects of geopolitical risks on energy markets (Jin et al., 2023), commodity markets (Gong and Xu, 2022), and agricultural markets (Hudecová and Rajčániová, 2023; Jana and Ghosh, 2023), revealing clear spillover effects of such risks.

Food security, as a fundamental issue for human survival, still faces a severe and complex situation (Dai et al., 2023). Volatility in the international agricultural market is not only subject to demand-side shocks (Elleby et al., 2020), but is also related to competition for natural resources, the homogeneity of input costs, and the substitution effects (Hudecová and Rajčániová, 2023). Furthermore, fluctuations in the international energy market can also lead to risks spilling over into the international agricultural market; the two interact and influence each other (Tiwari et al., 2022). Geopolitical risk shocks are also significant driving factors for volatility and turmoil in the international agricultural market. In recent years, geopolitical tensions have become increasingly frequent, especially those occurring in regions abundant in agricultural resources, which have exerted significant impacts on the international agricultural market. This impact is mainly manifested in price fluctuations (Hudecová and Rajčániová, 2023) and has chain reaction effects that rapidly transmit to other agricultural products (Yuan et al., 2020). Therefore, the connection between the volatility spillover effects and the information transmission mechanisms among international agricultural market prices has become more complex and requires further exploration. Meanwhile, fluctuations in international grain prices also cause social concern. Taking the Russia–Ukraine conflict as an example, Russia and Ukraine, being among the world's most important grain exporters – after the conflict started, the price of wheat surged rapidly from USD 281 per tonne in early February 2022 to USD 490 per tonne in early March 2022. This led to a steep increase in the cost of living in countries reliant on wheat imports and threatened the security of every consumer (Polat et al., 2023a). In this case, geopolitical risks impact agricultural markets through three key mechanisms: supply chain disruptions, cost transmission, and policy interventions (Polat et al., 2023a; Jin et al., 2023). Other economies have also provided compelling anecdotal evidence across different time periods. For instance, during the COVID-19 pandemic in 2020, panic buying of staple foods in multiple countries drove wheat futures volatility to surge by 58% (Mead et al., 2020). Similarly, the Arab Spring period saw wheat prices skyrocket by 96%, reflecting heightened social instability risks across the Middle East (Lagi, Bertrand and Bar-Yam, 2011). Therefore, the research motivation of this paper includes both concerns about the current escalation of international geopolitical risks and the future international political landscape, as well as concerns about the uncertain situation of the international agricultural market and the complex state of food security.

The research objectives of this paper are as follows: on the one hand, to reveal the asymmetric effects of geopolitical risks on different agricultural products; on the other hand, by exploring the risk spillovers existing between international geopolitical risks and the international agricultural market, to investigate the time-varying characteristics of risk transmission, to identify the dynamic impacts of critical events (such as wars, pandemics) on market linkage, and ultimately to provide risk early warnings and management recommendations for market participants and policymakers.

Based on this, this paper combines the cross-quantilogram method with the TVP-VAR-BK model, using daily data of the GPR index and futures prices of eight major international agricultural commodities from January 2000 to July 2024 as data sources, to systematically analyze the extreme shock effects of geopolitical risks on international agricultural markets and their risk spillover relationships, while examining their asymmetric interactions.The main contributions of this paper to the existing research field are as follows: 1. Compared to analyzing the risk spillover from the stock market to the agricultural market from a traditional perspective (Hernandez et al., 2021) or analyzing the risk spillover between the energy market and the agricultural market (Tiwari et al., 2022), this paper innovatively incorporates geopolitical risks into a systematic analytical framework for different types of agricultural product markets, revealing the asymmetric impact between different types of agricultural product markets and geopolitical risks.2. Compared to focusing on major geopolitical events in recent years, such as using the COVID-19 pandemic and the Russia-Ukraine war as research entry points (Hudecová and Rajčániová, 2023), this article takes the turn of the millennium as its starting point, conducting a data collection spanning twenty-four years. Through the analysis of representative periods with significant fluctuations in geopolitical risks, it aims to reveal the long-term changing trends in the relationship between the agricultural market and geopolitical risks, providing a more comprehensive perspective for research.3.Compared to analyzing agricultural products traded by a specific region experiencing a geopolitical risk outbreak (such as Russia and Ukraine) as a sample (Hudecová and Rajčániová, 2023), this paper selects more representative food crops (corn, wheat, soybeans, rice) and cash crops (cotton, sugar, cocoa beans, coffee beans) produced and consumed across eight regions spanning the globe as analysis objects. Consequently, it comprehensively, at multiple levels, and in a multi-dimensional manner examines the uniqueness of risk transmission.4.To assess high-frequency time series, we adopted a complex research framework including CQ and TVP-VAR-BK. These methods are robust to abnormal distributions and extreme values in high-frequency and long time series (Chatziantoniou et al., 2023; Gainetdinova et al., 2024), thereby enabling us, from the analytical perspective of asymmetry and time-varying dynamics, to comprehensively, at multiple levels, and in a multi-dimensional manner examine the uniqueness of risk transmission.

Literature review

Tuathail proposed the concept of geopolitics, primarily focusing on the long-term competition among imperialist powers, territorial expansion, and military strategy to explain the causal relationship between geography and international affairs (Gong and Xu, 2022). Geopolitical risk originates from international hostile actions, threats of war, armed conflicts, and terrorist activities (Lee and Lee, 2020). These factors not only affect political stability but also play a significant role in the economic sphere, especially in today's globalized world (Suárez-de Vivero & Rodríguez Mateos, 2017). Specifically, geopolitical risk is closely related to asset prices, financial market returns, market volatility, particularly in politically sensitive markets like oil, government investment and corporate debt costs, investor sentiment, and trading decisions (Gong and Xu, 2022). Geopolitical risk also exerts important influences on commodity market linkages (Gong and Xu, 2022). For example, the Russia-Ukraine war, as one of the most significant geopolitical events of the 21st century, has led to a notable increase in geopolitical risk since its outbreak, thereby triggering turbulence in the global economy and markets (Hudecová and Rajčániová, 2023).

In recent years, the frequent occurrence of geopolitical events has had a significant impact on international commodity markets, a phenomenon that has garnered widespread attention in academia. The outbreak of geopolitical risks, especially the violent fluctuations in the prices of key commodities such as energy, minerals, and agricultural products, has become a phenomenon that cannot be ignored (Fang and Shao, 2022). Existing literature generally confirms that geopolitical risk has a significant net transmission effect on energy markets (Jin et al., 2023). Taking the Russia–Ukraine war as an example, due to Russia's important position in global energy supply, the outbreak of the war has caused huge shocks to energy markets such as crude oil and natural gas (Jin et al., 2023). Su et al. point out that the existence of geopolitical events indeed affects crude oil prices (Su et al., 2021). For decades, crude oil, as one of the most critical commodities in the global economy, its price fluctuations have profound impacts on the global economy (Cunado et al., 2020a). The spillover effects of geopolitical risk on the volatility of raw material prices are equally noteworthy. Taking the metal market as an example, under normal circumstances, volatility spillovers among industrial metals are higher than among precious metals, but against the backdrop of geopolitical threats, the volatility spillover effects of precious metals often exceed those of industrial metals (Liu et al., 2021). The agricultural market has not been immune to the influence of geopolitical risks. Hudecová and Rajčániová explored the link between geopolitical risk, exemplified by the Russia–Ukraine war, and the prices of corn, cotton, lumber, milk, oats, rough rice, and soybeans (Hudecová and Rajčániová, 2023). Research by Micallef et al. also indicates that geopolitical risk has a significant impact on the future prices of agricultural products such as soybean oil, wheat, coffee, and oats (Micallef et al., 2023). The fundamental objectives of the aforementioned studies are largely consistent, namely the impact of geopolitical risk on commodity markets, but their specific focuses differ to some extent. Correspondingly, the phenomena these studies attempt to reveal also differ. Although existing literature has explored the impact of geopolitical risk on international commodity markets to a certain extent, research on agricultural markets remains relatively limited. Most studies focus on the impact of geopolitical conflicts in a single region or over a short time span on the price volatility of specific agricultural products. To more comprehensively understand the long-term and global impacts of geopolitical risk on agricultural markets, future research needs to expand its scope, considering broader regions and longer time spans, as well as the mutual influences among different agricultural products.

With increasing attention to commodity correlation and the complexity of economic activities, research on market spillover effects has shifted towards more systematic and comprehensive network analysis. The emergence of numerous analytical techniques facilitates the study of market volatility and connectedness or spillover effects between markets: traditional cointegration equations and Vector Autoregression (VAR) models (Chen et al., 2022), multivariate GARCH family models (Zeng et al., 2021), Copula function approaches (Wen et al., 2017), and spillover index models based on forecast error variance decomposition within the VAR framework (Tan et al., 2020). Among these, the GARCH model is a statistical model used to analyze heteroskedasticity in time series data, enabling more accurate predictions of future volatility. GARCH family models can be applied in multiple fields, for instance, utilizing the BEKK-GARCH model to explore risk spillover among geopolitical risk, climate risk, and energy markets (Jin et al., 2023), or employing the Copula-GARCH model to investigate co-movements between different agricultural markets (Yuan et al., 2020). The VAR model, as a fundamental linear regression model, is well-known among researchers in this field for its ability to explore nonlinear relationships in risk transmission between financial markets. The VAR model is highly applicable and widely used, such as in studying multivariate risk spillovers among carbon, non-ferrous metals, and energy markets (Zhou et al., 2022) and analyzing climate risk spillover from clean energy to the US stock market (Khalfaoui et al., 2022). The spillover index model developed by Diebold and Yilmaz, precisely based on the forecast error variance decomposition of the Vector Autoregression (VAR) model, provides an effective tool for analyzing volatility spillover effects among different financial markets (Diebold and Yılmaz, 2014). This model can not only reveal the risk spillover network between markets but also clarify the directional nature of volatility spillovers. A significant advantage of the DY model lies in its simplicity, allowing it to capture the dynamic characteristics of time series data through rolling window approaches. The DY model finds application in multiple domains due to its broad applicability, including research on volatility spillover effects in metal markets (Liu et al., 2021) and analysis of climate risk spillovers in European electricity markets (Zhao, 2024). Further, Baruník and Krehlík innovatively extended the DY model by decomposing DY spillovers into different frequency bands based on Fourier transformation, thus offering new perspectives for understanding the cyclical characteristics of market volatility. Although the DY model is a powerful tool for providing overall spillover information, it has limitations in distinguishing between short-term and long-term effects of shocks on the system (Liu et al., 2022). Baruník and Krehlik achieve this by converting impulse responses to shocks into spectral representations based on frequency responses to shocks for variance decomposition (Liu et al., 2022). By combining rolling window analysis across different time horizons, the BK spillover model effectively reveals the risk transmission paths between markets in the time and frequency domains, offering deeper insights for risk management (Jin et al., 2023). The application of the BK spillover model is equally extensive, for example, in analyzing the frequency dynamics of volatility spillovers between precious metal and industrial metal markets (Liu et al., 2021).

Focusing on asymmetry analysis and time-varying dynamics analysis is currently a cutting-edge direction in research. The Cross-Quantilogram analysis method is a research approach that integrates multi-dimensional, multi-source data and employs quantitative statistical techniques to uncover association mechanisms between variables. Its core lies in breaking the limitations of single data dimensions and revealing hidden patterns or causal relationships within complex systems through cross-domain data integration. The cross-quantilogram approach processes two time series according to the lead-lag causal relationship between two quantiles and determines their dependency structure. Consequently, this method offers superior advantages in predicting significantly lagged spillover effects and the subsequent potential cross-correlation patterns (Karim et al., 2023). The core strengths of this method are as follows: First is its robust adaptability to distributional structures. Without relying on any parametric assumptions, the method simultaneously analyzes central distribution and tail dependence through a quantile matching mechanism, accurately capturing the heterogeneous responses of agricultural product prices to GPR shocks—particularly suited for asymmetric transmission patterns between food crops and cash crops at extreme quantiles. Second is its excellent diagnostic power for extreme events. This method diagnoses differences in left-tail risk sensitivity using cross-correlation measures based on the quantile hit process, effectively circumventing the estimation bias of traditional mean regression for thick-tailed distributions and outliers. Due to its significant advantages in researching tail risk contagion mechanisms during extreme events, the cross-quantile method has been applied to study the impact of geopolitical risk on oil markets (Cunado et al., 2020b); research on symmetric relationships between climate policy and energy metals (Karim et al., 2023), and other extreme event-related fields. TVP-VAR-BK is a dynamic econometric model combining Time-Varying Parameter Vector Autoregression and Bayesian Kernel estimation, used to analyze dynamic spillover effects and risk transmission mechanisms between variables. This method exhibits high adaptability to non-stationary time series and outliers, allowing model parameters to adjust dynamically over time and accurately capturing the time-varying characteristics of risk spillover effects between markets (Luo et al., 2024). It captures the time-varying characteristics of market relationships, suits analysis of sudden events that break through the limitations of traditional static analysis, depicts risk transmission from time-frequency-space multidimensional perspectives, and provides more refined tools for cross-market risk management (Baruník and Křehlík, 2018). In recent years, as a frontier tool for analyzing dynamic spillover effects among financial markets or economic variables, this method has been used to study, for example, the macroeconomic spillover effects of geopolitical risk shocks (Asomaning et al., 2024), US monetary policy spillover effects (Crespo Cuaresma et al., 2019), agricultural market price volatility (Chuan, 2010), and the dynamic spillover relationship among geopolitical risk, climate risk, and energy markets (Jin, 2023).

Existing literature generally confirms the significant impact of geopolitical risks on commodity markets, with particularly consistent findings in energy markets, such as the widely verified shocks to crude oil and natural gas markets from the Russia-Ukraine war. However, research on agricultural markets remains relatively limited. Most studies focus on the impact of geopolitical conflicts in a single region or over a short time span on the price volatility of specific agricultural products, lacking comprehensive analysis of the long-term and global impacts on agricultural markets. In terms of analytical methods, existing studies employ various models to explore spillover effects between markets. These models each have advantages; for instance, GARCH models can analyze heteroskedasticity in time series data, while VAR models suit exploring nonlinear relationships in risk transmission between financial markets. However, these traditional models have limitations in distinguishing between short-term and long-term effects of shocks on the system. In recent years, research methods have gradually developed towards asymmetry analysis and time-varying dynamics analysis. New methods like the cross-quantilogram approach and TVP-VAR-BK model provide more powerful tools for studying the dynamic impact of geopolitical risks on commodity markets, but their application scope still requires further expansion, particularly in the domain of agricultural markets.

In conclusion, existing literature has made significant progress in research on the impact of geopolitical risks on commodity markets, but the depth and breadth of studies on agricultural markets still need strengthening. Future research should further expand the scope, consider broader regions and longer time spans, while integrating innovative modeling techniques to more comprehensively reveal the long-term and global impacts of geopolitical risks on agricultural markets. Moreover, regarding the limitations of current models—such as the issue of distinguishing between short-term and long-term effects—methodological innovations should also be employed to resolve these challenges, thereby providing more refined tools for cross-market risk management.

Methodology

Data. Geopolitical risk is a complex and difficult-to-quantify-directly concept (Engle and Campos-Martins, 2020). In the field of statistics, attempts to measure this risk using continuous variables often prove impractical. Therefore, introducing proxy variables or reasonable dummy variables is crucial for studying geopolitical risk and its influencing factors. However, because the attributes of geopolitical risk cannot be simply categorized as "yes" or "no," traditional dummy variable approaches are not applicable. Under these circumstances, finding a set of proxy variables becomes an effective alternative. With advancements in text analysis techniques, quantifying the sentiment tone of texts and analyzing the impact of news events have become feasible. Leveraging this technology, Caldara and Iacoviello constructed the GPR index by statistically counting the number of articles related to geopolitical risks in major international media outlets each month (as a share of total news articles) and calculating an index normalized to an average value of 100 (Caldara and Iacoviello, 2022). They focused on six groups of phrases related to geopolitical risks in news reports: Group 1 includes words explicitly mentioning geopolitical risks and references involving military-related tensions in the United States or large parts of the world; Group 2 includes phrases directly related to nuclear tensions; Groups 3 and 4 mention war threats and terrorism threats respectively; Groups 5 and 6 aim to capture news reports about actual adverse geopolitical events (rather than just risks). The GPR index synthesizes all these keywords, providing a multidimensional perspective to measure and understand global geopolitical risk (Jalkh and Bouri, 2024). The aforementioned index has been widely adopted in geopolitical risk research (Gong and Xu, 2022; Jin et al., 2023; Polat et al., 2023b), demonstrating its effectiveness as an indirect measurement approach. Thus, to facilitate research and ensure independent variables do not interfere with each other, we selected only the highly comprehensive GPR index as the independent variable to measure global geopolitical risk.

Drawing on existing research (Dai et al., 2023; Hernandez et al., 2021; Tiwari et al., 2022), we selected soybeans, corn, wheat, rice, cotton, sugar, coffee, and cocoa as representatives of the international agricultural market. These are among the world's most traded agricultural products and collectively constitute a good proxy for the agricultural market. Regarding specific indicators for characterizing agricultural markets, one body of literature employs agricultural indices for representation (Abid et al., 2023; Gong and Xu, 2022; Khalfaoui et al., 2024; Polat et al., 2023b), while another body utilizes prices of specific agricultural futures or spot markets (Dai et al., 2023; Hernandez et al., 2021; Tiwari et al., 2022). Futures prices directly reflect supply-demand dynamics and market expectations for agricultural products, demonstrating high sensitivity and timeliness. They not only rapidly respond to market information but also provide a vital risk management tool for market participants. In international trade, futures prices hold significant reference value, facilitating price comparisons and trade decisions across different countries and regions. Furthermore, compared to agricultural indices that aggregate prices of multiple products, futures prices capture supply-demand relationships and market expectations for specific commodities, offering more targeted market insights. Therefore, we adopted closing prices of main futures contracts for specific agricultural products to characterize the international agricultural market.

Table 1 Descriptive statistics.

Variable	Mean	Median	Max	Min	Std	Skew	Kurt	Adfs
GPR	0.014	−0.495	706.54	−245.93	41.64	1.09	17.79	−23.64***
Corn	−0.00013	−0.056	34.84	−47.75	2.95	−0.44	24.87	−29.34***
Wheat	−0.00056	0.036	22.03	−18.01	3.03	0.04	3.11	−28.52***
Soybean	0.00014	−0.016	27.05	−24.37	2.31	0.26	12.91	−28.12***
Roughrice	0.00036	−0.006	29.01	−47.25	2.64	−1.12	42.11	−30.10***
Sugar	0.00046	−0.005	26.63	−15.86	3.04	0.32	3.82	−27.89***
Cotton	−0.00055	−0.014	19.94	−16.92	2.53	0.03	3.04	−27.95***
Cocoa	−0.00115	−0.016	29.86	−31.06	3.00	0.11	6.69	−27.93***
Coffee	0.00066	0.027	25.61	−21.33	3.19	−0.06	3.11	−27.35***

***indicates significance at the 1% significance level.

It is important to note that imputing missing data may lead to biased results. Therefore, we decided to use samples with missing data excluded. Meanwhile, to ensure the stationarity of the data, we applied first-order differencing to the dataset. All GPR index data were sourced from http://www.policyuncertainty.com. This website was selected for its compelling timeliness, professionalism, and comprehensiveness of data, which have been widely adopted by numerous scholars. Agricultural futures price data were obtained from the WIND database (https://www.wind.com). The sample period for all data spans from January 10, 2000, to July 26, 2024, using daily data. The rationale for using post-millennium data is twofold: First, since 2000, the world has entered an era of information-driven modernity where the ease of information dissemination has significantly improved. This enables mainstream media to report global news—including geopolitical risks—more extensively, thereby enhancing the representativeness of the GPR index and ensuring more sufficient data coverage (Song et al., 2017). Second, a series of major historical events have occurred globally since the turn of the century, making geopolitical risks increasingly complex. Notable events during this period have exerted substantial impacts on agricultural markets.

Table 1 presents descriptive statistical analysis results for the studied variables. The GPR index exhibits volatility significantly higher than the returns of agricultural products. It is noteworthy that the ADF tests for all series significantly reject the unit root hypothesis, ensuring the stationarity of the time series, which indicates that VAR modeling can be directly applied.

Calculation of return. To obtain the return series of agricultural futures, daily returns are first calculated. The return series for each asset can be computed based on its daily closing price as follows::

$$r_t = (\ln \mathrm{p_t} - \ln \mathrm{p_{t-1}}) \times 100$$

where r_t represents the return of asset i at time t, the closing price of asset i at time t.

Cross-quantilogram approach. This study first employs the cross-quantilogram (CQ) method (Han et al., 2016) to analyze the extreme impact effects of geopolitical risk (GPR) on the returns of eight categories of agricultural futures. The CQ method exhibits strong adaptability to distribution structures, excellent diagnostic power for extreme events, and a dynamic transmission mechanism with a multi-window lag framework. It can effectively analyze the extreme impact effects of GPR on agricultural commodity prices and visualize them primarily through heatmaps, providing a more intuitive representation of the influence of extreme shocks across different time scales.

Under this method, the quantile hit process is expressed as:

$$\rho_\tau(k) = \frac{E[\psi_{\tau_1}(\mathrm{Crop_{it}} - q_{i,t}(\tau_1))\psi_{\tau_2}(\mathrm{GPR_{t-k}} - q_{\mathrm{GPR},t-k}(\tau_2))]}{\sqrt{E[\psi^2_{\tau_2}(\mathrm{GPR_{t-k}} - q_{\mathrm{GPR},t-k}(\tau_2))]}}$$

where Crop_{it} denotes the price return of the i-th crop ($i = 1,\ldots,8$) on day t, GPR_{t-k} represents the geopolitical risk index lagged by k days ($k = 1,5,10$), and $\tau 1$, $\tau 2 \in \{0.05,0.25,0.5,0.75,0.95\}$ denote different quantile combinations. The focus is on analyzing the transmission differences between extreme risks ($\tau = 0.05/0.95$) and normal conditions ($\tau = 0.5$).

Measuring spillover effects based on the TVP-VAR-BK model. In order to explore the risk spillover between the GPR index and the international agricultural market and its dynamic evolution pattern, this paper adopts the frequency connectedness framework based on TVP-VAR proposed by Chatziantoniou et al. (2023). The framework integrates the time-varying parameter vector autoregressive (TVP-VAR) model with the BK spillover index model, which can capture the intensity, size and dynamic evolution trend of cross-market spillovers from the time-frequency perspective. The connectedness approach based on TVP-VAR has been shown to overcome the specific shortcomings of the rolling window VAR approach. TVP-VAR can be summarized as follows:

$$x_t = \Phi_t x_{t-1} + \grave{O}_t, \grave{O}_t \sim N(0, \Sigma_t)$$

$$vec(\Phi_t) = vec(\Phi_{t-1}) + v_t, v_t \sim N(0, R_t)$$

where x_t, x_{t-1} and ϵ_t are $N \times 1$ dimensional vectors representing the sequence of all variables in t、$t-1$ and the corresponding error terms, respectively. Φ_t and Σ_t are $N \times N$ dimensional matrices representing time-varying VAR coefficients and time-varying variance-covariance, while $vec(\Phi_t)$ and v_t are $N^2 \times 1$ dimensional vectors and R_t is $N^2 \times N^2$ dimensional matrix.

The concept of process generalized forecast error variance decomposition (GFEVD) is based on the Wold representation theorem, so it is necessary to convert the TVP-VAR model into its TVP-VMA process by the following equality: $x_t = \sum_{i=1}^{p} \Phi_{it} x_{t-i} + \epsilon_t = \sum_{j=0}^{\infty} \Psi_{jt} \epsilon_{t-j}$。 GFEVD can be interpreted as the impact of a shock to variable j on the forecast error variance of variable i, and can be written as the following formula:

$$\theta_{ijt}(H) = \frac{(\Sigma_t)^{-1}_{jj} \sum_{h=0}^{H} ((\Psi_h \Sigma_t)_{ijt})^2}{\sum_{h=0}^{H} (\Psi_h \Sigma_t \Psi'_h)_{ii}}$$

Where, $\theta_{ijt}(H)$ represents the contribution of the spillover of variable j to variable i at time H to the variance of the forecast error. The standardized spillover index can be obtained by standardization:

$$\tilde{\theta}_{ijt}(H) = \frac{\theta_{ijt}(H)}{\sum_{k=1}^{N} \theta_{ijt}(H)}$$

Standardization ensures that the sum of the spillover indices in each time period is $\sum_{i=1}^{N} \tilde{\theta}_{ijt}(H) = 1$, and that the total spillover between the variables is $\sum_{j=1}^{N} \sum_{i=1}^{N} \tilde{\theta}_{ijt}(H) = N$.

After constructing the spillover indices in the time domain, they are next extended to the frequency domain. First consider the frequency response function: $\Psi(e^{-i\omega}) = \sum_{h=0}^{\infty} e^{-i\omega h}\Psi_h$, where $i = \sqrt{-1}$, and ω denotes the frequency that is continuous with the spectral density of x_i at frequency ω, which can be defined as the Fourier transform of TVP-VMA (Infinity) :

$$S_x(\omega) = \sum_{h=-\infty}^{\infty} E(x_t x'_{t-h})e^{-i\omega h} = \Psi_t(e^{-i\omega h})\Sigma_t \Psi'_t(e^{+i\omega h})$$

Frequency GFEVD is the combination of spectral density and GFEVD. We need to standardize the frequency GFEVD, and its formula is as follows:

$$\theta_{ijt}(\omega) = \frac{(\Sigma_t)_{jj}^{-1} \left| \sum_{h=0}^{\infty} (\Psi_t(e^{-i\omega h})\Sigma_t)_{ijt} \right|^2}{\sum_{h=0}^{\infty} (\Psi_t(e^{-i\omega h})\Sigma_t(e^{i\omega h}))_{ii}}$$

$$\tilde{\theta}_{ijt}(\omega) = \frac{\theta_{ijt}(\omega)}{\sum_{k=1}^{N} \theta_{ijt}(\omega)}$$

where, $\tilde{\theta}_{ijt}(\omega)$ represents the part of the spectrum of the i variable at a given frequency ω that can be attributed to the shock in the j variable. It can be interpreted as an intra-frequency indicator.

To assess the short-and long-run connectedness, rather than the connectedness of individual frequencies, we aggregate all frequencies within a specific range:

$$d = (a, b) : a, b \in (-\pi, \pi), a < b :$$

$$\tilde{\theta}_{ijt}(d) = \int_a^b \tilde{\theta}_{ijt}(\omega) d\omega$$

Finally, all connectedness metrics can be calculated as follows:

$$TO_{it}(d) = \sum_{i=1, i\neq j}^{N} \tilde{\theta}_{ijt}(d)$$

$$FROM_{it}(d) = \sum_{i=1, i\neq j}^{N} \tilde{\theta}_{ijt}(d)$$

$$TCI_t(d) = N^{-1} \sum_{i=1}^{N} TO_{it}(d) = N^{-1} \sum_{i=1}^{N} FROM_{it}(d)$$

Results and discussion

Dynamic changes in GPR index. Figure 1 displays the dynamic changes in the monthly geopolitical risk (GPR) index from January 2000 to July 2024. The figure reveals several significant peaks closely associated with major international events during this period. Between 2000 and 2005, the GPR index experienced dramatic fluctuations. The peak around September 2001 corresponds to the terrorist attacks by Al-Qaeda against the United States. The peak around March 2003 relates to the Iraq War. The high point in late 2015 primarily stems from a series of terrorist attacks in France. After 2016, the notable intensification of global geopolitical risk led to further increased volatility, a trend that persisted until 2020 with several smaller peak fluctuations occurring during this time. Starting in 2020, the GPR index reflects another significant surge in geopolitical risk volatility, driven by critical factors including the global COVID-19 pandemic, the Russia-Ukraine War, and the Israeli-Palestinian conflict.

Cross-quantilogram analysis. Based on the half-life property of commodity price shocks (Etienne et al., 2014) and the decay pattern of GPR impacts (Andersen et al., 2001), this paper constructs three-order lag windows at $k = 1$, 5, and 10 days: capturing immediate market sentiment-driven responses through $k = 1$ (next-day panic trading), diagnosing mid-term logistics and cost-transmission pressures through $k = 5$ (weekly shipping delay effects), and observing supply-demand rebalancing adjustments caused by trade flow shifts through $k = 10$ (fortnightly import substitution and inventory release). This framework effectively distinguishes the differential pathways through which lagged effects influence food crops versus economic crops.

Figures 2–9 employ quantile cross-correlation heatmaps to depict the nonlinear dynamic response patterns of geopolitical risk (GPR) shocks on four major food crop futures (corn, wheat, soybeans, rough rice) and four key economic crop futures (sugar, cotton, cocoa, coffee) at lags of 1 day (Lag = 1), 5 days (Lag = 5), and 10 days (Lag = 10). The analysis reveals significant heterogeneity in GPR impact across both the futures price return quantile (τ) dimension and the temporal dimension. These differences stem fundamentally from variations in the inherent financial attributes and supply elasticities of distinct crop types.

Corn exhibits the most rapid response to GPR shocks. During Lag = 1, a significant localized positive correlation (displayed as discrete orange speckles) emerges at the intersection of the GPR upper tail region ($\tau \geq 0.60$) and the medium-to-low quantile range of corn futures price returns ($\tau = 0.00$–0.20). This indicates that sudden geopolitical crises (e.g., escalation of the Russia–Ukraine conflict) immediately trigger short-term safe-haven capital flows toward low-priced corn futures contracts. By Lag = 5, this positive correlation zone expands significantly, demonstrating reinforced upward pressure on corn futures price returns resulting from heightened risks. However, at Lag = 10, the heatmap transitions predominantly to deep blue, meaning the correlation between GPR shocks and corn futures has largely dissipated, reflecting the market's attainment of a new equilibrium through self-adjustment.Unlike corn, wheat demonstrates relative sluggishness during initial GPR shocks (Lag = 1), exhibiting interactive signals only within limited quantile ranges. Its price sensitivity peaks on day 5 post-crisis (Lag = 5), when nearly all quantile ranges of wheat futures price returns show significant responses to GPR shocks, with particularly pronounced intensity at both price extremes (low τ and high τ). Nevertheless, by Lag = 10, this influence likewise largely subsides.

Soybeans also show predominantly positive responses at Lag = 1. When GPR is at medium-high quantiles ($\tau \geq 0.6$) while soybean futures price returns are at medium-low quantiles ($\tau = 0.05$–0.5), a significant positive correlation manifests, reaffirming short-term safe-haven capital's tendency to flow into low-priced futures. Notably, a significant positive correlation is also observed when soybean futures themselves are at high return quantiles ($\tau \geq 0.5$) while GPR remains at low levels ($\tau \leq 0.4$), highlighting soybeans' stronger financial speculation attributes. This positive correlation substantially contracts during Lag=5 and nearly vanishes by Lag = 10.

As another staple crop, rough rice exhibits similarities to soybeans at Lag = 1: A significant positive correlation emerges in the combined region of medium-high GPR quantiles ($\tau \geq 0.4$) and

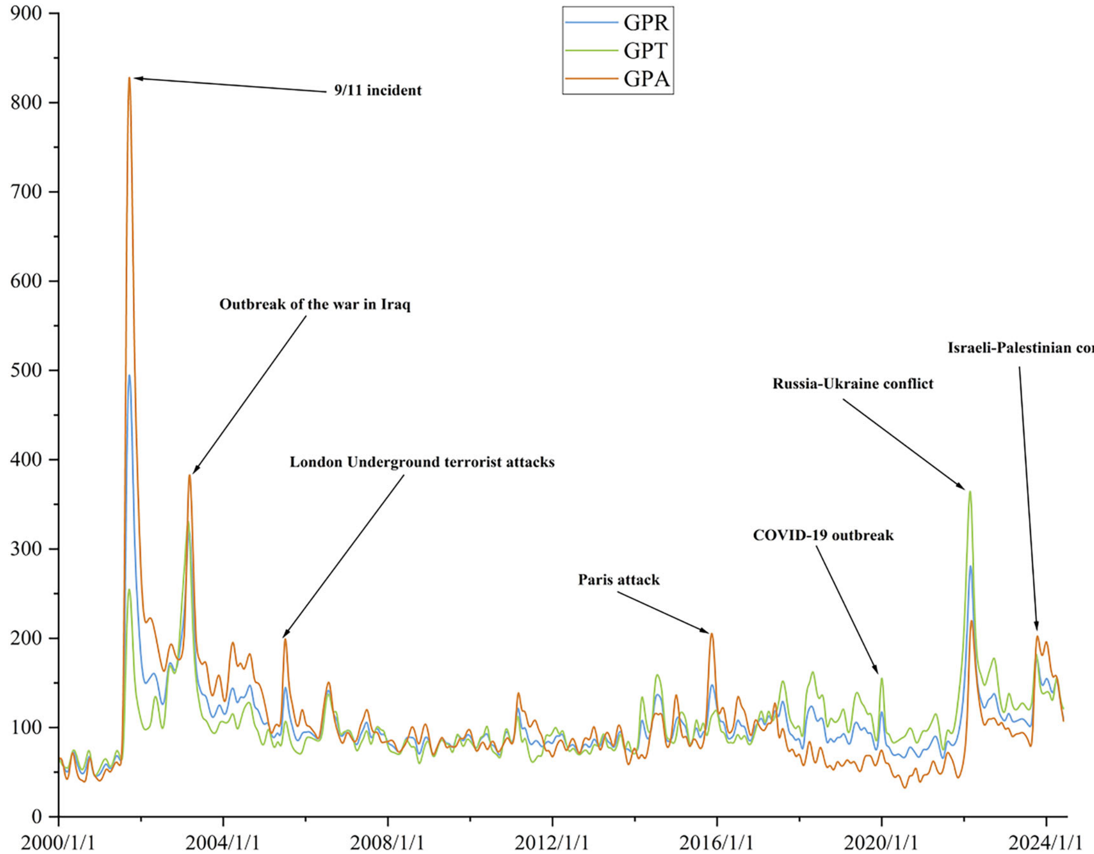

Fig. 1 Monthly GPR index for the sample period from January 2000 to July 2024.

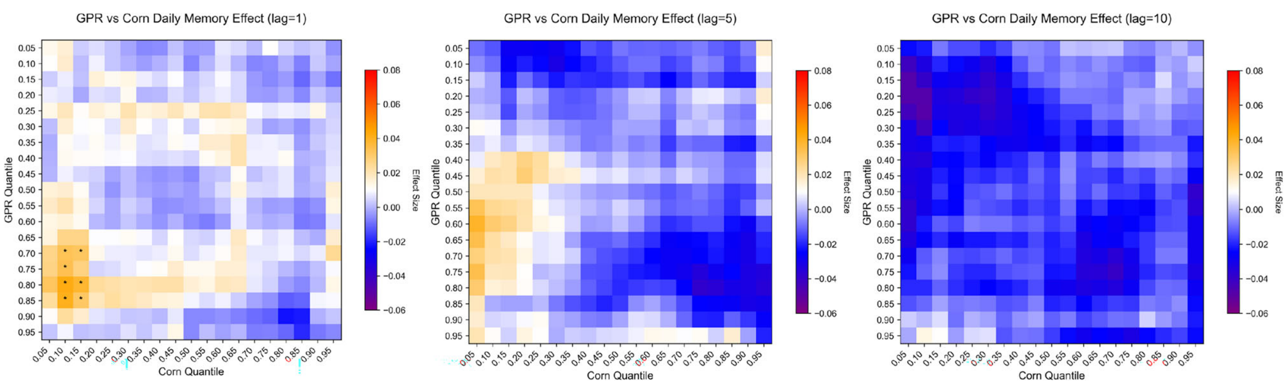

Fig. 2 Heatmap of the Cross-Correlation Between International Geopolitical Risk and Corn.

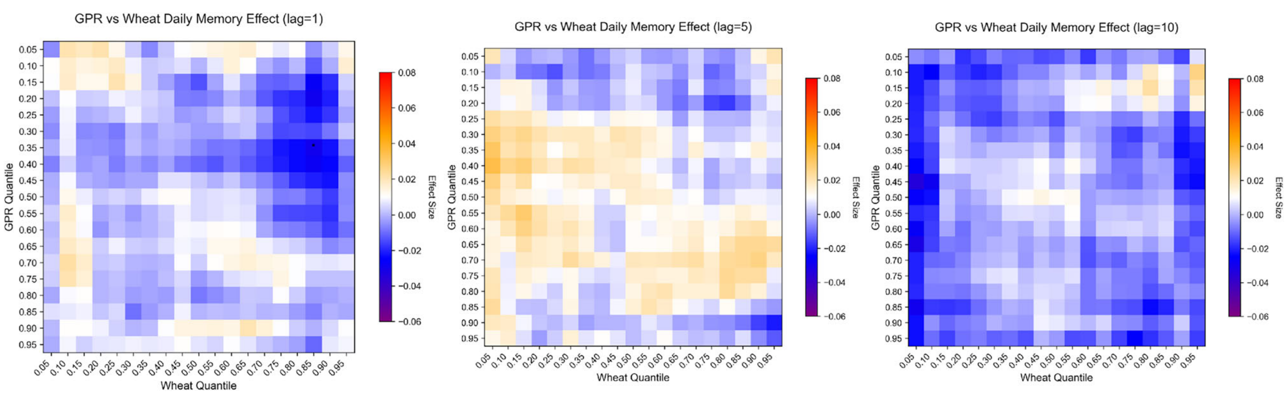

Fig. 3 Heatmap of the Cross-Correlation Between International Geopolitical Risk and Wheat.

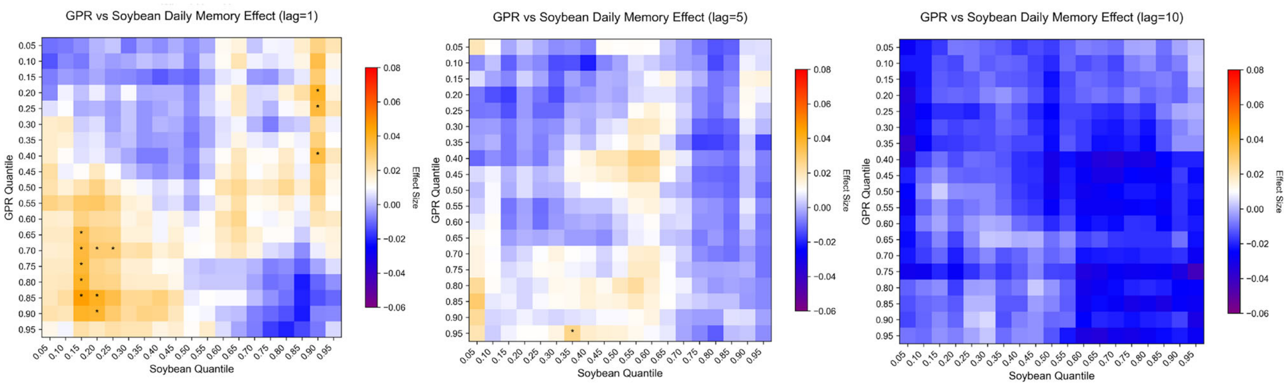

Fig. 4 Heatmap of the Cross-Correlation Between International Geopolitical Risk and Soybean.

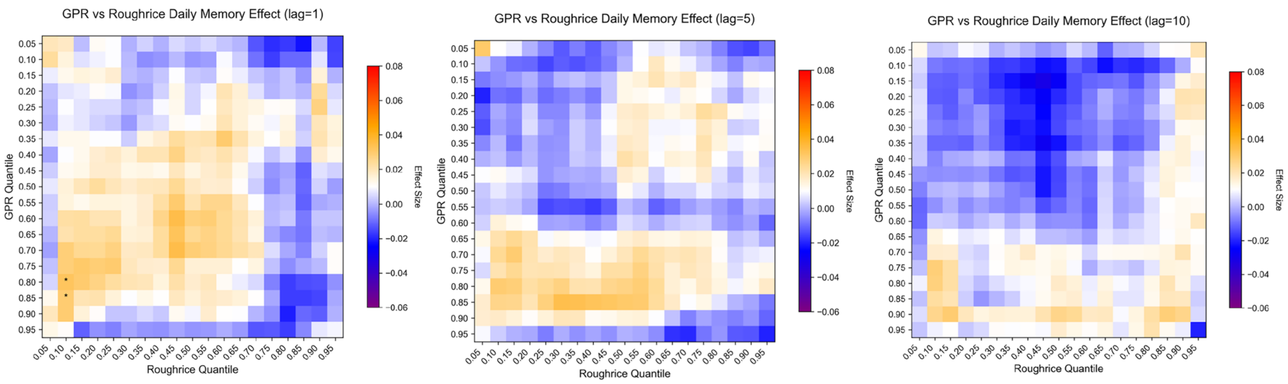

Fig. 5 Heatmap of the Cross-Correlation Between International Geopolitical Risk and Roughrice.

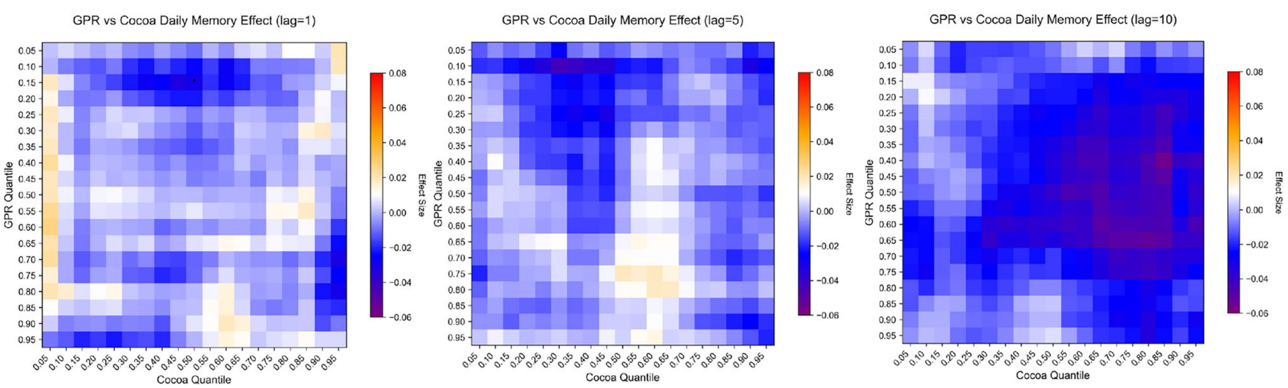

Fig. 6 Heatmap of the Cross-Correlation Between International Geopolitical Risk and Cocoa.

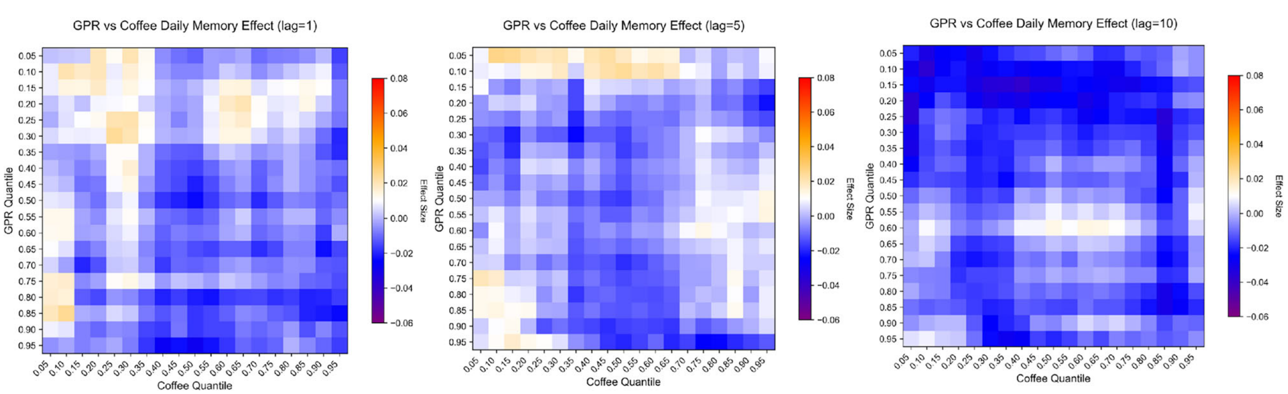

Fig. 7 Heatmap of the Cross-Correlation Between International Geopolitical Risk and Coffee.

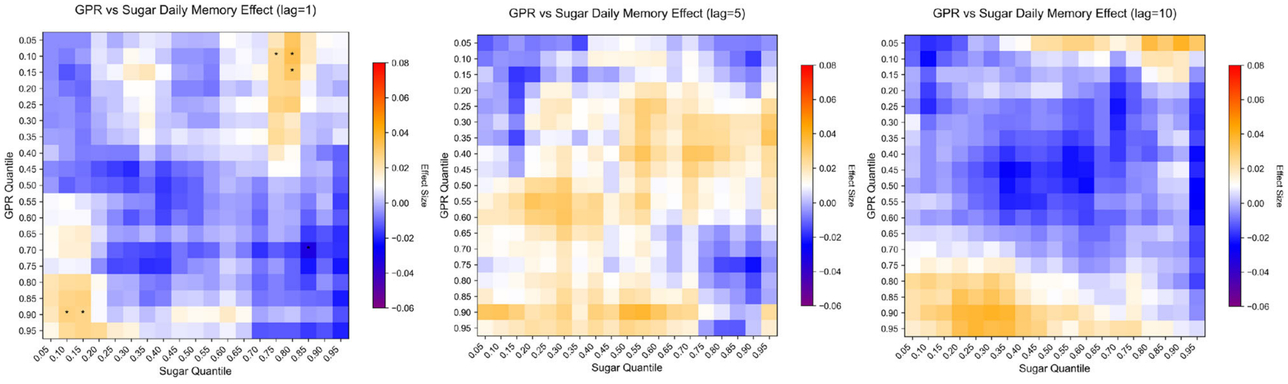

Fig. 8 Heatmap of the Cross-Correlation Between International Geopolitical Risk and Sugar.

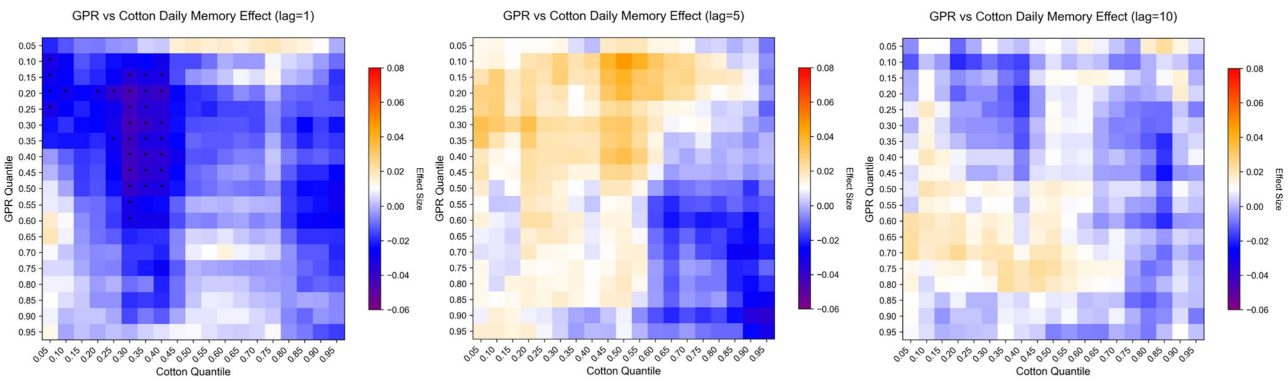

Fig. 9 Heatmap of the Cross-Correlation Between International Geopolitical Risk and Cotton.

medium-low rough rice futures price returns ($\tau = 0.05$–0.65). Moving to Lag = 5, the positive correlation area contracts and becomes more concentrated within high GPR quantiles ($\tau \geq 0.85$). This may reflect temporary export restrictions by major-producing countries amid heightened geopolitical risks, subsequently driving up international prices. By Lag = 10, responses largely subside, indicating completion of the market rebalancing process. As a regionally dominant staple, the core of rough rice's long-term pricing reverts to its local supply-demand fundamentals.

The futures price return changes of economic crops exhibit two distinct patterns in response to GPR shocks. Cocoa and coffee exhibit similar performance: the heatmaps appear predominantly blue-white across most regions, overall indicating that GPR shocks exert negligible impacts on their prices, leaving only exceptionally minimal traces of influence on isolated extreme price ranges at Lag = 1.In stark contrast stand sugar and cotton. Sugar displays weak reactivity to GPR during initial shocks (Lag = 1), likely due to its relatively weaker financial attributes failing to attract immediate safe-haven capital. However, by Lag = 5, sugar futures price returns demonstrate exceptionally strong positive responses to GPR shocks across all quantile ranges. We infer that the surge in geopolitical risks elevates energy prices, thereby significantly increasing energy-intensive sugar production costs (e.g., fuel, fertilizers) (Jin et al., 2023). This intense pressure effect persists until Lag = 10 before gradually stabilizing, ultimately converging in two specific zones: sugar futures returns still show significant positive correlations with GPR when GPR is at high quantiles ($\tau \geq 0.75$) or low quantiles ($\tau = 0.05$), implying persistent transmission of long-term energy cost pressures.Cotton's performance follows: no significant response at Lag = 1; during Lag = 5, medium-to-low quantile ranges of cotton futures returns ($\tau = 0.05$–0.65) exhibit powerful responsiveness to GPR; by Lag = 10, this responsiveness weakens considerably, leaving only a faint positive correlation at the intersection of medium-high GPR quantiles and medium-low cotton return quantiles.

TVP-VAR-BK results

Average dynamic connectedness. Based on the existing literature (Chatziantoniou et al., 2023) and empirical guidance, this study sets the lag order of the VAR model as 1 and the forecast step size as 100. To deepen the understanding of the relationship between geopolitical risk and international agricultural commodity markets, we analyze their interaction at two time frequencies, short term (no more than 5 days) and long term (more than 5 days). In Tables 2, 3 and 4, the "To" column and "From" row identify the direction and source of the impact, respectively, while the bottom row labeled "NET" indicates the net spillover level, whose value is derived by subtracting "From" from.

First, we present in Tables 2, 3 and 4 the average results for the population and the sub-short and long run, respectively, which cover the entire sample period and do not take into account the specific dynamic effects of events at specific points in time. Table 2 reveals significant spillover effects between geopolitical risks and international agricultural markets. In the whole sample period, 25.05% of the variation in the connectedness of the two systems is caused by the spillover effect within the system. Among them, corn, wheat, and soybeans have high "FROM" values, indicating that these commodities are more vulnerable to external factors, and they also have high "TO" values, indicating that they may act as an important source of risk or information dissemination in the system. Based on the net spillover perspective, the "NET" values of corn and wheat are 6.73% and 3.54%, respectively, which marks them as net exporters to the system; Conversely, the

Table 2 Total average dynamic connectedness between markets.

	GPR	Corn	Wheat	Soybean	Roughrice	Cotton	Sugar	Cocoa	Coffee	FROM
GPR	90.18	1.22	1.42	1.08	1.08	1.21	1.14	1.32	1.35	9.82
Corn	0.89	58.03	16.21	14.17	2.62	2.71	2.18	1.12	2.08	41.97
Wheat	0.83	17	61.02	10.08	2.92	2.01	2.4	1.69	2.06	38.98
Soybean	0.73	15.57	10.23	60.88	3.11	2.92	2.42	1.44	2.7	39.12
Roughrice	0.88	3.6	3.63	4.06	81.39	1.67	2.02	1.1	1.65	18.61
Cotton	0.9	4.01	2.82	3.86	1.62	79.77	2.94	1.74	2.33	20.23
Sugar	1.07	2.77	3.68	2.89	1.64	2.59	79.1	2.11	4.14	20.9
Cocoa	1.08	1.45	1.72	1.95	1.02	1.83	1.94	85.54	3.47	14.46
Coffee	1.09	3.09	2.8	3.19	1.63	2.12	4.06	3.41	78.61	21.39
TO	7.48	48.71	42.52	41.28	15.65	17.07	19.1	13.92	19.77	TCI
Net	−2.35	6.74	3.54	2.16	−2.96	−3.16	−1.8	−0.54	−1.62	25.05

Note: TCI represents the total spillover effects of the system.

Table 3 Total average spillovers at short-term frequencies between markets.

	GPR	Corn	Wheat	Soybean	Roughrice	Cotton	Sugar	Cocoa	Coffee	FROM
GPR	82.9	1.15	1.37	1.03	1.03	1.16	1.09	1.25	1.29	9.37
Corn	0.86	54.31	15.19	13.21	2.44	2.51	2.05	1.07	1.92	39.25
Wheat	0.79	15.88	56.94	9.41	2.75	1.88	2.24	1.62	1.92	36.48
Soybean	0.7	14.6	9.57	57.03	2.93	2.71	2.25	1.36	2.53	36.65
Roughrice	0.84	3.34	3.39	3.77	75.36	1.54	1.93	1.05	1.54	17.38
Cotton	0.86	3.75	2.65	3.6	1.53	74.1	2.78	1.64	2.18	18.98
Sugar	1.02	2.6	3.51	2.71	1.55	2.4	73.8	2.02	3.87	19.68
Cocoa	1.04	1.38	1.6	1.84	0.97	1.71	1.79	79.92	3.24	13.58
Coffee	1.05	2.91	2.62	2.98	1.55	1.99	3.78	3.25	73.46	20.12
TO	7.16	45.6	39.9	38.53	14.74	15.91	17.89	13.27	18.49	TCI
Net	−2.21	6.35	3.42	1.88	−2.65	−3.08	−1.79	−0.3	−1.63	23.50

Table 4 Total average spillovers at long-term frequencies between markets.

	GPR	Corn	Wheat	Soybean	Roughrice	Cotton	Sugar	Cocoa	Coffee	FROM
GPR	7.27	0.06	0.06	0.05	0.06	0.05	0.05	0.07	0.05	0.46
Corn	0.03	3.72	1.02	0.96	0.18	0.19	0.13	0.05	0.16	2.72
Wheat	0.04	1.12	4.08	0.67	0.18	0.13	0.16	0.06	0.13	2.5
Soybean	0.03	0.97	0.66	3.85	0.19	0.21	0.17	0.08	0.17	2.47
Roughrice	0.04	0.26	0.25	0.29	6.02	0.14	0.09	0.05	0.11	1.23
Cotton	0.04	0.26	0.18	0.26	0.1	5.67	0.16	0.1	0.15	1.24
Sugar	0.05	0.17	0.17	0.19	0.08	0.19	5.31	0.09	0.27	1.22
Cocoa	0.04	0.07	0.11	0.11	0.05	0.12	0.15	5.62	0.23	0.88
Coffee	0.04	0.18	0.18	0.22	0.08	0.13	0.29	0.16	5.15	1.27
TO	0.32	3.1	2.62	2.75	0.91	1.16	1.21	0.65	1.27	TCI
Net	−0.14	0.38	0.12	0.28	−0.32	−0.08	−0.01	−0.23	0	1.55

"NET" values of cotton and brown rice as net recipients are −3.16% and −2.96%, respectively.

Tables 3 and 4 further detail the spillover effects between geopolitical risks and international agricultural markets in the short and long run. The short-term total connectedness index reached 23.50%, significantly higher than the long-term 1.55%. Both in the short and long run, corn, wheat, and soybeans exhibit high values of "FROM" and "TO", again emphasizing their central role in the overall system. Moreover, although corn, wheat and soybeans maintain the role of net exporters, while geopolitical risk, brown rice, cotton and sugar are net importers, the "NET" values of cotton and sugar decrease significantly in the long run. It is worth noting that this phenomenon is particularly prominent in the longer time frame where all values are substantially reduced.

The Total Connectedness. The total connectedness index (TCI) is an important indicator to measure the overall interactivity and interaction degree among variables in a system. Figure 10 presents the overall evolution of the TCI between 2000 and 2024, as well as its dynamics in the short-run (green shaded area) and long-run (orange shaded area) frequencies.

From the general development trend of TCI: during the period from 2000 to the beginning of 2003, the level of TCI was relatively low, indicating that the correlation between markets was not high at that time. However, with the outbreak of the Iraq war in early 2003, the global geopolitical environment and the stability of agricultural markets were challenged, leading to sharp fluctuations in the prices of major agricultural products, which in turn led to the rise of TCI. Between 2008 and 2009, TCI rose sharply and reached historic highs, mainly as a result of the global

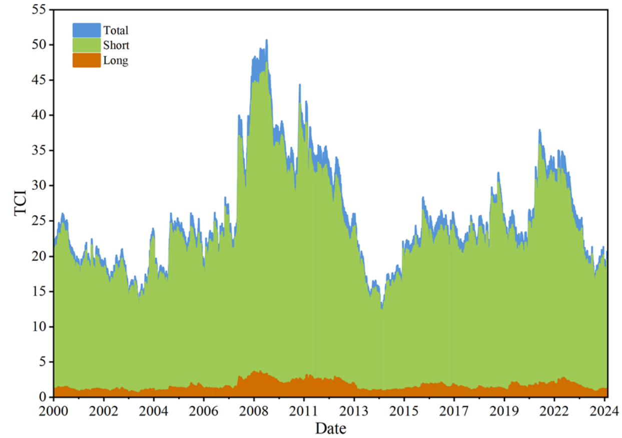

Fig. 10 Dynamic total connectedness. Note: The blue area illustrates the dynamic total connectedness while the short-term and long-term dynamic total connectedness are illustrated in green and orange, respectively.

economic crisis. The TCI again shows a small peak in 2011 and then experiences a significant decline until 2014. However, from 2014 to 2019, TCI showed a trend of slowly rising amid fluctuations. From 2020 to 2021, TCI increased sharply again and hit a new peak, reflecting the strong risk spillovers and interactions within the system due to the combination of COVID-19, lockdowns and economic stimulus policies. After entering 2022, the TCI gradually fell back from the high level, indicating that the extreme linkage effect was alleviated as the system adapted to the new routine state. At the same time, with the gradual recovery of economy and production, the correlation between different agricultural products and geopolitical risks has returned to a relatively differentiated situation.

From the perspective of frequency analysis, the dynamics of connectedness are mainly driven by short-run rather than long-run factors. Specifically, the long-run total spillover index (TCI) only reaches a significant peak around 2008 and 2022, but even then its contribution to the overall TCI remains relatively small. In contrast, the trends in short-and long-run volatility reveal a high degree of consistency between short-run spillovers and overall spillovers. This shows that the spillover effect between the international agricultural market and international geopolitical risks is mainly affected by short-term shocks. Regarding the integration of international agricultural commodity markets with the international geopolitical risk system, they show a higher degree of integration in the short term; That is, the interaction within the system is closer in the short run. However, in the long run, the degree of integration is low, indicating that the relationship between variables gradually becomes loose over time and the response of the system to external shocks becomes more differentiated.

Net total directed connectedness. In order to deeply explore the dynamic spillover effects between geopolitical risk and agricultural commodity markets and capture the changing roles of these factors in different time and frequency intervals, this study visualized the net spillover trends of each market as well as geopolitical risk. These indicators reflect the difference between the amount of spillovers transmitted by a particular entity to the system as a whole and the amount received from the system.

Figure 11 shows the net spillover effects of each market in terms of time and frequency. The data show that between 2001 and 2003 geopolitical risk (GPR) was a net exporter; Over longer time horizons, however, the GPR exists primarily as a net receiver. In contrast, corn, wheat, and soybeans mostly play the role of net exporters throughout the observation period, with a particularly significant effect for wheat. Brown rice, cotton and sugar are more likely to be net recipients, while cocoa and coffee are more evenly split between the two. It is important to note that significant volatility peaks in net aggregate directional connectedness in agricultural markets tend to occur after major events, such as the period following the 2008 global financial crisis and the period following the onset of the COVID-19 pandemic in 2020. This shows that various agricultural products are highly sensitive to extreme events, showing their vulnerability in this environment.

Discussion

Results of CQ analysis. Quantile cross-correlation analysis reveals that geopolitical risk (GPR) shocks exhibit significant time-lag heterogeneity (Lag = 1, 5, 10) and price-condition heterogeneity (quantile τ) in their impact on agricultural futures price returns, primarily driven by two attributes: differences in financial attributes (attractiveness to short-term capital) and variations in supply elasticity/production cost structures (particularly energy dependency).- From the perspective of food crops, they universally demonstrate short-term positive responses, especially within low-return quantiles (low τ), reflecting short-term safe-haven capital flows (corn, soybeans, rough rice at Lag = 1). Response peaks predominantly emerge at Lag = 5 (e.g., full-quantile responses for wheat; rough rice responses concentrated in high GPR quantiles $\tau \geq 0.85$, the latter potentially linked to export restriction expectations), yet influences largely dissipate before Lag = 10, indicating market rebalancing capacity. Among these, corn exhibits the most rapid reaction, while soybeans also show a Lag = 1 positive correlation in the combination of their own high-τ interval (i≥ 0.5) and low-GPR τ ($\tau \leq 0.4$), highlighting their stronger financial speculation attributes.

Conversely, from the perspective of economic crops, polarization emerges. Cocoa and coffee demonstrate extreme insensitivity to GPR shocks, reflecting weak financial attributes and lower risks of direct supply chain disruptions. Sugar exhibits a unique "delayed-strengthening-local persistence" pattern: weak responsiveness at Lag = 1, explosively strong positive responses across all quantile ranges at Lag = 5. The core mechanism lies in GPR driving up energy prices, substantially increasing energy-intensive sugar production costs (fuel, fertilizers). Although this effect weakens by Lag = 10, significant positive correlations persist within extreme GPR quantile zones ($\tau \geq 0.75$ or $\tau = 0.05$), validating the endurance of the "GPR → Energy Prices → Production Costs" transmission pathway. Cotton displays moderate responsiveness—significant in medium-low price quantiles during Lag = 5, but largely subsiding by Lag = 10.

This outcome demonstrates dynamic heterogeneity in agricultural futures price returns' responses to GPR shocks, indicating that the impact of GPR on agricultural futures cannot be uniformly characterized as its intensity, pattern, and persistence critically depend on lag horizons, crops' intrinsic market price conditions, and variety-specific characteristics. Such heterogeneity confirms the existence of a "financialization gradient" in markets' shock absorption capacity (corn > soybeans > rough rice > cotton > sugar > cocoa/coffee; Tang and Xiong, 2012), while concurrently reflecting GPR shocks' dual transmission mechanisms whereby response heterogeneity is jointly shaped by financial attributes (driving short-term capital flows) and supply elasticity/cost structures (particularly energy transmission). Sugar's case powerfully validates the critical importance of energy prices as key mediating variables.

Results of TVP-VAR-BK analysis. Time-Varying Parameter Vector Autoregression–Frequency Domain Decomposition

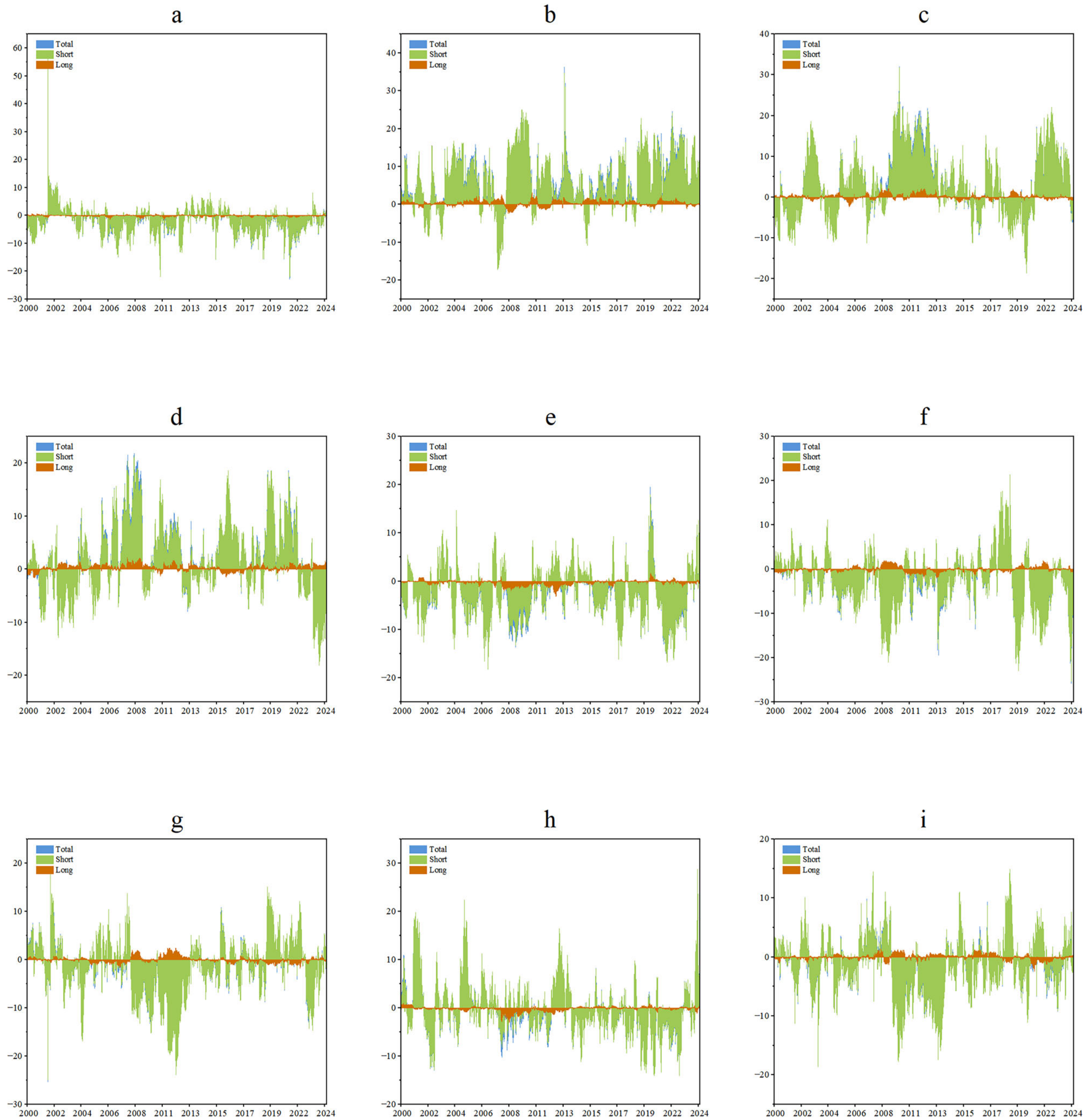

Fig. 11 Net total directed connectedness. a GPR, **b** Corn, **c** Wheat, **d** Soybean, **e** Rough rice, **f** Cotton, **g** Sugar, **h** Cocoa, **i** Coffee.

(TVP-VAR-BK) analysis unveils the complex dynamic relationship between geopolitical risk and international agricultural markets, providing fresh insights into their interactions. Our key findings highlight significant disparities between static and dynamic spillover effects, particularly concerning the roles and influence intensities across various agricultural markets.

Average dynamic connectedness results indicate that corn, wheat, and soybeans occupy central positions within the system, closely tied to their economic significance as globally dominant staple crops. These crops not only experience high international trading volumes but also exert profound impacts on global food security and agricultural economies through their price fluctuations. Corn and wheat, as net transmitters, demonstrate a greater propensity to transmit risks or information to other markets within the network, likely stemming from their extensive interlinkages across agricultural production, trade, and financial systems. Conversely, cotton and rough rice as net receivers reflect their heightened sensitivity to external shocks arising from market structure and price formation mechanisms.

Regarding short- and long-term spillover effects, short-term total connectedness markedly surpasses its long-term counterpart, indicating that interactions between international agricultural markets and geopolitical risk are predominantly driven by short-term shocks. This short-term-dominated dynamic likely relates to the market's immediate reaction mechanism—where rapid responses from market participants to geopolitical events induce near-term price volatility. However, connectedness significantly diminishes over the long term, potentially mirroring the market's adaptive capacity to enduring shocks alongside a gradual loosening of inter-variable relationships. This phenomenon further implies the existence of a market self-regulation capacity that mitigates persistent impacts from external disturbances over extended horizons.

The temporal evolution of the TCI reveals how external event shocks influence the integration degree between the international agricultural market and geopolitical risk system. The outbreak of the 2003 Iraq War, 2008 Global Financial Crisis, and 2020 COVID-19 pandemic all precipitated significant TCI surges, indicating enhanced information spillovers and interactions within the system. These events not only reshaped short-term market volatility patterns but also exerted profound impacts on long-term market structures. Particularly after COVID-19's emergence, substantial TCI growth reflected composite effects from global supply chain disruptions, trade restrictions, and economic stimulus policies. This event-driven connectedness shift underscores the strong interdependency between geopolitical risk and agricultural markets, alongside markets' heightened sensitivity to major crises.

From a frequency-domain perspective, short-term connectedness dynamics contribute more substantially to overall TCI than long-term components, reaffirming short-term shocks' dominant role in systemic transmissions. This short-term-dominated connectedness pattern likely stems from market liquidity, rapid information dissemination, and participants' expectation adjustments. In the immediate term, market participants' swift reactions to geopolitical events trigger pronounced price fluctuations that amplify market connectedness. Over extended horizons, however, markets progressively adapt to new economic environments while inter-variable relationships gradually loosen, consequently diminishing connectedness.

Analysis of net total directional connectedness uncovers evolving roles between geopolitical risk and agricultural markets. Geopolitical risk acted as a net transmitter during 2001–2003 but transitioned predominantly to a net receiver over longer spans. This role shift correlates with transformations in the global geopolitical landscape: increased complexity in international relations and diversified geopolitical conflicts have attenuated direct impacts on markets, channeling influences increasingly through intermediary variables. Conversely, corn, wheat, and soybeans predominantly functioned as net transmitters throughout the observation period, indicating stronger risk propagation capacity attributable to their core positions in agricultural production, trade, and financial systems, coupled with heightened sensitivity to supply-demand dynamics.

Significant volatility peaks in agricultural markets' net directional connectedness consistently followed major crises—notably post-2008 financial crisis and post-2020 pandemic phases. This demonstrates agricultural markets' exceptional vulnerability to extreme events, rooted in sector-specific characteristics: prolonged production cycles induce lagged supply responses to price fluctuations, while deepening financialization complicates participants' risk expectations and speculative behaviors. Consequently, extreme events trigger abrupt NET fluctuations, reflecting markets' rapid response and adjustment mechanisms.

Conclusion

Geopolitical risk is associated with events such as wars, terrorist acts, and political tensions, which affect the normal and peaceful development of international relations. In recent years, geopolitical tensions have become increasingly frequent, with geopolitical risk shocks emerging as significant drivers of volatility and instability in international agricultural markets. This paper selects the Geopolitical Risk Index (GPR Index) and the futures prices of eight major agricultural commodities. The sample period spans from January 2000 to July 2024, encompassing multiple major global events and crises. Methodologically, this study innovatively couples the Cross-Quantilogram (CQ) approach (capturing asymmetric effects of extreme risk shocks) with the Time-Varying Parameter Vector Autoregression Frequency Domain Decomposition (TVP-VAR-BK) model (revealing time-varying network structures and frequency-domain evolution mechanisms of risk spillovers), thereby constructing a dual-dimensional "extreme shock-systemic transmission" analytical framework.

Through the CQ method, we find that the impact of geopolitical risk (GPR) shocks on agricultural futures prices exhibits significant time-lag heterogeneity (Lag = 1, 5, 10) and price-condition heterogeneity (quantile τ), primarily driven by two attributes: financialization attributes and differences in supply elasticity/production cost structures. For food crops, significant short-term positive responses (Lag = 1) emerge, with safe-haven properties prominent in low-price intervals, while financialization gradients determine response intensity (corn > soybeans > rough rice). Economic crops show polarization: sugar displays a "delayed-strengthening" pattern (peak at Lag = 5) due to energy cost transmission, whereas cocoa/coffee exhibit near immunity. Using the TVP-VAR-BK model, we analyze the dynamic connectedness between geopolitical risk and international agricultural markets, revealing their interaction mechanisms across short-term and long-term frequencies: 1. Dominant Role of Core Crops: Corn, wheat, and soybeans occupy central positions in both international agricultural markets and the GPR system, primarily acting as net transmitters during most of the sample period. This indicates these staple crops not only absorb external shocks but also transmit risks/information to other markets. 2.Short- vs. Long-Term Connectedness Differences: Short-term total connectedness significantly exceeds long-term, demonstrating that GPR-agricultural market interactions are predominantly driven by short-term shocks. Rapid market responses to near-term events amplify connectedness, while declining long-term connectedness reflects market adaptability and gradual loosening of variable relationships. 3. Event-Driven Connectedness Shifts: Major geopolitical events (e.g., Iraq War, Global Financial Crisis, COVID-19) substantially elevate the TCI, highlighting their profound impact on market integration. Short-term connectedness surges post-events, whereas long-term connectedness remains relatively stable with minimal contributions. 4.Dynamic Net Directional Connectedness: GPR acted as a net transmitter during 2001–2003 but transitions to a net receiver long-term. Corn, wheat, and soybeans persistently serve as net transmitters, while cotton, rough rice, and sugar predominantly function as net receivers. Agricultural markets exhibit high sensitivity to extreme events (e.g., 2008 crisis, 2020 pandemic), revealing their vulnerability in such contexts.

Based on our research findings, we propose the following policy recommendations: Implement differentiated regulations at the national level by establishing resilient reserve systems; conduct dynamic reserve adjustments for highly financialized crops such as corn and wheat to curb short-term speculative volatility; create energy-price linkage buffer mechanisms for energy-intensive commodities (sugar) to hedge against production cost shocks. Concurrently, strengthen crisis response networks through tiered early-warning mechanisms, enabling real-time monitoring of systemic risk transmission based on risk spillover hierarchy networks. Enhance supply chain resilience for net-receiver crops like rough rice and cotton (e.g., through distributed storage) to reduce vulnerability to exogenous shocks.At the international cooperation level, innovate collaborative risk-response platforms by establishing an FAO-based alliance to monitor short-term capital flows, thereby suppressing cross-market speculation during crisis events. Create an International Stabilization Fund for Energy-Dependent Crops (sugar) to alleviate transmission pressures induced by GPR. Additionally, developing countries should introduce precision agriculture technologies from developed nations to weaken terminal supply-chain risks, while jointly constructing cross-border agricultural logistics information chains among nations to shorten market rebalancing cycles during geopolitical conflicts.

In future research, we will deepen our methodology by integrating Social Network Analysis (SNA) with TVP-VAR-BK to decode the structural roles of nodes in risk spillover networks, incorporating machine learning methods (e.g., LSTM) to capture nonlinear transmission pathways. Building upon this foundation, we will also conduct cross-market extensions by embedding energy and financial derivatives market variables to construct a third-order GPR-Energy-Agriculture spillover network, achieving more comprehensive cross-market integrated analysis.

Data availability

All data generated or analysed during this study are included in this published article and its supplementary information files.

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Author contributions

X.R. made the most significant contribution to this manuscript and pioneered the practice of Cross-quantilogram method in this manuscript. The main body of the manuscript was completed by X.R., including: 1. The main part of Introduction section 2. Half of the Methodology, Results and Discussion sections 3. The entire Conclusion section. Additionally, visual and tabular materials (Figs. 2–9 and Table 1) were exclusively created by X.R. T.W. made the second most significant contribution to this manuscript. During the preparatory phase, he was responsible for data collection and pioneered the introduction of the TVP-VAR-BK method, which was comprehensively integrated into our manuscript. In terms of writing, he completed part of introduction section and half of the Methodology, Results and Discussion sections. Additionally, visual and tabular materials (Figs. 1, 10, 11 and Tables 2–4) were exclusively created by T.W. Z.L. was responsible for the literature review and the subsequent revision work of the literature review part. He also offered many constructive suggestions during the initial preparatory work. H.X. assisted T.W. to collect and analysis relevant data during the preparatory phase. He also supplemented and optimized the writing part of this article, and completed the art designer work for the manuscript. The subsequent revision and improvement of the article was mainly done by X.R. and T.W.

Competing interests

The authors declare no competing interests.

Ethical approval

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Additional information

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Correspondence and requests for materials should be addressed to Xinghan Ren.